Analysis of Predictive Maintenance in Industry 4.0: A review

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Abstract: Any unplanned downtime of industrial equipment or systems may degrade or disrupt a company's core operation, resulting in substantial fines and long-term brand harm. Traditional maintenance methods have certain assumptions and limitations, such as high repair costs, overtime costs, mathematical deterioration processes that are inefficient and manual function extraction. Smart manufacturing, as well as advances in the Internet of Things (IoT), machine learning (ML), artificial intelligence (AI), and advanced powerful and inexpensive sensors, are leading to Industry 4.0's predictive maintenance (PdM). It is possible to collect massive amounts of operational and process condition data produced by several pieces of equipment and harvest data for automated fault detection and diagnosis as a result of the digital transformation towards industry 4.0, information techniques, computerized control, and communication networks, with the goal of minimizing downtime and the utilization rate of the component. Predictive maintenance allows industry to intervene before harm happens, saving both time and money. PdM is unavoidable in Industry 4.0 for long-term smart manufacturing. In this project, we focused on the study of equipment, predictive maintenance methods and implementations, as well as the creation of a model for a modern predictive maintenance system in Industry 4.0 and a market analysis of predictive maintenance.

Key Words: Predictive maintenance, Industry 4.0, artificial intelligence, Machine learning, Industrial IoT, COVID-19, PdM market

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1. Introduction

In recent years, predictive maintenance (PdM), also known as online monitoring, condition-based maintenance, or risk-based maintenance, has gotten a lot of attention. Predictive maintenance describes an advanced approach in which machines and systems are maintained before failure of the system occurs, on the basis of permanently collected data from the system through sensors, IoT, ML and different highly advanced devices [13]. Predictive maintenance has come from modern Industry 4.0 and it has become an integral part of today's smart production system. On the basis of machine's data predictive maintenance uses measurement data from machines and its systems to determine maintenance gap of the particular components and machines. The aim of predictive maintenance is to take care of machines and systems before they fail, reducing breakdown times and maintenance efforts to a minimum level. Ideally, predictive maintenance is used to accurately predict malfunctions and issues so that an industry can take action before real failures occur and problems can be solved. In PdM, currently, automatic strategies are used to monitor the status of the under observation system and machines. These approaches employ advanced signal processing techniques like pattern recognition, machine learning (ML), neural networks (NN), and artificial intelligence (AI).

2. Literature Review

A thorough analysis of the literature on the various variables and essential parameters of predictive maintenance in Industry 4.0 has been performed and summarized below.

2.1 PdM (Predictive Maintenance) with Neural Network

Neural networks (NN) have the nature of complex algorithms, according to scientists. The NN-based “cerebellar model articulation controller performance estimation model (CMAC-PEM)” is a modern model that can measure the hazard rate and the mean time between failures (MTBF) in a real-time online system [3]. The neural network approach is used to locate defects in the machine that are unlikely to have occurred during the operation. Thermal defects in electrical equipment such as temperature drops, insulation cracks, faulty relays, and unbalanced loading can all be detected using a neural network. This thermal imaging method is used internally and externally for adequate maintenance, both to detect defects in machine components.

2.2 PdM with Big Data

PdM, with the help of machine learning, takes out data from loggers of possible sources which were previously stored data created. Random Forest is an algorithm that classifies large, complex data into feasible, possible working outcomes. It is a method which works on pattern recognition to structure the data with conditional decision making like random unbalanced data and remains useful in Industry 4.0. The database saves data on replacement data, follow-up scheduled data and repair data of machine components which are serviced, like the Volvo service record and logged vehicle data. These approaches are often used when analyzing data from the product life cycle. "Researchers use IoT technology for data mining and decision making in order to optimize product life cycle management for better performance in manufacturing and maintenance processes. In real-world industrial cases where data analysis such as support vector regression for unscheduled fault prediction can be easily detected, researchers have successfully combined the Autoregressive Moving Average model with data-driven techniques [3]. " Researchers used this model to control the shut-off valve in an engine bleed valve.

2.3 Single component data driven PdM

"For modelling the degradation process of a system or finding a degradation threshold, researchers have used PdM, degradation function likelihood (Kaiser & Gebraeel, 2009). Sensor data, historical data (Curcuru, Galante, & Lombardo, 2010), operating machine data (He, Han, Gu, & Chen, 2018), processing the parameters data (Liu, Dong, & Peng, 2013), and performance quality data (Lindstrom, Larsson, Jonsson, & Lejon, 2017) as shop floor information have all been used to improve the information system [1]. " Some researchers did not consider all data sources at the same time, but only a small number of them [15].

