Review

A heuristic approach on predictive maintenance techniques: Limitations and scope

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Abstract
In view of the trend towards Industry 4.0, intelligent predictive monitoring and decision-making processes have become a crucial requirement in today's manufacturing industries to safeguard data exchange and industrial assets from damage that would thus prevent the achievement of overall company goals. For enhanced reliability and safe operation of machines, frequent maintenance of the process equipment and the linked auxiliaries in a plant is highly desirable. Poor maintenance of assets can add to downtime, which can in turn affect the overall cost-effectiveness of the plant. With traditional maintenance strategies and planned or timed-based maintenance, one replaces the faulty systems when they are found to be damaged or broken. However, an early and proactive prediction of machine or equipment fault and failure state enables the industry to take the necessary action to replace the faulty system well before it stops operating entirely. This paper briefly reviews the available predictive maintenance techniques for different applications from the perspective of Industry 4.0. Furthermore, the associated challenges and opportunities are identified and discussed.

Introduction

Industrial revolution is currently in its so-called fourth generation (also referred to as 'Industry 4.0'). From its inception in the mid-18th century, the revolution has been gaining strength and has now spread worldwide. Industry 1.0, or the first industrial revolution, resulted in the transition of manual labour to mechanisation through the usage of water and steam power. Textile industries were the first to implement this strategy, and this transformation spread throughout Europe (including British industries) and the United States. The successful handling of machine works prompted other industries such as agriculture, mining, and the iron industry to adopt these strategies, thus resulting in a greater extent of machine usage.[1]

Industry 2.0, or the second industrial revolution, extended from the late 19th century to the beginning of the 20th century. This revolution was marked by technological advancements in the field of telegraph and transportation, which facilitated easy movement of the masses. Electricity was introduced for use in production lines. Mass production strategies were implemented, which boosted the industrial economy and productivity. The only major drawback was that unemployment was at its peak as many manual labour jobs became mechanised.[1,2]

Industry 3.0, or the third industrial revolution, showed its importance in the post-war scenario of the

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late 20th century. This era marked the beginning of digitisation. Automation, supercomputers, and wireless communication technologies were employed in production lines, which had a dynamic role in an increased overall productivity and efficacy of machines and their components. Machines dominated production lines, performing menial and repetitive jobs with extremely low error rates.[2]

Industry 4.0 (IR4.0), or the current fourth industrial revolution, perceives the extensive employment of cyber-physical systems to monitor the working of virtual systems in line with physical ones. These systems are capable of decision making and prediction, taking an autonomous approach to efficiently deliver highly scalable, valuable, and optimised products.[3]

IR4.0 system, comprises of four main components[4]

- Internet-of-Things (IoT) or Industrial Internet of Things (IIoT)
- Cognitive computerised systems
- Cyber-physical system
- Cloud-based system

Figure 1. Typical technologies linked with IR 4.0.

Subsets of the above-listed systems include mobile or handheld devices, GPS or location-tracking systems, human-machine interfaces, robots, cybersecurity, 3D printing, analytic and advanced computer algorithms, remote monitoring, augmented reality, visualisation, fault detection, etc.[5,6]

The core functioning of IR 4.0 can be classified as:

- Digitisation of industrial assets.
- Digitisation of product- and service-centric markets.
- Digitisation of client/consumer systems.[7]

In a nutshell, Industry 4.0 is intended to ensure the smooth transition of data and automation among the systems in the manufacturing processes through the use of major technological components, as mentioned previously. In the present era, artificial intelligence has played a hugely significant role in leveraging the 'smart factory', which efficiently takes decentralised decisions. Predictive maintenance equipped with advanced technologies and smart sensor networks, which can predict faults and failures while machines are in operation, has also been made possible because of Industry 4.0. Employing such a technology helps to provide cost-effective and optimised methods for detecting failures well before the machine or system failure occurs. Figure 1 outlines the Industry 4.0 usage.

Building such an advantageous system in the manufacturing industries is also fraught with challenges. High maintenance costs, adaptability of business models, unemployment, lack of certification and regulations, reliability issues and deficient skills amongst
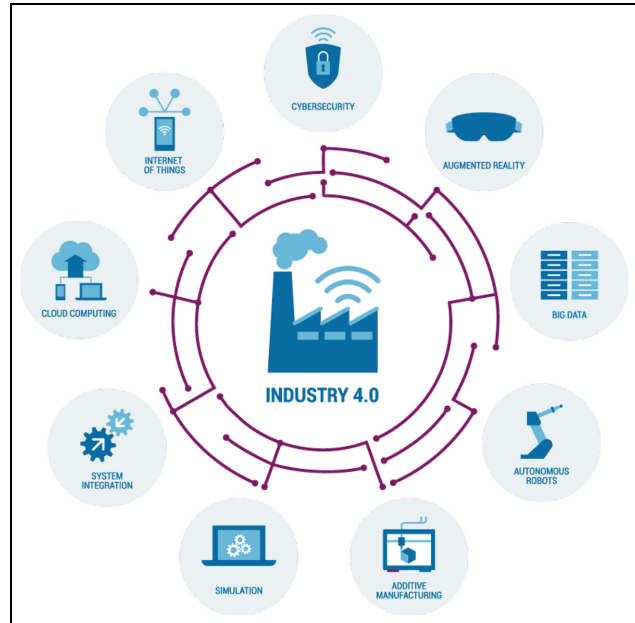
operators are just some of the challenges that the researchers and technologists from all walks of life are attempting to resolve. One of the sectors that has witnessed all the transitions of the industrial revolution is the manufacturing or production industry. With advancements in the usage of machines in the production lines, there is an urgent need for their proper maintenance to ensure smooth operation, efficiency of the machines, on-demand and continuous manufacturing, and a low-cost impact of undesirable downtime.[8]

