Convergence Of Artificial Intelligence And Internet Of Things In Predictive Maintenance Systems – A Review

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Abstract— Operations and Maintenance costs have always posed a heavy burden in wind turbines and the main aspects in spending are on unplanned unscheduled breakdowns, repairs and down time costs. Technology enhancements with connectivity between wind farms and operations control center would reduce risk and improve efficiency during maintenance by continuously analysing the data acquired. Digital solutions of industrial internet of things and machine learning have made inroads and are the real game changers with the potential to supervise, predict and prevent catastrophic failures. Generating the insights from the data to understand the wear pattern and to formulate replacement strategies for reducing frequent maintenance costs and to increase the production. This paper shall discuss and review about the prognostics and diagnostics of the wind turbines, machine learning algorithms, identifying their inter-dependency within the subsystems and the available digital solutions for effective handling of data in predictive maintenance schedules.

Keywords— condition monitoring;Industrial IoT;predictive maintenance;fault diagnosis;machine learning;prognostics;

INTRODUCTION

Wind power is one of the fastest-growing renewable energy technologies due to multi-fold increase in energy generation capacities both at onshore and offshore. According to International Renewable Energy Agency [1], almost 75% of new electricity generation capacity built in 2019 uses renewable energy, out of which wind energy accounts to 25% as shown in the Figure-1. Latest data from IRENA shows solar, wind and other green technologies provide more than one-third of the world's power.

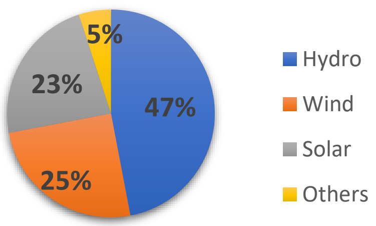

Figure-1: Renewable energy generation capacity

Renewable energy generation capacity is increased by 7.4% in 2019 of which solar along with wind energy continued to lead capacity expansion by 20%, and 10% respectively. These are the two sources of energy that are growing with a pace. India too is experiencing an exponential growth [2] in the production capacity from the onshore wind turbines (WT) as shown in the Figure-2.

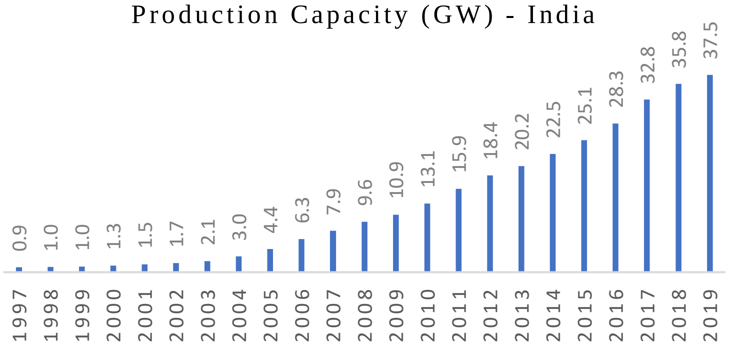

Figure-2: Production capacity of wind energy in India

II. BACKGROUND STUDY

The challenges faced during the operation and maintenance at wind farms with number of wind turbines scattered and positioned in remote areas has been exceedingly difficult for a quick access and is also expensive. The wind energy industry typically follows reactive maintenance approach or run-to-failure maintenance. This form of maintenance has been the most critical practice available to operators. Reactive maintenance work costs four to five times as much as proactively replacing worn and damaged parts. When an equipment fails due to lack of awareness of degraded performance there may incur immediate costs because of insufficient productivity, inventory backup, delay in replacing the parts. Preventive maintenance is another scheduled periodic maintenance which enables a routine check up of wearable components at prefixed intervals. The breakdown of the different types of maintenance [3] have been stated in the Figure-3 and briefed in the Table-1.

