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Challenges and Opportunities of Condition-based Predictive Maintenance: A Review

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Abstract

The concept of maintenance has advanced significantly over the last decades from a reactive service activity towards a pro-active one with more C-level attention. Among them, predictive maintenance has become a widely used term in industrial arena and academic research. This is being developed constantly by engineers and researchers based on monitoring historical data, modeling, simulation, and failure probabilities to predict fault and system deterioration over their useful life. Generally, the effective lifetime of machines depends on available and accessible data. However, certain unexpected situations may arise that are hard to predict, such as shock damage and unwanted degradation of the tool. Researchers are still working on understanding these problems and their effects on predictive maintenance. This paper presents an overview of condition-based predictive maintenance solutions that aim to avoid unexpected and unplanned failures during the manufacturing and operational process based on advanced data analytics. Furthermore, a brief illustration & discussion is presented on the challenges and opportunities of condition-based predictive maintenance and conclude a summary on future research.

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Keywords: Predictive Maintenance; Condition based maintenance; Reliability; Manufacturing

1. Introduction

Manufacturing describes a diverse field with multiple areas of application. With industries going through several revolutions, we are currently in Industry 4.0. One objective is to reduce excessive scraps, and this made researchers think about reusing strategies in a different way. The term "useful life of machines" is guiding the development in the industrial sectors that are combined with reliability, sustainability, productivity, performance as well as in supply chain, automation, enterprise etc.

Today, manufacturing processes still encounter certain issues. One of the features that are getting a lot of attention recently is conditional maintenance. Reliability and decision making of machine parts usage need better analysis with methods that might lead us to reduced maintenance cost and uncertainty as well as increased uptime. The timely overhaul, repair, conditional monitoring of machine health helps them to understand when and why machines fail. In practice, corrective and preventive maintenance problems are dealt with since the early 90s. After that, introduction of automation, information technology, communication and modern manufacturing process, Predictive Maintenance (PdM) and Condition-Based Maintenance (CBM) appeared. Since then, a focus shifted on various maintenance problems such as corrective, preventive, predictive and CBM. In this paper, the authors will discuss utilization of such methods by engineers over the last 15 years

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for Condition-based Predictive maintenance problems and how these convey results in different machine parts or process.

2. Background

2.1 Evolution of maintenance

Starting with the second industrial revolution (mass production), engineers and scientists are frequently working to develop models, methods, and features to minimize costs, optimize production and increase reliability [1]. Degradation of parts and machines is quite a common scenario in an industry where there is always a call for repair, replace as early as possible to maintain continuous production [2]. As performance is the key factor for achieving an optimal result, cost became an issue. To achieve optimal performance, continuous prognostic activities must be conducted to identify any irregularities in operations. Moreover, the range of working periods, tool changing time, repair & cost estimation have also become part of the performance equation. Hence, CBM emerged significantly over the last 10 years. Recent advances in data analytics and information technology provide the means to collect & analyze manufacturing process data in real time and inform the maintenance operations [3]. This enables development of variety of maintenance strategies. In this paper, they will look at the current state of these strategies & what data analytics tools are frequently used for certain types of problems.

2.2 Selection of papers

In this paper, the authors are going to investigate predictive and CBM strategies, the technologies used and the reported use cases. To capture the current state of the art, they at first looked through online journal searching webpage named "Web Of Science" search engine and used the initial search strings: "predictive + maintenance", "Condition+based+maintenance", "maintenance+cost". After that they searched over 100 papers on these topics published since 2003 to till today, eventually reducing the number to 70 relevant journal papers. To reduce the number to 70 they added the following keywords in the papers: "Markov+Process", "Bayesian+Network", "Regression+Model", "Artificial+Neural+Network", "Monte+Carlo+ Simulation", "Scheduling". As the main focus of this paper is mostly into Predictive Maintenance (PdM) and Condition-based Maintenance (CBM) concept with reported impacts on "maintenance cost" and "scheduling" we looked into models mentioned above.

After analyzing those papers, This lead to a further reduction in the number of relevant papers to 35 articles. These selected subset of papers are enough to provide logical explanation and enthusiasm because these papers are being selected after much crucial reading. After narrowing down those articles our main projection is to find detail methodologies that occurred from 2003 to 2018. Finally, the authors can able to express their viewpoint with respect to proper examples and applications.