Real-time data was used in some studies to create dynamic models, while historical data of failures was used in others, and some studies considered both types of data. "Data science techniques have recently gotten more attention by using historical data (Baptista et al., 2018) or sensor data sources to analyze all forms of data sources (Dong et al., 2017)."

2.4 Multi-component data driven PdM

Researchers have discovered that different types of dependencies exist between machine components [1]. "Previous research on multi-component maintenance in economic dependencies looked at a grouping policy for initiating maintenance based on cost analysis (Wildeman, Dekker, & Smit, 1997). Furthermore, a number of studies have been conducted in this form of PdM (Pargar, Kauppila, & Kujala, 2017) and (Nguyen, Do, & Grall, 2017). "(Lee & Pan, 2017) suggested structural dependencies in a multi-level hierarchical system structure, while (Srivastava & Mondal, 2016) looked at multi-components in a PdM N-series structure."

2.5 PdM with Different Technologies

"In PdM, there are various monitoring technologies and their various applications studied, such as temperature, air pressure, noise level in mine ventilator equipment, and vibration monitoring sensors by monitoring sensors (Dong, Mingyue, & Guoying 2017). Also, (Ribeiro et al., 2014) used current and voltage transducers to analyze the conditions of hydro generators, and (Ribeiro et al., 2014) used infrared thermography technology for electrical equipment (Huda & Taib, 2013). "

2.6 PdM with Model Based

"(Yiwei, Christian, Binaud, Christian, & Haftka, 2017) proposed a prognostic model for measuring fatigueless crack failure development in the fuselage panel of a fleet of short-range commercial aircrafts, as well as potential damage size distribution. " (Macek, Endel, Cauchi, & Abate, 2017) proposed a model for the dynamic system of biomass-fired boilers in terms of performance, for the application of heat generation, and to quantify failures such as soot accumulation during the thermal boiler operation period."

For fault diagnosis and prognosis, there are various models, such as Markovian process-based models, Gaussian process-based models, Wiener process-based models, proportional hazard models, exponential models, and linear system models, among others. These models are used to maintain and troubleshoot a variety of parts, including the aircraft's redundant systems, lithium-ion batteries, building automation systems, gearboxes, bearings, and rotors. Different types of dependencies occur between computer components in complex machine systems, such as structural, stochastic, and economic dependencies. As a result, several techniques for multi-component systems are used. As a result, machine learning algorithms are widely used in most research methods to improve the performance of model-based approaches [1].

2.7 PdM with Rule Based

Rule-based PdM, also known as the expert system, is an online data performance management system based on rules developed by expert knowledge (ES). Human experts' knowledge is encoded in the form of laws and regulations on computers. Model verification and validation, information acquisition, and knowledge representation are all part of the ES development process.

Systems are diagnosed, PdM activities are planned, and the system is interpreted and monitored using ESs. Gul et al. have suggested a risk management process in a rail transportation mechanism that incorporates the Fine Kinney method and a fuzzy rule-based expert framework. In a data integration situation like IIoT, "Kharlamov et al. proposed the rule-based language SDRL for component diagnostics." Industry 4.0 will profit from it further.

2.8 Recent studies on anomaly detection for PdM in Industry 4.0

"Tang, Z. et al. proposed a new anomaly detection concept for a long-width cable-stayed bridge." The convolutional neural network was used to investigate the descriptions of anomaly patterns (CNN). For anomaly classification, the researchers used a semi-supervised deep learning system [2]. "Future research for PdM should concentrate on unsupervised classification."

When researching anomaly detection in industry, Li, X., and colleagues discovered data augmentation techniques. This study was carried out with high precision and accuracy, as well as with a limited original training dataset, because obtaining the correct labelled data is extremely difficult in practice. Person augmentation strategies were found to be more accurate than a hybrid approach.

Grab, A., et al. proposed "a new Generic Anomaly Detection to detect faults in a real reflow oven for production lines with the help of old sensor data that had been saved for over seven years." Despite this, the method did not investigate the relationship between faults in multivariate results. Future research will concentrate on improving how to compare different dimensions of data within specific different measures in order to detect flaws in equipment.