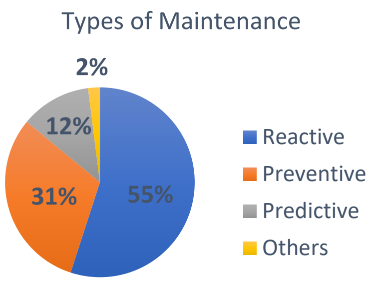

Figure-3: Types of maintenance

Maintenance	Description
Reactive Maintenance	▪ Allows components/assembly to run to failure ▪ Catastrophic failure which may lead to collateral damage ▪ High risk due to higher downtime ▪ High maintenance cost ▪ May lead to damage other sub-assemblies
Preventive Maintenance	▪ Prevents failure before they occur ▪ Chances of catastrophic failure is less ▪ Lower risk and lower downtime ▪ Less chances of damaging other sub-assemblies
Predictive Maintenance	▪ Full asset visibility ▪ Initial cost to benefit is high ▪ Early detection of wear and tear in components/assembly ▪ Increases asset life cycle ▪ Lowest downtime ▪ Significant reduction/complete elimination of unscheduled breakdowns.

Table 1: Features of different types of maintenance

Sudden failures can also happen due to higher wind loads in times of strong seasonal winds. The wear damage of components, dry or water contaminated lubrication, transient loads with sudden accelerations and finally uneven load sharing are the causes of high edge stresses. If early detection or preventive action is not in operation this may lead to plant shutdown causing heavy expenditure and hampering production.

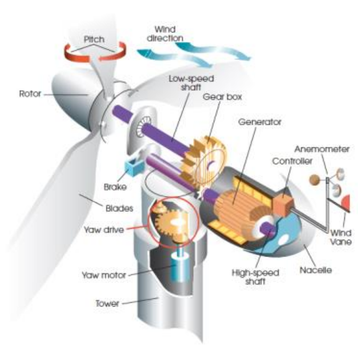

Figure-4: Components of a horizontal axis wind turbine

The different parts of the horizontal axis wind turbine [4] are shown in Figure-4 that are prone to wear and tear that require continuous monitoring such as tower, generator, gearbox, rotor, blades and the drive train. A review [5] enlists the rate of failures for the gearbox, generator, and blades that contribute huge downtimes as shown in Figure-5 both in offshore and onshore.

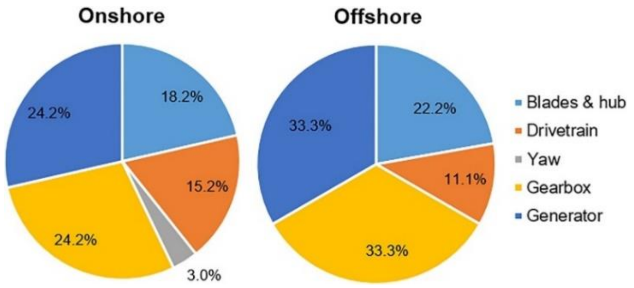

Figure-5: Critical components of onshore and offshore wind turbines

The overview of the components in the gearbox that frequently fail [6] have been shown in Figure-6.

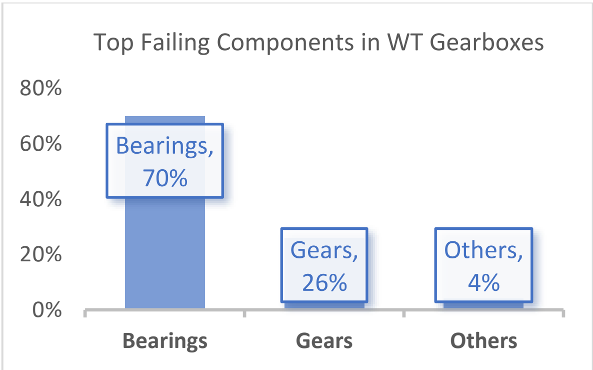

Figure-6: Top failing components in wind turbine gearboxes

Wind turbines do have commonly arising faults in its tower, nacelle and sub-assemblies as depicted in the Figure-7.