Maintenance costs make up between 15% and 60% of the manufacturing cost of the finished product. For heavy industries, this cost is even greater and can be as high as 50% of the total production cost. This data helps us to understand why there is the utmost need to maintain the machines and their components used in the production line. For example, a bench press machine having a stoppage time of 5 min/h leads to a downtime of 40 min in an 8-h shift. For a production at the rate of 14 units/min, this amounts to 560 pieces in loss of production for a short stoppage of 5 min in a day shift. This number gives a glimpse of how production downtime can lead to a disastrous number of unit losses to the production company, thereby adding to the direct cost of the production of finished products.[9]

Ineffective maintenance management strategies result in undesirable losses that lead to unreliability and the inability to provide quality finished products. One of the major reasons for this issue is incorrect or missing data on running conditions, stability, troubleshooting, and maintenance of the plants and the provided machinery.[10]
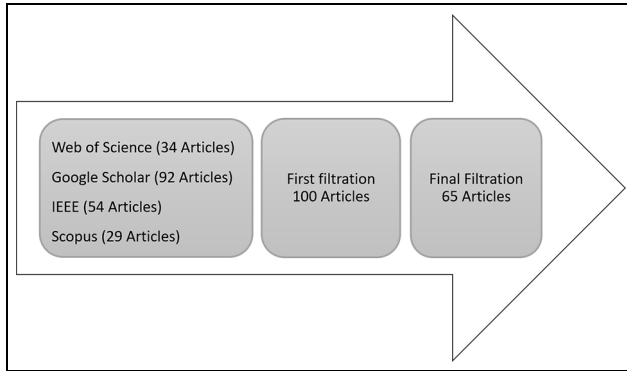
Figure 2. Filtering process of relevant articles.

Figure 3. Different maintenance strategies.

Search strategy

In this review paper, the authors have investigated different predictive maintenance strategies along with the usage of technologies. Different state-of-the-art systems were studied looking through journals available online. 'Web of Science', 'Google Scholar', 'Scopus' and 'IEEE' were the main platforms through which the review was conducted. Different search strings such as 'predictive + maintenance', 'vibration + monitoring', 'predictive + analysis', 'Industry + 4.0' were passed to find the most relevant papers. Over 200 papers from 1996 onwards were considered in the selection process. The emphasis was placed on papers which were published in the last 5 years. 100 relevant papers were filtered to match additional keywords with 'Machine + learning', 'Artificial + Neural + Network', 'Thermography', 'Deep + Learning'. Further analysis of these papers yielded 65 potential articles. On detailed reading, these papers became the basis of this review article to determine the challenges and future scope for researchers. Figure 2 represents the filtration process of the relevant articles for review.

In this paper, section 3 reviews the different maintenance strategies, both past and present, employed by manufacturing and production lines. Section 4 describes the various techniques used to perform efficient maintenance. Section 5 presents the challenges faced and the solutions provided by researchers for different modelling frameworks. Section 6 summarises the major challenges and presents the conclusions.

Maintenance strategies

The development and implementation of predictive maintenance is not a new concept but is often complicated by the challenges faced by the various widely used maintenance management strategies. Typical maintenance strategies are broadly described in Figure 3.
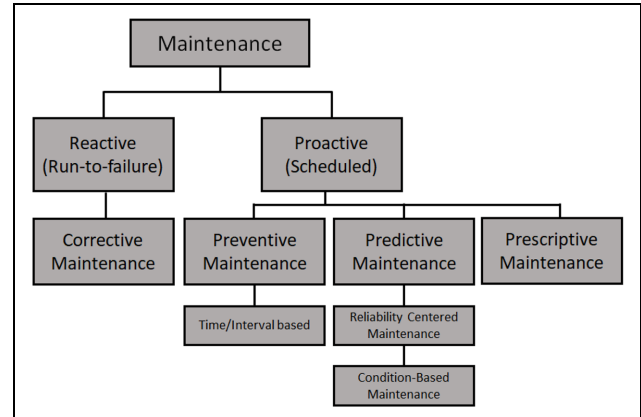
Run-to-failure management

This management strategy basically means that as long as the machine keeps running, there is no need to fix it. This method is simple and reasonable as the management does not have to invest anything until a productive machine stops completely. The only exceptions are certain basic precautions such as oil lubrication and minor operational adjustments that are performed in a proactive manner. This strategy falls under the reactive type, which is also considered a 'no-maintenance' policy form of management. Reactive maintenance is the strategy in which maintenance-related decisions are taken after a breakdown occurs. On further consideration of this tactic, it is evident that the management waits to perform maintenance until a failure of a components, or components, arises. However, this is the costliest maintenance strategy, where these costs are attributed to the spare parts inventory, overtime costs to fix the issue, and associated low production output.[9,10]

Preventive maintenance

The challenges faced in the run-to-failure type of maintenance led to the refinement of the strategy to encompass time-based or time-driven maintenance. These refer to maintenance activities scheduled in a timely manner based on the operational complexities and total cycle time of the equipment that has been running since the inception of the overall process. The bathtub curve or the mean-time-to-failure (MTTF) in Figure 4 depicts the performance of a machine during its lifetime.

