Predictive Maintenance: A Review

Purvesh Y. Parmar[1], Jagdish Pampania[2], Vyomesh Buch[3]

Department of Mechanical Engineering

Parul Institute of Technology, Vadodara, India

Email: *Purveshparmar225@gmail.com[1],Jagdish.pampania@paruluniveersity.ac.in[2], yomesh.buch165001@paruluniversity.ac.in[3].*

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Abstract

Frequently, manufacturing equipment is utilised without a planned maintenance approach. Such a procedure regularly results in unplanned downtime, owing to unexpected failures. Scheduled maintenance replaces components regularly to avoid sudden equipment stoppages but increases the time associated with machine non-operation and maintenance costs. In today's rapidly changing scenario, the fourth industrial revolution has started implementing worldwide. New concepts were born together with this new revolution, such as predictive maintenance. This study investigates failure prediction, and the prediction of failures considers concepts as predictive maintenance. We conduct literature to analyse academic articles that were published until the beginning of October 2020. This article adds to the field of predictive maintenance to feature the difficulties of implementing and use-case. We finish up by calling attention to that predictive maintenance trending topic in the context of Industry 4.0.

Keywords: - *IoT, Industry 4.0, Predictive maintenance*

INTRODUCTION

Revolution, as you know that English which means this term is essentially some shift, some abrupt modification that's needed to remodel the manner things have been happening. Associate degree abrupt change within the way things are being done, so that is that the revolution. If you consider revolutions in the past earlier, if we tended to return quite 10,000 years ago, our predecessors won't collect food through hunting routines. So, wandering around collecting food, delivering them, eating the food through the collected food materials like fruits, vegetables, etc., whatever they used to find.

Further, foraging behaviour was remodelled to farming. Completely different crops were grown, different vegetable plants, different fruits, food plantations were started. The result of this transformation from foraging to farming was increased production and increased communication between other humans. There was a growth in food production as the population growth increased. Wetend to are talking regarding this quite 10,000 years back.

Then appeared the industrial revolution, wherever new technologies, new machines were produced, new approaches to the production processes were introduced. This shifted the economy from a primitive economy with easy agrarian-centric economies to more aggressive machine-oriented production systems. So, that was the industrial revolution.

The industrial revolution once more went through totally different stages. Back in the 1760s to 1840s, the first industrial revolution started. Moreover, this 1st revolution was created with the invention of the external-combustion engine, the introduction of trains, mobility inflated, construction of railways stimulated the overall revolution.

Then came the second industrial revolution that was throughout the transition from the 19th century to the20th century, with the appearance of electricity and increase of electricity within the society. This resulted in mass production; machinery may use electricity for large scale and faster production.

Then came the third industrial revolution that was during the 1960s. It was around that time computers were starting to get popular in the industry. So, gradually with the increase of computers and computing devices, peripherals etc. in the industries.

The fourth industrial revolution, or industry 4.0, has its foundation in the German economy. The individual industries having individual IT infrastructure everything was through the third industrial revolution. With the introduction of sensors, actuators, along with the regular infrastructure, the IT infrastructure, the internet together basically was able to transform the existing IT-based infrastructure in the companies to more efficient ones to connected, sensed machinery and so on, so that was the fourth industrial revolution And this is fourth industrial revolution or the Industry 4.0 that we are going through at this moment.

Predictive maintenance is similar to preventive maintenance. This activity needs particular present conditions. In our analogy to human health, this component can be compared with screenings or precautions recommended for an individual at higher risk for a particular disease due to hereditary or lifestyle considerations. If technicians discover that a particular piece of equipment suddenly shows outside normal parameters, they trigger a predictive maintenance protocol to schedule a repair or prevent future breakdowns conveniently. It is highly recommended to invest in a computerised maintenance management system, which will give you the measurements and data required to make smart decisions. This investment can reduce unneeded maintenance tasks, minimise maintenance costs, develop a robust overall maintenance program, and monitor the equipment and systems to keep your facility up and running. The difference between preventive and predictive maintenance is preventive maintenance is periodically scheduled while predictive maintenance is scheduled based on asset conditions. Predictive maintenance reduces labour and material costs, whereas preventive maintenance costs less to implement.[1]

LITERATURE REVIEW

Compare et al.[2] described a deeper understanding of this dynamic maintenance paradigm's limitations and strengths, difficulties and opportunities. They have done extensive research and analysis of the scientific and technical literature. On this basis, the work outlines some main research issues for the successful development and deployment of IoT-enabled PdM in the industry. The development for PdM has thus considerably mainly concerned hardware and software for remote tracking the health situation of monitored equipment. Indeed, thePdM value chain is much longer, including many activities upstream and downstream, the collection of data and the execution of the maintenance labour.