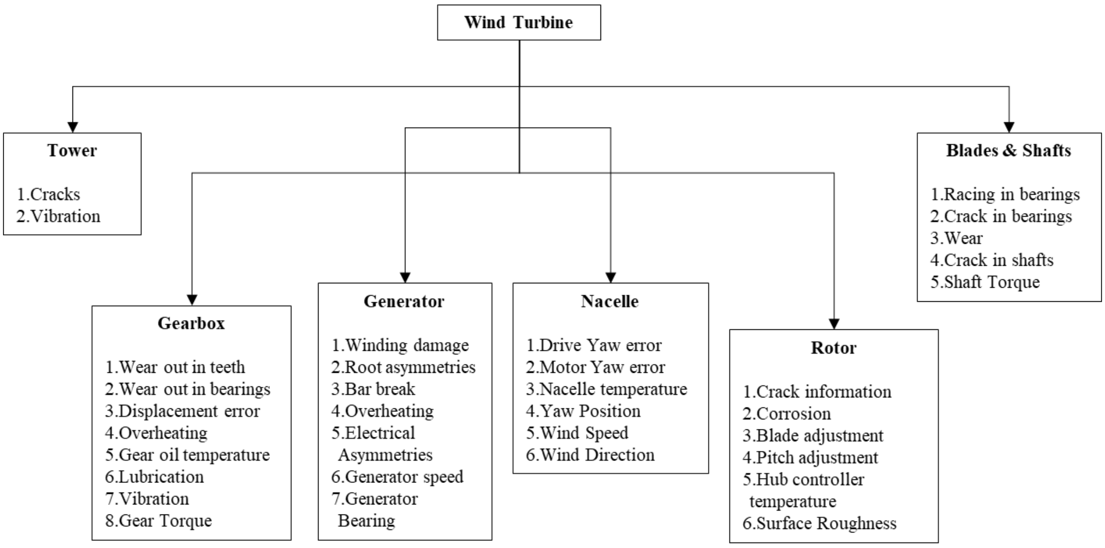

Figure-7: Commonly arising faults in different parts of the wind turbine

Traditional Predictive Maintenance (PdM) using SCADA with limited sensor data that enables threshold setpoint limits for notifications to operators. Traditional PdM has a few limitations – (1) root cause of the failure due to unknown circumstances and sources; (2) lack of visibility due to downtime, reducing the efficiency (3) Monitoring the asset is only local. With the recent advent of Industry 4.0, IoT enabled PdM reduces the Operation & Maintenance (O&M) costs with an increased life of the devices and continuous production yield of wind energy. Detailed insights of the devices can be analyzed by using Artificial Intelligence (AI) based on their execution patterns both in normal working conditions as well as abnormal working conditions.

Industrial IoT (IIoT) along with AI assists in consistent observation of the machines detecting the wear conditions and enable the technician schedule repairs and thus reduce downtime. Technology explosion with Industry 4.0 solutions has brought several changes and challenges in remote monitoring and remote data collection. IoT edge devices can be used to monitor and acquire instantaneous reports that leads to analysing and detecting the abnormal behaviour in the set parameters. These generated reports at specified intervals can be evaluated by experts and the action team to formulate strategies for predictive and preventive action and to reduce huge down time costs. To avoid sudden catastrophic failures of a component in a system and subsequent breakdown cost and loss of time involved, Condition Monitoring Systems (CMS) is a deployable early warning system for the preventable failures and is similar to predictive maintenance which relies on sensors data to predict any failure or remaining useful life of the device.

With the advancements in Industrial IoT and Machine Learning (ML), predictive maintenance has taken a pivotal role in adopting the above technologies for an increase in operating efficiencies. Recently, Deep Learning (DL) models have also been explored and evaluated for the same. PdM was highlighted as one of the primary applications in IIoT [7] and continue to dominate. Analysts such as Gartner, PwC have made strong forecasts of potential success and identified the critical success factors [8] as shown in the Figure-8.