From the graph, it is evident that the probability of equipment failing is the highest at the start of the operating cycle because numerous adjustments, rearrangements, and fine-tuning of the equipment will be carried out during this period. As the phase of initial arrangement passes, the probability of failure decreases with time, and the machine or equipment tends to perform
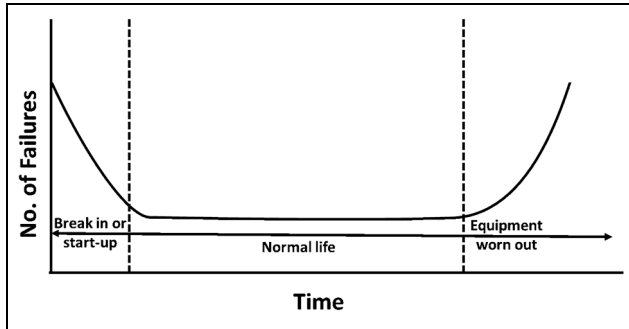
Figure 4. Bathtub curve of a machine train.

Figure 5. Predictive maintenance – event criticality.

in a stable manner until it reaches the end of its normal lifecycle. However, once the normal phase is exceeded, the probability of equipment failure starts to increase. In this phase, the equipment or the sub-components start to degrade and thus fail to operate.

With the preventive maintenance strategy, the machine or equipment is taken offline and under maintenance before the probability of its failure becomes too likely. This scenario could be understood using a similar graph for the equipment drawn to the chart given in Figure 4. The only challenge here is that the graphs are drawn with the assumption that the machine will only fail after a certain timeframe. However, many dynamics, such as the actual manner of operation and maintenance activities performed over the lifetime, can alter the true performance of the equipment and result in its failure before the highest probability of the occurrence of a failure is reached.[9,10]

Among all the preventive maintenance strategies, Condition-Based Maintenance (CBM) is the most widely used tactic. As the name suggests, this maintenance activity involves monitoring different real-time parameters of the process conditions over a period of time in terms of events and alarm situations. By measuring the wear and tear of the system components and measuring the failure states exceeding the permissible engineering limits, potential failure conditions can be diagnosed and sent to the supervisory or decision-making team for record purposes.[11]

Predictive maintenance

In contrast to the preventive maintenance strategy, which relies on statistical data, predictive maintenance monitors factual data from the plant assets, their overall health conditions, efficiency, capacity and optimum policies so as to decide when the machine or system will fail. These data are monitored by operators, supervisors and management, where action taken in a timely manner helps minimise unscheduled breakdowns of overall plant assets. This tactic provides a platform for
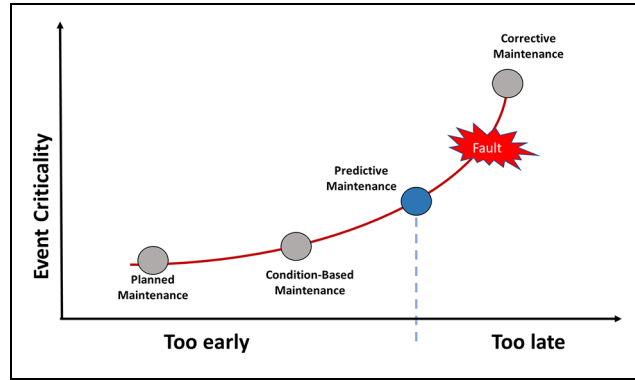
the management to detect and predict failure states before the associated issues become serious.

For instance, in a mechanical system, monitoring vibrations is crucial to the recognition of common failures since all components within the system have their unique vibration frequency patterns which can be easily isolated and then examined. Additionally, the individual amplitudes of these vibrating components will remain constant until and unless there is a change in the total operating dynamics of a particular component present within that system. These data are crucial to root cause analysis and deriving failure modes according to the cause and effect of these components.

As seen in Figure 5, predictive maintenance helps to establish a maintenance requirement only when a breakdown of the system occurs. This approach results in optimum maintenance policies and helps industries to sustain the overall health of their assets with minimal downtime.[10,12]

In general, five non-destructive techniques have historically been employed for predictive maintenance, which include machine or system vibration monitoring, monitoring of plant parameters, tribology, thermography and visual inspection. These techniques are unique in the sense that each one provides sufficient data to address any maintenance requirements through notifying the maintenance supervisor and the management board.

Prescriptive maintenance

Prescriptive maintenance is an evolving strategy that has gained in importance in recent business value technology and can be described in many ways. It operates in such a way as to progress to predictive maintenance to forecast a failure in a system or an asset, and provides details to technicians about how to organise the information and control the detected faults or failures. This type of maintenance is based on the incorporation of an intelligent framework that helps to define and

ISO 2372 – ISO Guideline for Machinery Vibration Severity					
Ranges of vibration Severity		**Examples of quality judgment for separate classes of machines**			
Velocity – in/s - Peak	Velocity – mm/s - rms	Class I	Class II	Class III	Class IV
0.015	0.28				
0.025	0.45				
0.039	0.71				
0.062	1.12				
0.099	1.8				
0.154	2.8				
0.248	4.5				
0.392	7.1				
0.617	11.2				
0.993	18				
1.54	28				
2.48	45				
3.94	71				

A – Good
B – Acceptable
C – Still Acceptable
D – Not Acceptable

Figure 6. Vibration standard – ISO 2372.

organise solutions for managing faults. However, it is not an end-to-end maintenance solution, but rather only a part of such.