T. Zabinski et al. proposed "a framework for new fault detection and classification using a toolkit using a CNC milling tool as an example for intelligent condition monitoring systems." Measurements of CNC tool head imbalance have yet to be investigated using a real-time online sensing system.

"Liang, Y. C., et al. proposed a fruit fly optimization (FFO) algorithm method for more accurate fault detection of equipment by using threshold values based on historical data. Various data sources, such as temperature, vibration, and force data, were still not configured for better fault detection prediction. " This approach did not look at deep learning algorithms.

3. Analysis of Predictive Maintenance in Global Market

We looked at the PdM market on a global scale in terms of solutions and services, deployment mode, company size, and location.

From 2020 to 2027, the global predictive maintenance (PdM) market is projected to expand at a "CAGR of 28.8%, from USD 4331.56 million in 2019 to USD 31965.49 million in 2027." The increasing demand for and use of emerging and new technology to obtain valuable benefits, as well as the need to minimize maintenance costs and downtime of machinery equipment, are all key drivers of market growth.

3.1 COVID-19 will spark the beginning of industry 5.0

Since society is on an exponential curve, the capacity to distinguish business paradigms is fading. The exponential nature was not apparent when it started a couple of hundred years ago. It's difficult to imagine 0.0000001 being 0.0000002.

The only way to see it now is to look at the numbers. This crisis has accelerated our progress. It results in widespread acceptance of emerging technology as well as a flow of venture capital into next-generation innovations that will almost certainly be studied in the future. The singularity is considered to be the starting point for Industry 5.0. That is when, among other things, computers will be able to create better new machines than humans. That's about ten years away, depending on whose data you want.

Is this pandemic hastening the imminent transition to Industry 5.0? Yes, indeed. However, I assume that only historians looking at data 30 years from now will be able to tell how much has changed.

3.2 COVID-19 Impacts on the Global Predictive Maintenance Market

The COVID-19 pandemic had a significant impact on the manufacturing and industrial sectors, as well as IT (information technology) spending, which fell by 3 to 4%.Because of this, the predictive maintenance market has also been affected. Still, in the healthcare, energy and utilities sector, demand for PdM solutions is hoped to grow during the forecast periods of this pandemic.

Industries are taking care too much of their machinery and manufacturing equipment because the personnel and employees are fewer and disruption of the global supply chain as well as demand for goods have increased during the COVID-19 pandemic, which has encouraged awareness in industries to increase the output of input. Because of this situation, the demand for predictive maintenance solutions across the whole world has increased [20].

Many companies have begun to use smart sensors, advanced artificial intelligence systems (AI), and the industry internet of things (IIoT) technologies to track the health and performance of expensive machinery used in their manufacturing process in order to prevent costly production downtime.

Predictive maintenance solutions allowed industries to handle periodic monitoring, simple machinery troubleshooting and online working systems with limited workers during the COVID-19 pandemic, as a "work from home" system was possible because of predictive maintenance.

3.3 North America to hold the largest market size in Predictive Maintenance

"North America has the largest predictive maintenance sector, while Asia Pacific (APAC) is expected to develop at the fastest CAGR (Compound Annual Growth Rate) over the PdM forecast period." Private and public sector companies in APAC are investing heavily in maintenance solutions, which are driving up the demand for PdM solutions, which are used for industry automation and protection. North America is a leader in the adoption and development of predictive maintenance technologies. "The predictive maintenance market is increasing as a result of increased investments in emerging technologies such as IoT, AI, and machine learning, as well as the growing contribution of predictive maintenance suppliers and government support for regulatory demands and proposals [20]."