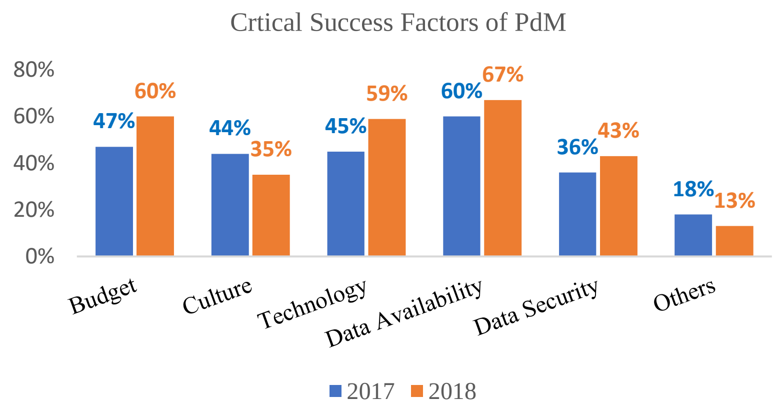

Figure-8: Critical Success Factors of IIoT enabled PdM

Majority of the analysts and researchers in their reports have commonly highlighted that PdM would benefit in reducing the maintenance costs, breakdown costs downtime costs together with an increased production, extended lifetime and optimum return on investment (ROI). A study [9] unveils IoT enabled predictive maintenance prevents equipment devices from malfunctioning, while 44% of the manufacturers have already deployed, and another 27% are planning to do in the near future. The different fault signals considered for the CMS of a wind turbine have been enlisted in Table-2 with respect to the different sub systems. These have been collated together both from field study as well as a few literatures [10].

	Different Signals for Fault Prognostics			
Parts of Wind Turbine	**Vibration**	**Current**	**Thermal**	**Acoustic**
Blades	þ	þ	þ	þ
Shaft	þ	þ	þ	
Bearing	þ	þ	þ	
Gearbox	þ	þ	þ	
Braking System		þ	þ	
Generator		þ	þ	
Tower	þ			þ

Table-2: Different signals considered for fault prognostics of different parts of the wind turbine.

III. ENABLING TECHNOLOGIES FOR PREDICTIVE MAINTENANCE

With CMS in place the data indicators warn the deterioration of key components and the likely decrease/failure in performance of the equipment in advance. Furthermore, they act as troubleshooters through real time messaging and real time monitoring.

Recently AI and ML have been the most popular, widely accepted and adopted technologies to analyse in several applications:

- Automatic fault detection by recognizing the fault patterns and associating them together.

- Detection of faults at an early stage for a cost-effective planning maintenance keeping the systems operational and improve production capacity.
- Prognostics in calculating the remaining useful life of the wind turbine components.

ML / DL Model	System Device Data Description	Sensors used to monitor	Major Insights (Reference with *)	Applications for PdM	References
RF	Wind turbine	Accelerometer	▪ Predictive models generated upon processing the historical wind turbine data using big data frameworks. ▪ Experimentation and evaluations achieved optimum level of success.	Condition Monitoring	[*12, 13, 14, 15, 16]
k-NN	Bearings	Accelerometer	▪ Applied Mahalanobis distance with KNN classifier as an improvised manifold learning approach instead of default Euclidean distance. ▪ Classification of bearing faults normal and racing were analyzed in both time and frequency domain.	Fault Diagnosis	[20, *26, 27, 28, 29]
SVM	Wind turbine	Accelerometer	▪ Applied SVM and SVR along with Hilbert Huang transform to classify the faults and determine the remaining useful life of the bearings.	Condition Monitoring, Fault Diagnosis, Remaining Useful Life	[*23, 24, 25]
SVM, k-Means, k-NN,	Bearings	Accelerometer, Displacement, Velocity, torque	▪ Evaluated multiple ML models for bearing fault classification. ▪ Investigated similarity of models and proposed collaborative recommendation approach that can recommend with 93% accuracy.	Condition Monitoring, Fault Diagnosis	[*20, 30]
ANN	Wind turbine	Accelerometer	▪ Evaluated the time domain vibration signatures for critical components. ▪ Healthy and faulty condition vibration signature have been analyzed by using ANN classification model achieving an accuracy of 92.6%.	Condition Monitoring, Fault Diagnosis	[*17, 21]
CNN	Bearings, Vibration signals data	Accelerometer	▪ CNN model applied on image representation of vibration signals of bearings and classifying their faults. ▪ Three time-frequency analysis methods (STFT, WT, and HHT) were compared and respective image representations of the vibration signals have been evaluated in 2 different image dimensions.	Fault Diagnosis	[18, *22]