According to Miklovic, in prescriptive maintenance the system itself informs the operators when it needs to be fixed rather than experts deciding when such assets must be maintained. The operators are guided by the prescriptive analytics, which are developed by exploiting various machine learning tools, with regard to the procedures to be followed for effect repairs. The most important aspect of this tool is its unique capability to access various data sources and make predictions with the help of visualisation. With the use of data analytics, by analysing multiple historical trending data and understanding the root cause of an issue, the prescription generated from the diagnosis should help to control any failures.[13,14]

Various predictive maintenance techniques

Vibration monitoring

Most components under inspection or maintenance are mechanical in nature. Vibration monitoring is the most generic methodology used for analysis. Monitoring the vibrations of machines can help in root cause analysis of probable failures. Rotating equipment usually operates at a very high frequency, and these systems are frequently subjected to extensive wear and tear. During machine operation, heavily vibrating components face direct impacts such as damage, misalignment, and loosening of parts, thereby causing eccentricity in connected systems. Analysing the vibration amplitude in different frequency ranges can help in fault diagnosis. The allowable tolerance range of vibrations with increasing running speed of a shaft in a piece of rotating equipment, as per ISO 2372 standards, is shown in Figure 6.[15,16]

In 2013,[17] discussed vibration analysis using the classical Fast Fourier Transform (FFT) method. In their analysis, the authors have taken defects such as unbalanced rotary parts, loosened machine components, gear defects, and misaligned gear coupling into consideration, and indeed their results were subsequently validated. In 2016,[18] employed vibration signal analysis, behavioural patterns of bearings in wind turbines have been studied with machine learning models that included the Support Vector Machine (SVM) and k-Nearest Neighbour (k-NN). In 2019,[19] assumed an advancement approach to smart maintenance and applied IoT-enabled sensors to overcome some gaps in the methods that are commonly used for condition
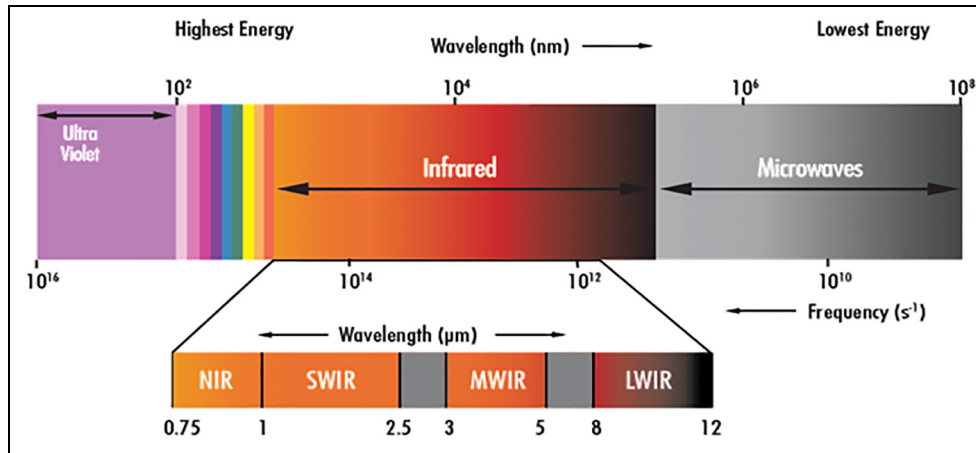
Figure 7. The electromagnetic spectrum.[24]

monitoring of rotating machinery. The researchers effectively demonstrated the usage of predictive maintenance in their study. Along with the Backpropagation Neural Network models discussed in 2020,[20] advanced neural network methodologies such as the Convolutional Neural Network (CNN) have also been implemented for Assets Predictive Maintenance.[21] Some of the listed references related to the architecture of smart and predictive maintenance systems are well aligned with IR 4.0 principles. In 2020,[22] which considered the shipping industry, a model that employed monitoring data from a real-time system grounded on computational machine learning methodology was explored, and the advancement of a predictive maintenance resolution to this challenge was presented.

Vibration analysis has been proven to be the most effective and powerful predictive maintenance methodology, also in terms of return of investment (ROI), in particular when used with a diagnostic decision-making system focussed on both system operation and process criticality.

Thermography

Thermography is another widely used predictive maintenance methodology. Instruments such as infrared sensors for temperature measurement, line scanners, and infrared imaging methods are employed to monitor the overall health condition and events in equipment. Infrared servicing is based on the principle that all objects emit energy or radiation within the condition that the temperature is above absolute zero ($-273.15°C$). Infrared radiation is a part of this discharged energy. According to our understanding of radiated energy, infrared radiation have the shortest wavelength and their visualisation is possible only with special instrumentation.[15]

Owing to its high precision and the ability to execute non-contact analysis and diagnostics, infrared thermography has become one of the most sought-after tools in electrical maintenance programmes.[23] Figure 7 depicts the spectrum of electromagnetic waves. The infrared band is separated into two parts: short-wave infrared ($<5\,\mu m$) and long-wave infrared ($<12\,\mu m$).