This paper is structured on (a) explanation of Predictive and Condition-based maintenance, (b) previous works are done by researchers, (c) scopes of application of Predictive and Condition-based maintenance and (d) Present and future aspects of Condition-based Predictive maintenance.

Researchers have applied numerous models and algorithms such as Markov process, Bayesian Network, Artificial Neural network, Monte-Carlo Simulation, Big Data etc. in various prospects of Condition-based Predictive maintenance. Among them, we scrutinized and separated those 35 articles based on their individual research pattern in table 1.

Table 1. Overivew of considered papers with their specific research areas.

Methodologies	Predictive Maintenance (PdM)	Condition-based Maintenance (CBM)	PdM + CBM
Markov process	6	3	-
Bayesian Network	3	-	-
Artificial Neural Network model	4	-	-
Monte-Carlo simulation	2	1	-
Big Data	3	1	-
Scheduling	3	1	1
Maintenance Cost/ Management	14	5	2

These journal papers are academically well explained and motivating to others for future work. Some papers have a brief explanation of theoretical models on system behavior. Next, we are evaluating their ideas, models, and results consisting of finding optimal and effective maintenance strategy.

2.3 Definitions of selected maintenance policies

2.3.1 Predictive maintenance (PdM)

PdM optimizes a trade-off between maintenance and performance cost and increases availability and reliability. It measures efficiency, productivity, and remaining useful life for scheduling before happening any breakdown. It includes condition monitoring and prognosis of future system maintenance to obtain decision making whether remaining useful life expects to be increased [4]. Assessment of models in different scenarios tends to compare results of maintenance indicators which enables to recognize approaching troubles, a possible breakdown to prevent unannounced failure.

Performing PdM is to know in advance that the actions should be taken to prevent production stoppage under different conditions. Physical structures of machines and the nature of failure are correlated in an approximation of defending unanticipated problems [5]. Hence, the evaluation of PdM models is a combination of mathematical models that are helpful to identify when problem arise and when to perform maintenance action [6]. Therefore, PdM helps to measure and record physical parameters continuously for analyzing and comparing data to make maintenance decisions.

2.3.2 Condition-based maintenance (CBM)

CBM is an extended version of PdM where automatic triggering alarms are activated before obtaining any breakdown. Multi-variable complex methods and algorithms are being used to satisfy condition whether to apply CBM [7]. In CBM policy,

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the predictive threshold is assumed as degrada-tion based failure that must cut down to an acceptable level for better efficiency. It projects future components health by signal processing techniques that provide decision support for PdM [8]. Real-time prognostics and data acquisition help to predict a sign of possible hazard and prevent them from happening.

With the help of data analytics, sensor adaptation, data structure experimentation and decision variables CBM technique has emerged worldwide after the 2010s. [9] Real-time data with computer-based monitoring technologies has grabbed most attention among scientists that they now can emphasize historical feature data and eliminates risks. Main types of CBM policies are real-time continuous monitoring, online-based alarm system, periodic inspection [10]. Hidden Markov model, Inverse Gaussian, Proportional hazard model, Semi-Markov decision process are well fitted in CBM policy. For example, Semi-Markov process is used when the problem statement can be solved by loosening up strict conditions of Markov process. Hidden Markov process is used when the system is potentially monitored [4].

3. Literature review

According to definitions of PdM and CBM policy, reliability and machine useful lifetime can be optimized with precise data analysis, condition monitoring also minimal cost can be obtained in maintenance scheduling. From a brief and rigorous selection criteria, we finally have chosen 35 articles from preliminary 70 articles. These articles may help us to understand present state of art of Condition-based Predictive Maintenance.

3.1 PDM and CDM with Markov Model

There have been several publications on PdM. After the 2000s things have changed in predicting maintenance when not only failure and replacement but also degradation over times in Single and multi-state systems has come up before us. However, as system ages to wear out over time, not all degradation process is qualified for evaluating failure rates in multi-state systems. They [11] used the simulated model to make a significant impact on maintenance quality on system reliability. Hence probabilistic approach and improvement factor were used to make the system ''as-good-as-new'' condition. A new stochastic dynamic programming maintenance model called hidden semi-Markov model consists of transition probabilities among multi-failure states especially works best in inventory. Also [12] a piece-wise-deterministic Markov process generally known as a stochastic hybrid process is used where random natural failures that took place during operation. Thus [13] PdM has expanded to a discrete-time Markov chain to know both the machine status and the current number of jobs in the system. Traditional job-based threshold policy under semi-Markov decision process (SMDP) framework is augmented to optimize discounted costs and make better scheduling for operation.