ML / DL Model	System Device Data Description	Sensors used to monitor	Major Insights (Reference with *)	Applications for PdM	References
			▪ High performance of 99.9% has been showcased.		
LSTM	Gearbox	Vibration	▪ Investigated LSTM with different activation functions (Sigmoid, tanh, ReLU) and optimized with multiple Swarm Intelligence algorithms (ACO, FA, CSO, PSO) in a hybrid approach. ▪ Detail observations have been analyzed herewith for 10 different loads to classify healthy or broken tooth condition of gears. ▪ Compared the hybrid LSTM results with conventional LSTM. ▪ This hybrid deep learning approach achieved highest accuracy of 87.5.	Condition Monitoring, Fault Diagnosis	[*31]

Table-3: Summary of few ML and DL models widely used for predictive maintenance applications.
(* - Reference cited explained in brief among the other references enlisted that are closely related to similar models.)

Vibration analysis is performed to evaluate the performance of non-stationary components and is widely used for condition monitoring of bearings (gearbox bearings and generator bearings) blades and tower of wind turbines. A variety of AI models have been explored and investigated on vibration analysis approach more on bearings and gearbox that frequently fail with different types of sensors on wind turbines. Random Forest (RF), Support Vector Machine (SVM), Artificial neural Network (ANN) are few of the extensively used machine learning models and recently Convolutional Neural Network (CNN) and Long-short Term Memory (LSTM) are few of the extensively applied deep learning algorithms widely applied for PdM of wind turbines. Recently, the AI models are evaluated more in a hybrid approach with swarm intelligence algorithms. A research [26] showcases how different activation functions of the LSTM model have been optimized with Ant Colony optimization (ACO), Cuckoo Search Optimization (CSO), Firefly Algorithm (FA) and Particle Swarm Optimization (PSO) to derive the condition of the gears in a gearbox of the wind turbine. Table-3 enlists Summary of few ML and DL models widely applied for predictive maintenance applications.

The COVID-19 pandemic has been the primary driver to increase the need of adoption of AI and ML for the IoT digital initiatives in most of the recent industrial and manufacturing use cases. This has been increasing rapidly during this period with heighted need of digitization. One of the surveys [32] in the year 2020 states 69% of the respondents have been using the AI and ML in their IoT deployments. Further, 41% increase in budget has been anticipated by the end of 2020 and 51% expected an increase by the first quarter of 2021.

The most emerging technologies of AI in the applications of PdM are – Big data and Transfer learning. Big data technologies enable collection, storage and process large volumes of data. It can also indicate the condition of the equipment based on vibration, current signatures, acoustic, temperature and lubrication including thermal images. Big data enables to derive the insights, develop, and deploy PdM systems, that supports plant operators for timely accurate estimation of lifecycle parameters together with the remaining useful life of the equipment.

A research [12, 19] states how big data analytics approach has been applied for PdM of wind turbines. Adoption of the big data application frameworks improves in accessing the historical data storing it in the cloud. This helps in providing the ability to scale up the computing and processing the data of multiple wind turbines in a fault-tolerant manner. The concept of prognostics and health management has been playing a significant role in performing the analysis of industrial big data and smart manufacturing. In addition, it helps in monitoring the health status of the industrial equipment too [33].

Transfer learning enables the AI models to acquire the knowledge from one system and apply it on another system by quickly adapting the parameters. A study [34] exhibited a novel versatile inductive exchange learning technique for wind turbine ice recognition. The information move is accomplished by offering a moderately steady expectation for target task through the built-up model prepared in source task.

In addition to AI, few other emerging technologies in IoT have taken in-roads with condition monitoring - Digital Twins and Edge Computing and an amalgamation of AI and IoT can also be applied as well. According to a survey by Gartner in 2020 [35], a quote by Lheureux states -

> "Digital twins can help companies recognize equipment failures before they stall production, allowing repairs to be made early or at less cost. Or a company can use digital twins to automatically schedule the repair of multiple pieces of equipment in a manner that minimizes impact to operations."