In 2019,[25] the analysis based on the temperature differences in the thermographic images of an induction motor to detect bearing damage coupled with thermographic camera has been discussed. This method proved to be beneficial as it eliminated the need for additional sensors and the application of algorithms that would otherwise require extensive computational resources. In 2019,[26] the application of thermography for detecting the failure states of photovoltaic modules was examined. Detecting faults in the inner constructions of wind turbine rotor blades using active thermographic inspection was also discussed in Schwahlen and Handmann.[27]

Apart from the conditioning monitoring of electrical systems, other applications[28] in which thermography has been successfully employed include gas detection, civil infrastructure inspection, surveillance, agriculture, aviation and the nuclear industries.

Thermography, when used correctly, is a valuable predictive maintenance methodology. In instances where the annual surveying of roofs or the trimestral reviews of electro-mechanical systems is inadequate, the paybacks are restricted. When critical plant or asset performance is regularly supervised and surface temperature or temperature circulation indicating reliability or operational condition is regularly measured, this method can yield significant benefits. To maximise the profits from the investment in IR systems, one must use them to full capacity.

Tribology

Tribology, in its simplest form, refers to the interaction and behaviour of relative motion with the operating dynamics and design of bearings and other lubrication-rotor support assemblies typically used in machine-train systems. Many tribology practices that can be applied for predictive maintenance exist, some examples of which are lubricating oil analysis, ferrography, spectrographic evaluation, and wear particle analysis. Lubricating oil analysis is a technique for analysing and defining the condition of the lubricants used in different parts of electrical or mechanical systems. However, the process is not used to help regulate the operating conditions of a system. In a secondary form, oil analysis provides a true quantifiable breakdown of each element present in a chemical, together with the contaminants and oil additives found in the sample oil. Hence, evaluating the volume of contaminated trace metals in oil samples proves to be a reliable way of detecting impending machine failures, such as wear particle patterns of oil-moistened lubricated parts in equipment assets.

Generally, the following examinations are commonly conducted during lube oil analysis[15]:

- Viscosity
- Contamination
- Dilution of fuel
- Solids contents
- Fuel soot
- Oxidation
- Nitration
- Particle counts
- Spectrographic analysis

Wear particle analysis is analogous to the study of oil; however, here, the wear particles under examination are gathered by taking a test specimen of lubricating oil from the operational machine train. While oil analysis provides only the absolute state of the oil sample, particle analysis gives thorough evidence of the condition of wear of the machine train. The contaminated particulates in the oil lubricants of a machine can provide useful data on the health of the equipment. The shape and structure of a particle, its composition, size and amounts in which it is present are studied, and information is extracted for further analysis. Wear particle analysis can be conducted in two ways. The primary technique is frequent monitoring along with trend analysis of the solid particles present in the lubricant of the system being inspected. The information on the number, structure and size of particles from the lubricant specifies the actual machine condition.

Usually, a train is capable of inhibiting small solid particles that are less than $10\,\mu m$ in size. However, when the machine progressively degrades, there is a surge in the amount and size of the solid particles present. Unlike the primary method in which frequent monitoring is required, the secondary wear particle method directly accesses and analyses the oil particulates in each lubricant sample.

Generally, there are five forms of wear found[10]:

- Wear due to rubbing
- Wear due to cutting
- Fatigue due to rolling
- Rolling and sliding wear
- Extreme sliding wear

General spectrographic examination is restricted to the contamination of oil with particulates that are 10 microns or less in size. Larger contaminants are ignored, thus limiting the benefits of this technique.

Ferrography is analogous to spectrographic examination, but has two key drawbacks. First, in ferrography, the particulate contaminants are separated using a magnetic field, which is in contrast to the sample burning employed in spectrography. Since the electromagnetic field is used to isolate contaminants, this procedure could be used in applications involving ferrous or magnetic particles only.

In 2020,[29] the researchers used oil analysis data to classify machine conditions to investigate failures such as overheating, water leakage, dust accumulation, component wear, oil, and other problems with the use of different machine or neural learning methods such as random forests, feed-forward neural networks, and the logistic regression model. In Jimenez et al.,[30] transformers based on the entropy quality of oil have been discussed while using distinct deep convolutional learning methods and residual neural networks. In 2019,[31] the analysis of insoluble substances present in in-service wind turbine gear oil by means of infrared spectroscopy is discussed. In Raposo et al.,[32] predictive maintenance policy based on a degradation model involving oil exchange for condition monitoring has been investigated by obtaining lubricant data from a fleet of diesel engines used in urban buses. In 1996,[33] contaminant examination of oil lubricants used in a local power plant for a turbine-generator system has been performed by assessing the state of tribo-components, such as bearing deflectors and gears, using statistical analysis. The modelling of a hard and a soft failure that might arise when the concentration of solid particles reaches its critical value in a piston combustion engine is discussed in Vališ and Žák.[34] Tribo-diagnostics such as the Wiener and Ornstein-Uhlnbeck methods were used to analyse certain processes such as stochastic diffusion.

Of late, tribology analysis has come to be viewed as a sluggish and exorbitant process. The analysis involves

obsolete laboratory-based techniques, and enormous trained labour is required. To mechanise most of the analyses of oil lubricants, versatile microprocessor systems are now being employed to reduce the efforts related to manual lubrication.