Markov process is also used in CBM where scientists do research in critical conditions regarding complex algorithms & simulations. [9] An optimal economic manufacturing quantity (EMQ) is obtained by rigorous theory and calculate actions to minimize overall cost in the long run. CBM process uses optimization of sudden breakdown & wears out where it considers production rate, maintenance cost per cycle, and inventory holding cost. [15] The Markov model is based on order of events during the operations counting several failures, repairs, and replacements. The authors have posed a CBM method of a parallel system that optimizes economic dependence maintenance set-up costs by Markov decision process. This maintenance policy successfully reached a result as a close-to-optimal solution for multi-component systems.

3.2 PdM and CDM in Cost maintenance

Although a PdM program is difficult to set up and maintain when uncertainty remains in the system, in subsystem it works comparably well. Therefore, components, parts of machines have their individual program that allows operators to find when to act. However, unbalanced forces, misalignments, improper lubrication of ball bearings, metal fatigue and cracks of a machine lead to maximize maintenance costs considerably because it utilizes available assets and life of machines [16]. Several iterations are done from low level to high-level period of failure state and probabilistic predictive function may appear a good result in cost maintenance. Minimization of long-term mean maintenance cost can be obtained by dynamic maintenance policy to predict "remaining useful life" [17]. Reliability Centred Maintenance (RCM) is defined as testing, inspection and analyze system reliability. Cost model and analytical methods are performed with Monte Carlo method and Bayesian Networks conforming optimal maintenance strategy [18]. Often that future reliability depends on present prognostics of damage size distribution and the cost ratio between maintenance modes and performs optimal panel repair policy [19]. Therefore, Evaluation of quality of components, degradation state and quality-reliability chain of manufacturing system may have decision-making policy to determine total cost and ways to reduce cost according to the effectiveness of quality. Maintenance policies are generally about the breakdown, wear, corrosion & overhauling and for that purpose real-time predictions of possible events is necessary [20]. Later, a cost management strategy for predictive maintenance is evaluated by complying joint optimization strategy of both maintenance and inventory of spare parts. The performance of maintenance strategy is not only depends on components failure mode analysis but also costs associated with repetitive actions taken for maintenance [21]. The decision parameters are evaluated by Monte-Carlo Simulation with frequent inspection among a critical group of components.

Many types of research have been conducting CBM in the early 2010s & among them, RCM policy is one of them. Prognosis of this model helps to calculate the remaining useful life. [22] In some cases, PdM lay behind where reliability centered CBM has advanced their technique through practical real-time data monitoring, diagnostic & signal to process multi-level data fusion. [23] Here the probabilistic analysis approach is applied to influence risk reduction of possible costs caused by the unannounced failure. The failure rate caused by the breakdown of components tends to increase repetitive use where they evaluated stochastic dependence model using Lévy

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copulas & implement it in classic maintenance policies [24]. Since aging is gradually happened due to operations conditions are reevaluated with replacement cost during machine lifetime.

3.3 PdM and CDM in Scheduling

Hybrid multi-objective immune algorithm (H-MOIA) supported by minimal impact of the disrupted operation on the schedule (MIDOS) for scheduling predictive maintenance program is based on the least flexible job first (LFJ) and the longest processing time (LPT) algorithm [25]. Closely monitored warning limits save downtime and maintenance costs and it estimates periodic maintenance policy which incorporated with the Random coefficient model (RCM) and Gamma process [26]. While the previous study about PdM was about deterioration and remaining useful life of machines, [27] this model is based on scheduling decision that minimizes total expected cost gradually. A "dummy age of machine" compared to the real-time age of machines when it comes to degrading potentially works smoothly.