Jimenez et al.[3]attempted to develop a predictive maintenance solution in the shipping industry based on a computational artificial intelligence model using real-time monitoring data.The results of their research have great potential to establish a predictive model. Yet, some elements such as failure modes identification, detection of potential failures, and asset criticality are just some of the issues that need to be solved before developing a solution based on artificial intelligence. These failures could be reduced with a predictive maintenance strategy. The benefits of utilising the PdM technique are the power of artificial intelligence allows the identification of patterns and anomalies that would otherwise escape from the human eye; a PdM grant to predict previously unpredictable events, anticipate failures and maximise the lifetime of the equipment.

Montero Jimenez et al. [4] reviewed using a modern technological system to keep the system in an optimal state. As the complexity of technical systems increases over time, single-model strategies hardly fulfil all functions and objectives for predictive maintenance systems. They commonly find that research studies combine different models in multi-model approaches to overcome the complexity of predictive maintenance tasks.

Kimera & Nangolo[5]Provides a predictive maintenance procedure for an early warning maintenance/failure warning system using machine learning instead of sensor technology. This method is used to process and analyse the dock pump operating parameter to draw inferences from data via MATLAB. For the analysis component, the operating parameters were like Backpressure, flow rate, amperage, RPM and suction pressure, operating parameters, monitored for 40 weeks. To define which parameters will accurately predict the pump failure?

Grebenişan et al.,[6]investigate working tool, a component of the Predictive Maintenance Toolbox ™, produced by Matlab (MathWorks), in the case of monitoring the operation of mechanical systems, to diagnose a failure of the process and to determine the remaining useful life. With some appropriate calculations, it can predict the RUL of similar components using predict RUL.

Dalzochio et al. [7] reviewed the key enabling systematic review of the literature (SLR) to analyse academic articles published online in the context of the fourth industrial revolution and PdM. Several concepts were carried in conjunction with the fourth industrial revolution, such as predictive maintenance. Their survey showed that predictive maintenance is a leading topic in Industry 4.0.

Dekhandji et al.[8]introduce predictive maintenance to Three Phase Induction Motors.

MATLAB/SIMULINK simulation is used in this work to detect and analyse faults such as overloading, single phasing, unbalanced supply voltage, phase reversal, ground fault, under-voltage, and over-voltage. On the induction motor.

Meyer[9]describes a challenge to draw a statement on the reliability of the PdM methods. The challenges found in the scientific literature are Financial and organisational obstacles, data source limitations, limits of machine repair activities and optimisation narrowness. They have been found that no universal statement about the reliability of PdM methods applies to all companies.

Lee et al.[10]presented an idea to implement predictive maintenance and monitor two critical machine tool system elements: the cutting tool and the spindle motor. The AI-based algorithms also introduce within. A data-driven modelling procedure will be described, and it will be utilised to examine the tool wear and the bearing failures. The flank wear and the bearing's RUL are monitored and used, respectively, as a metric to represent the component's conditions like normal, warning, and failure in the systems. To analyse the state of the tools, the SVM and ANNs (RNN and CNN) methods are used with the different feature extraction techniques. They found out that PdM of machine tool systems can overcome machine downtime and improve the RUL of a component.

Chen et al.[11]proposed that fleet management can be beneficial if an automobile's time-between-failures (TBF) can be predicted. Conventionally prediction models in predictive maintenance are installed using historical maintenance data or sensor data. They introduce geographic information systems data into TBF modelling and research their impact on automobile TBF using deep learning. Experimental outcomes show that better TBF prediction can be achieved with the help of GIS data. This research can be beneficial to fleet management companies to optimise their maintenance strategy.

Massaro et al.[12]implemented predictive maintenance by an artificial neural network algorithm to predict humidity in a controlled environment. They also design tools for suitable production sensing and actuation processes allowing automation for the pasta industry. Theirs focused on production traceability, image vision quality inspection and predictive maintenance.