Visual inspection

To maintain the qualitative aspects of industrial machines and assets, visual inspection (VI) is one of the oldest and most widely applied methods that constitute a part of the maintenance strategy. This technique is also advantageous if defects are missed or discarded by other predictive analytics. VI is one of the most modest techniques for structured inspection, which is sometimes performed as part of daily practices as an unconscious activity.[10]

By considering the human-in-loop approach, defects such as stains, dirt accumulation, scratches, cracks, surface dents, and patchiness of the colour and material coated on the surface of the parts are inspected and corrected. One of the key requirements of VI is that the devices or tools used to detect the fault should not directly interact with the machines. Thus, non-destructive techniques (NDT) are popularly applied during inspections. The following are some of the more frequently used NDT methods [35]:

- Body Senses: Smell, Sound, Sight, Taste, Touch.
- Temperature: Thermocouple, Thermometer, Infrared, Radiation, Heat flow.
- Vibration Wear: Accelerometer, Ultrasonic Listening, Stethoscope, Laser Alignment.
- Materials Defects: Eddy currents, Magnetics, Radiographs, Penetrating Dyes, Ultrasonic.
- Deposits, Corrosion, and Erosion: Ultrasonic, Radiography, Weight.
- Flow: Manometer, Gas sensor, Quick-closing Gauges.
- Electrical: Cable fault sensor, Multimeter, Oscilloscope, Circuit-breaker Tester, Frequency Recorder, Phase Angle Meter, Transient Voltage Check.
- Chemical/Physical: Humidity, Spectrographic Analysis of Oil, Presence of Water Particles or Moisture in Gases/Liquids, pH, O2.

In 2019,[36] the researchers studied the different defect shapes on a surface to be inspected and derived the relationship between defect profile and defect detection rate by employing peripheral vision (luminance). The shapes of defects, their locations, and the characteristics of 12 objects were considered as the experimental data. The researchers concluded that the line defect rate was less than that of other geometrical shapes irrespective of the contrast of luminance between the surface size and the

defect. The findings reported in Charles et al.[37] suggest that experience and knowledge of the past are crucial to easy and efficient design processes that incorporate pictorial examples for visual comparison of defects.

In 2017,[38] with an aircraft preflight maintenance strategy in place, robot-installed pan-tilt-zoom cameras were employed to perform visual inspections. This autonomous robot was capable of identifying discrepancies in the air-flight by comparing the images obtained with those stored in its database. Zheng et al.[39] proposed the usability of smart technology-based applications in wearable augmented reality devices for cable assemblies for aircraft maintenance. To detect the type of cable brackets and their quality, the convolutional neural network technique was applied to quickly read the texts on the cable. The images obtained via a wearable augmented reality (AR) device mounted on a camera was fed to this network. In 2019,[40] the visual inspection feasibility approach embedded in an unmanned aerial vehicle was applied to determine the defects in the blade of a wind turbine system using different image processing methodologies.

Ultrasonic

The ultrasonic testing method is quite similar to vibration monitoring except that it is applied in the high frequency range of >20 kHz. Ultrasonic monitoring is primarily used for leak detection, noise-frequency analysis, and component testing. Since most ultrasonic instruments use a frequency bandwidth similar to the natural frequency of a rolling bearing, there is a probability of getting false positives for recognition during the measurement phase. Hence, the ultrasonic method is highly avoided while monitoring bearing components. One of the major limitations of this monitoring technique is that the sensitivity of the data stored corresponding to the machine conditions and parameters cannot always be separated.[10]

In 2019,[41] a solution was proposed for wind turbines to bridge the data gap between the ultrasonic monitoring technique with other process and load parameters. A pattern recognition algorithm was built to create a dynamic alarm threshold by the meshing of different frequencies. This approach augments the overall productivity and health of the equipment. In 2017,[42] the application of an ultrasonic transducer for removal of fouling in a submerged/marine structure was discussed. In 2019,[43] Root Cause Analysis (RCA) was applied to a monitoring system based on ultrasonic inspection, rather than relying on the use of an autonomous system, in order to increase the turbine shaft's remaining useful lifetime while using ultrasonic inspection. Failure is alarmed when the shaft's useful lifespan falls below 96%. Surface layer cracking from the main rotating shaft of a wind turbine was monitored using the

Table 1. Summary table of different methodologies of predictive maintenance.

Type	Year	References	Methodology
Vibration	2013	Patil[17]	Fast Fourier transform
	2016	Durbhaka and Selvaraj[18]	Support vector machine and k-nearest neighbour
	2019	Khademi et al.[19]	IoT-enabled sensors
	2020	Kuspijani[20]	Backpropagation neural network models
	2019	Silva and Capretz[21]	Convolutional neural network
Thermography	2019	Morales-Perez et al.[25]	Thermographic images with thermographic camera
	2019	Cipriani et al.[26]	Thermography for detecting the failure states of photovoltaic modules
	2018	Schwahlen and Handmann[27]	Active thermographic inspection
Tribology	2020	Sarawade and Charniya[29]	Random forests, feed-forward neural networks and logistic regression model
	2019	Alam[30]	Deep convolutional learning methods and residual neural networks
	2019	Zhang[31]	Infrared spectroscopy
	2019	Raposo et al.[32]	Degradation model
	1996	Ahn et al.[33]	Wiener and Ornstein-Uhlnbeck
	2017	Vališ and Žák[34]	Statistical analysis
Visual Inspection	2019	Nakajima et al.[36]	Peripheral vision (luminance)
	2015	Charles et al.[37]	Pictorial examples for visual comparison
	2017	Leiva et al.[38]	Pan-tilt-zoom cameras
	2020	Zheng et al.[39]	Wearable augmented reality devices
	2019	Rao et al.[40]	Image processing methodologies
Ultrasonic	2019	Tareen et al.[41]	Pattern recognition algorithm
	2017	Lais et al.[42]	Ultrasonic transducer
	2019	Galarza-Urigoitia et al.[43]	Root cause analysis
	2020	Cheng et al.[44]	Finite element analysis

ultrasonic method in Cheng et al.[44] Analysis using Finite Elements (FE) was applied to simulate the propagation of an ultrasonic wave to detect the axial position of cracks. However, the model does not help to quantify cracks or determine their directions.