A review [36] proposed a digital twin-based methodology for remaining useful life prediction of fixed and floating offshore wind turbines by considering the influencing factors of thermal loads due to environmental condition and electrical system. The adoption of digital twin methodology helps to improve the capability of the wind turbine during the generation of energy. This assists to improve the remote asset monitoring and to reduce the frequency of in-person monitoring.

Edge computing has been widely used in industrial IoT despite cloud being present. AI on the edge is the highest edge computing workload in comparison to the data acquisition, sensing, and actuators. Challenges in leveraging the AI on the edge devices are understanding and interpreting the data. Recently, fog computing devices have been in place between the edge nodes and the cloud. There are certain use cases where edge nodes may not be able to directly relay the data to cloud due to less transmission power or non-availability of consistent continuous network. In such cases, edge devices relay the data to the nearest routing devices (known as fog nodes) from which the data shall be periodically relayed to the cloud.

The local control units connected to the machinery terminal units widely known as edge nodes to the towers and inside the nacelle at the wind turbine can be made intelligent enough to detect and diagnose on its own and take some action to reduce the huge down time costs. Identifying the inter-dependency of the parameters within a subsystem to state the present health condition of the wind turbines, rectification, and likely behavior pattern. The study of behavior pattern of different devices and subsystems shall be monitored and evaluated to perform health monitoring of the wind turbines.

Few of the top IoT platforms widely used in the industry for predictive maintenance applications [37] have been listed here in the Table-4. In addition to them there do exist few other proprietary industrial IoT platforms.

S No	IoT platforms	Description
1.	Siemens MindSphere	A cloud based IoT operating system that establishes connectivity and harness data from the physical assets.
2.	GE Predix – Asset Performance Management (APM)	An IIoT platform for handling industrial data from edge to cloud with big data processing along with analytics and machine learning. APM is a software suite to optimise the performance of the industrial assets.
3.	IBM Predictive Maintenance and Quality (PMQ)	This helps to monitor, analyse, and report the equipment data enabled by cognitive intelligence engine IBM Watson.
4.	Microsoft Azure IoT Hub	A managed platform as service developed by Microsoft.
5.	AWS IoT Core	A managed service that is used for IoT on Amazon Web Services (AWS).
6.	Google Cloud IoT Core	A managed service that is used for IoT on Google Cloud Platform (GCP).
7.	Presenso	A Cloud platform widely used for real time for predictive asset management.
8.	PTC ThingWorx	Application development in IIoT platform that can be leveraged to carry out predictive maintenance and other IIoT applications.
9.	MATLAB Predictive Maintenance toolbox	Analyse and label sensor data from local as well as cloud storages and estimating the remaining useful life of the devices.
10.	Bosch IoT Suite	A platform as a service with a set of cloud services and software packages for development of IoT applications.
11.	Hitachi Lumada	IoT techniques significantly improve maintenance efficiency, asset availability and lifetime value both computing at networks and operating at the utility or device level.
12.	Honeywell Forge APM	Asset performance management in real-time, machinery analytics solution to monitor the assets health performance,

S No	IoT platforms	Description
		issues and deterioration and predicting the remaining useful life.
13.	ABB Ability	Digital technology with remote support to wind turbines by increasing turbine uptime and lower the O&M costs.

Table-4: Top IoT platforms used for predictive maintenance.

CONCLUSION

This review paper discussed and highlighted the frequent operational failures that occur in wind turbines and its sub systems. Technologies that can be applied for monitoring wind turbines such as internet of things and artificial intelligence to analyze the data and their amalgamation has been discussed for predictive maintenance to formulate schedules and strategies. Key points about the different AI models and methods applied for deriving the insights from the condition monitoring systems of wind turbines were reviewed. Few widely used industrial IoT platforms for predictive maintenance applications were enlisted. A few facts and statistics of the predictive maintenance have also been shared. The wind turbine industry should interpolate effective use of data to maximize generation and reduce operating maintenance costs.

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