Massaro et al.[12]have reviewed machine learning methods applied to predictive maintenance. ML techniques implemented to PdM, showing which are being investigated in this field and the performance of the current state-of-the-art ML techniques. Their main focus is on scientific databases and provides a useful foundation on ML techniques. They concluded that ML process such as SVM, RF, ANN, deep learning and k-means, have been successfully applied to design PdM applications. Implementation of PdM applications depends on the appropriate choice of the ML method.

Zhang et al.[13]presented work on artificial intelligence based on data-driven methods. That has become the most effective solution in predictive maintenance PdM to approach smart manufacturing and big industrial data, especially for performing health perception and fault diagnosis and remaining life assessment. In addition, they proposed a PdM scheme for automatic washing equipment. Also, they reviewed the industrial applications of PdM in the recent five-year timeframe both from ML and DL perspectives. The five indicators such as signal type, application scenario, target, accuracy, and data source are selected for summarising the application of these algorithms.

Trivedi et al.[14]introduce predictive maintenance to Three Phase Induction Motors. MATLAB/SIMULINK simulation is used in this work to detect and analyse faults such as overloading, single phasing, unbalanced supply voltage, phase reversal, ground fault, under-voltage, and over-voltage. On the induction motor. They implemented Predictive Maintenance in Air Conditioning Systems Using Supervised Machine Learning. The decision tree machine learning algorithm detected two common types of faults in AC systems like gas leakage and capacitor malfunction. The faulty operating air conditioners data was collected using sensors, microcontroller, and dedicated circuitry and analysed using MATLAB Classification App Learner Toolbox. It can identify the air conditioner that is faulty and predict the type of fault at an early stage to do maintenance beforehand.

Cachada et al.[15]focused on maintenance as a strategic issue to attain company goals. The implementation of predictive maintenance approaches demand a well-structured design and may be increased through the Internet of Things (IoT), cloud computing, advanced information analytics and increased reality. Therefore, they describe the structure of an associate intelligent and predictive maintenance system aligned with industry 4.0. That considers the advanced and online analysis of the gathered information for the sooner detection of attainable machine failures.

Aremu et al.[16]introduced Predictive maintenance (PdM) within asset management for improved savings in operational cost, productivity, and safety management capabilities. Moreover, a standard method for ensuring asset data is in a form conducive to ML algorithms and ensuring retention of asset information necessary for optimum PdM during the data transform. They also state that PdM is dependent on ML algorithms.

Li et al.[17]hey describe Fault diagnosis and prognosis in mechanical systems developed in the last few decades at a surprisingly fast rate. Moreover, they investigate fault designation and prognosis in machine centres supported data processing approaches to formulate a scientific approach and acquire data for predictive maintenance in the industry 4.0 era.

Linn et al.[18]presented a Predictive Maintenance method that utilises the condition monitoring (CM) data to predict the future machine conditions and makes decisions on this prediction. The data could be an operational situation, history of machine usage and perform maintenance actions. This research work and investigation did in two manufacturing companies from the automotive industry.

Zio & Compare[19]presented the importance of maintenance in the growing industrial situation. The technological advancements of recent years have allowed modern maintenance approaches such as condition-based maintenance and predictive maintenance. This work addressed an example concerning the stochastic crack growth of a mechanical component subjected to fatigue degradation. They have shown that modelling and analysis give information helpful for installing a maintenance policy.

Bahga & Madisetti [20]introduce a novel framework, Cloud View, for storing, processing, and analysing massive machine maintenance data collected from many sensors installed in industrial machines in a cloud computing environment. Cloud View catches the failure cases over a large number of machines and gives the failure information to the local nodes in the form of case-base updates that occur in a time scale of every few hours. At local nodes, the real-time sensor data from a group of machines is continuously matched to the cases from the case-base for predicting the incipient faults from previous faults. The case-base is updated regularly on the cloud to include new cases of failure, and these case-base updates are pushed from Cloud View to the local nodes to predict unusual faults.

CONCLUSION

After refereeing those papers, the following conclusions are drawn:

- Predictive maintenance is a trending topic in the context of the fourth industrial revolution
- PdM Detect problems before they cause downtime
- Manufacturers frequently collect big data from the Internet of Things (IoT) sensors in their facilities and products and using different algorithms for the collected data to detect warning signs of expensive failures before they occur.
- Reduce maintenance costs by 12%[21]
- Improve uptime by 9%[21]
- Reduce safety, health, environmental, and quality risks by 14%[21]
- Improve safety and extend the lifetime of an ageing asset by 20%[21]

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