Other testing

Apart from the techniques mentioned above, predictive maintenance also includes other methods such as acoustic emissions, eddy currents, electrical resistance, magnetic resonance testing, X-ray inspection, load tension and widely used classical non-destructive methods. A summary of different methodologies used in this paper is outlined in Table 1.[45]

Predictive maintenance and analysis models

Fault is basically a state of deviation within a system, and failure is an event, usually permanent disruption, caused by a fault. With fault detection, evidently, one can predict the failures that might otherwise disrupt the operation of a machine or component. The prediction of a fault or failure depends on the data acquired from the process or the system. This data is processed and fed to the different analysis models. Different modelling techniques are

available for processing the data from real-time networks, which are raw and abstract in nature. These techniques are quite similar in the process. With feature construction, the missing or abstract data is initially constructed to reduce the input dimensionality and enhance prediction capability to effectively manage a large set of inputs by transforming them into a completely new feature. This goal is achieved by performing feature extraction, which is yet another process whose aim is to reduce the redundancy of the features. This method ensures that the data relevant to the prediction are considered and other less important features are removed.[46]

Knowledge based models

Heuristic knowledge from the process and subject matter knowledge can play a vital role in predicting faults. Mathematical or physics-based modelling is not available for this method, and it solely depends on the domain knowledge of the experts. Fuzzy logic and logical condition/rule based (IF, THEN or ELSE) are the most common methods for deriving this model. Owing to the high complexity in transforming the expert knowledge into logical conditions, this method cannot be used alone. Typically, with the help of data from a physics-based approach, this complexity can be reduced considerably.[47,48]

In 2017,[49] the researchers developed a fault detection method that relies on an ontology-based integration outline for the computerised knowledge-based fault diagnostics of a conveyor system in an industrial application. Delgoshaei and Austin,[50] developed a scalable and comprehensive knowledge-based framework for a heating ventilation and air conditioning system over a reasoning based on inference to derive information on the anomalies in the process. In 2020,[51] for an electric railway system, a fuzzy-based complex approach with thermography was posited for prognostic maintenance activities.

Data-based models

Data-driven approaches have been well used, considering the different statistical and machine learning methods achieved via the vast pool of historical trend data from various sensors. With past information and states from this trending data, it is possible to predict failures in the current state. Since it is quite possible to have machine learning libraries and real-time sensor data, data-driven methods and the algorithms derived from them have gained more popularity than other methods for predictive maintenance. However, since this method does not integrate knowledge or the actual physical implementation of the process, the accuracy achieved with this model cannot be fully determined in the best possible way. Furthermore, the actual failure mode at its root cannot be fully recognised with just a black box approach. Most of the research has been performed with open-source data, and very little has been taken directly from the mechanical or electrical equipment in actual usage. This aspect makes it challenging to determine the reliability of reusing these models for other equipment in the instance of manufacturers providing custom-made machines. This leads to immense fine-tuning and parameterisation of the model when used for other customised equipment.[52]

In aircraft maintenance, the components which are in the out-of-service zone of operation are at times not discarded, thus leading to potential failure. In 2018,[53] a framework with data-driven approaches involving an autoregressive moving average model (ARMA) was proposed. The predominant health indicators of a battery, the remaining useful life (RUL) and state-of-health (SOH) of a lithium-ion battery are widely monitored. In 2019,[54] using a data-driven approach with the Deep Neural Networks (DNN) method, a predictive model (e SoH and the RUL of the lithium-ion battery) was developed. Using advanced big data and the random forest algorithm. In 2017,[55] researchers developed a platform with a dashboard which shows the predicted failures in a wind turbine. With the usage of a Gaussian hidden Markov model and the Wavelet Packet Decomposition technique, the remaining useful life of a wind turbine bearing has been discussed in Tobon-Mejia et al.[56] Different machine learning methods, such as supervised, unsupervised, reinforcement and deep neural network-based algorithms, are widely employed to predict failures using the vast pool of data from machines or systems.

Physics-based models

Mathematical models of pieces of equipment or a process that involve numerous differential equations are realised to form physics-based models from first principles. With accurate models, predictive models can be designed to provide reliable predictions. These models are implemented using various experimental and empirical data, and they require a thorough knowledge of a system and the associated failure modes. Degradation models are designed to forecast the remaining useful life of the machine. Different statistical methods are used to update the constraints of the model. Having a rigorous knowledge of the system, and building an accurate model from them is a tedious task that is not, in any case, always achievable. Parameter identification also requires exhaustive experimentation. Not all failure modes can be considered while building such models, making it a not-so-obvious method for complex system architecture.[57]

In 2012,[58] the degradation model of a rolling element bearing that relies on physics-based modelling was simulated, and a health-monitoring system was discussed. The remaining useful life of a component in a multiple operational mode that depends on a physics-based prognostic method was suggested in Namburu et al.[59] Using advanced physics-based predictive maintenance with digital-twin implementation, the digital image of an industrial robot and its methodology were discussed in Aivaliotis et al.[60] Reliability is a factor which is more important in the tidal power sector than in conventional wind power systems. For tidal stream turbines, to forecast the remaining useful life of the bearing of a pitch system, a reliability-focussed physics-based model was employed.[61]

Hybrid models

Today, to overcome the complexities of other models and to achieve a certain betterment, hybrid models are extensively used. Such models combine knowledge, data, and physics-based models to achieve a better trade-off between these models, offering more reliable and accurate predictive and degradation models.