4. Results and Discussion

A. 4.1

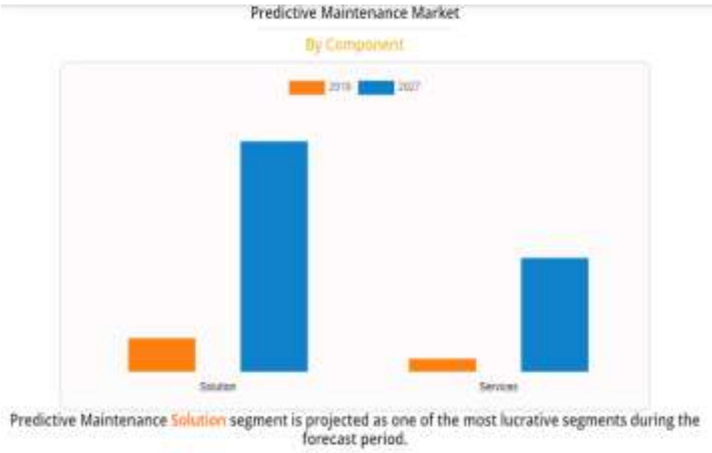
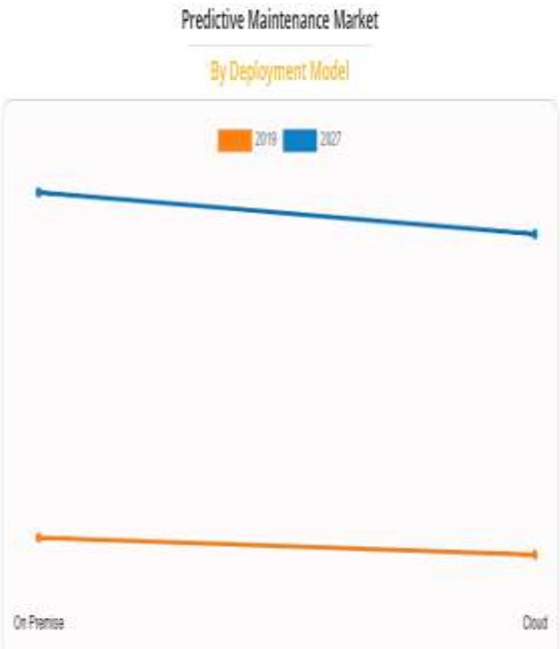


Figure 1: PdM market by Component

4.2

Figure 2: PdM market by Technique

4.3



"On-Premise Segment to Augment the Market during the Forecast Period"

Figure 3: PdM market by Deployment Model

4.4

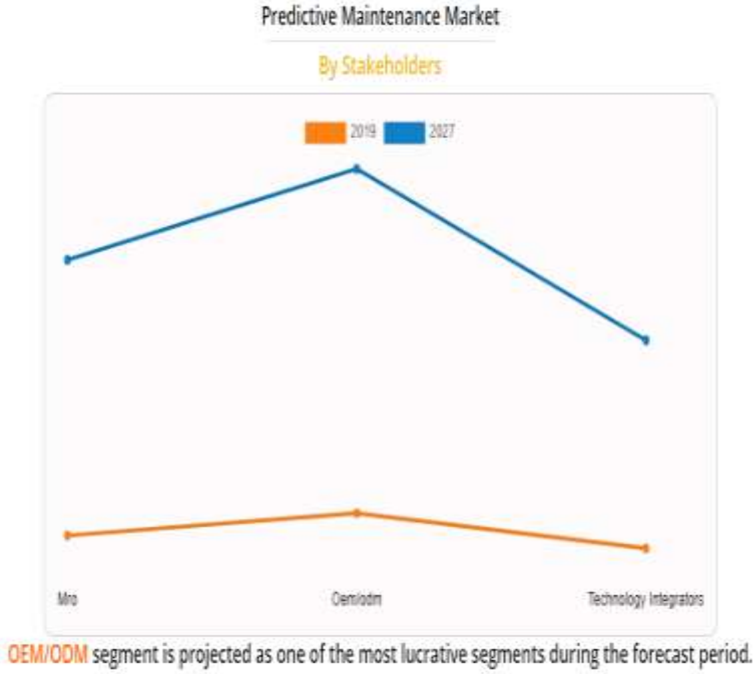


Figure 4: PdM market by Stakeholders

Mro- Maintenance, Repair, and Operations
Odm- Original Design Manufacturer
Oem- Original Equipment Manufacturer

4.5

"Manufacturing segment accounted for the Largest Market Share"

Figure 5: PdM market by Industry Vertical

4.6

Figure 6: PdM market by Region

5. Conclusions

PdM is unavoidable in Industry 4.0 for long-term smart manufacturing. "Machine tools with Industry 4.0 capabilities can improve availability through predictive maintenance, while others can improve performance and workpiece quality through process supervision and optimization." In this project, we focused on the study of equipment, predictive maintenance methods and implementations, as well as the creation of a model for a modern predictive maintenance system in Industry 4.0. We also examined the predictive maintenance market strategies and forecasts for the years 2020-2027.We also covered the Covid-19 impact on predictive maintenance as well as on Industry 4.0. We focused on the PdM application and its deployment in the industry, as well as the market analysis of predictive maintenance.

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