The usage of hybrid models in the remaining life estimation of a lithium-ion battery while incorporating a particle filter and other techniques was discussed in Liao and Köttig.[62] In 2009,[63] the summary of a hybrid system using both physics- and data-

based approaches to condition-based monitoring was discussed. A hybrid technique based on adaptive mode with regression-based predictive models for health monitoring of a rolling element bearing was discussed in Ahmad et al.[64] A digital-twin powered hybrid model for a CNC machine tool was implemented and discussed in Luo et al.[65]

Challenges and opportunities

Evidently, many programmes have been built on predictive maintenance strategies, but have otherwise failed to yield productive results. Technologies, although advanced, have limitations in terms of predicting failure states in order to make necessary changes. For instance, industries undergo cultural changes. There is an imminent need to alter the perceived notion that predictive maintenance technologies have only been formed for maintenance management. The company's management should understand the importance of these tools since those at higher management levels are often quite oblivious, with little or no knowledge, about the need for maintenance. Poor maintenance strategies can cause unnecessary downtime, and delays in production output are purely the result of poor maintenance of the machines and their components.

Predictive technology should be used as an optimisation tool for the plant. It must be employed to sense, segregate, and offer resolutions for non-conformities with the appropriate overall performance, which results in improper measurements, bad values, extraordinary expenses, or safety hazards to workers. Extensive use of technologies must be enabled to cover this important role; however, this strength is no longer being exploited. To accomplish this revolution of changes within production companies, the usage of predictive technology needs to be exchanged between the department of maintenance and the reliability group charged with accountability and responsibility for asset optimisation. Such a group needs to have authority over all functional groups and should attempt to implement alterations that mitigate the issues exposed through continuous evaluations.

Additionally, there are other challenges as the research developed to date emphasises theoretical assumptions; thus, its applicability in solving real-time process issues in an industry is somewhat limited. The models are created using a fixed amount of data by considering limited scenarios and hence cannot be easily transferred, even to solve similar challenges. A lot of rework involving the parametrisation and retraining of the models needs to be performed from scratch. For instance, a model based on single component and single-state optimisation cannot be transferred to a multicomponent system. The latter system is usually
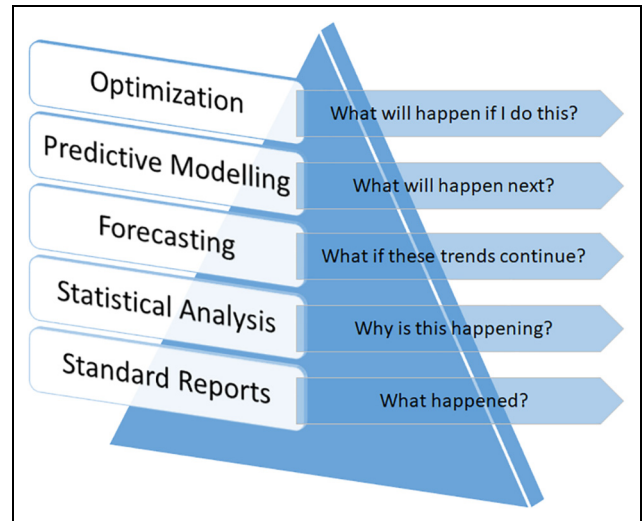

Figure 8. Typical Predictive maintenance and analytic pyramid.

dependent on the cost of the components with which the system is interacting, and is quite complex.

Moreover, physics-based models alone are used for failure prediction, and data-driven methods are usually neglected. Thorough data analytics can provide useful information and recognise data that is more relevant to predicting a particular fault. It is vital to consider both data-driven and physics-based models to arrive at a better solution, particularly, for instance, for stochastic systems.

Generic pyramid flow for a predictive maintenance and the analytic is outlined in the Figure 8.[66] This helps to understand how to optimise the current assets.

In the future, prescriptive analysis is likely to gain popularity amongst researchers. Creating an opportunity for prescriptive analysis of the ongoing predictive maintenance research will be beneficial to many investigators, and has the potential to unearth great capabilities with regard to future research contributions.

Conclusion

Industry 4.0 has resulted in the favourable usage of predictive maintenance for manufacturing processes. With the advancements in sensing techniques, data for such is easily available. Exploiting this information from a plant or asset is crucial to providing cost-effective prediction results. This paper has presented the opportunities one might expect from predictive maintenance, along with the different techniques that are available to improve associated decision-making capabilities. Currently, most of the available review papers focus on one or, at best, a few predictive maintenance techniques. On the other hand, this paper has presented most of the available techniques for data capacities and

has summarised the challenges inherent to each. Selected investigations on different predictive maintenance and modelling techniques along with the challenges and opportunities have been discussed, which could provide a clear future direction as well as novel ideas for other researches.

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