3.4 PdM and CDM with Bayesian Approach

Knowing possible failure is a great help to schedule maintenance program in PdM that increases safety, quality and availability yet lack of analysis renders false decision making. Therefore, a combination of methods is necessary to compare results in a way to have the ability to decide at the critical moment. Predictive Maintenance Program (PMP) is generated by various tools such as Analytic Hierarchy Process (AHP), Bayesian techniques that contribute to reducing uncertainty [28]. In the hierarchy process, quantitative and qualitative data are gathered, analyzed and enable proper judgment for a maintenance program. A case study is being shown named as MINICON project where certain characteristics like vibrations, temperatures, performance losses etc. are evaluated to acquire system knowledge, improve dynamic strategies on all range of industrial and civil machinery [29]. Bayesian approach evaluates degradation process to which predict the failure time and consequently schedule the maintenance activity. Periodic inspection and observation redirect a few system failures in the system & obtain optimal maintenance cost associated with progressive deterioration and sudden shock. [30] Also Reliability and forecasting model are simulated under PdM policy emphasizing the probability of occurring incidents so that proper timing for maintenance may be forecasted in advance.

3.5 *PdM and CDM with Neural Network*

Once the intelligent complex numerical analysis has evolved scientists have started to understand the true nature of complex algorithms such as a neural network (NN). An introduction of cerebellar model articulation controller NN-based machine performance estimation model (CMAC-PEM) with real-time online performance estimation model appears to determine hazard rate and mean time between failures [31]. With practical simulated data and neural network model researchers have shown the motion of direct current (DC) motor for high-performance capabilities and abnormalities that happened during operation. They used neural network method to find out defects unlikely occurred in the range of operation time [32]. Another application of Neural Network is to identify thermal defects in electrical equipment, unbalance loading, cracks in insulation and defective relays. The optimality of the thermal condition of components is carefully measured both for internal & external damage for a proper maintenance issue [33].

3.6 PdM and CDM with Big Data

The introduction of Machine Learning has eased PdM by pulling off data from loggers of possible outcomes that were originally generated from input data for previous years. A classifier algorithm named "Random Forest" is essentially a great tool that separates large data set into feasible optimistic outcomes. [34] This follows a pattern recognition method to facilitate data structure for a long period of time with conditional decision making such a remaining useful life and random unbalanced data in the automobile industry. Repair data, replacement data, and follow-up schedule data are saved in databases as Logged Vehicle Data (LVD) and the Volvo Service Records (VSR). These methods are widely used where they evaluate data focusing on product life-cycle. [3] They applied IoT technology for data mining in Manufacturing and maintenance process (MMP) where they achieved decision making for optimization of product lifecycle management (PLM). An interesting model called Autoregressive Moving Average model along with data-driven techniques have worked well in the real industrial case where data analysis such as support vector regression for unscheduled prediction of faults can be identified [35]. They applied this model into an engine bleed valve (EBV) to regulate the shut-off valve in the engine.

4. Results

From searching and brief understanding of paper of the last 15 years, authors gathered much information about Condition-based Predictive maintenance. They have considered major research and publications that are relevant to their analysis and found that around 30 countries all over the world have worked on these domains. China, USA, and France are a pioneer of PdM and CBM policies. The following figures show when the papers were published based on PdM and CDM accordingly.

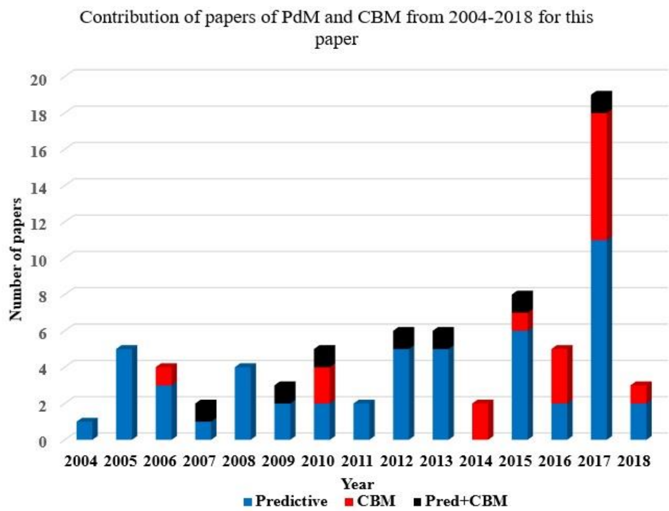

Fig 1: Contribution of journal papers found from 2004-2018

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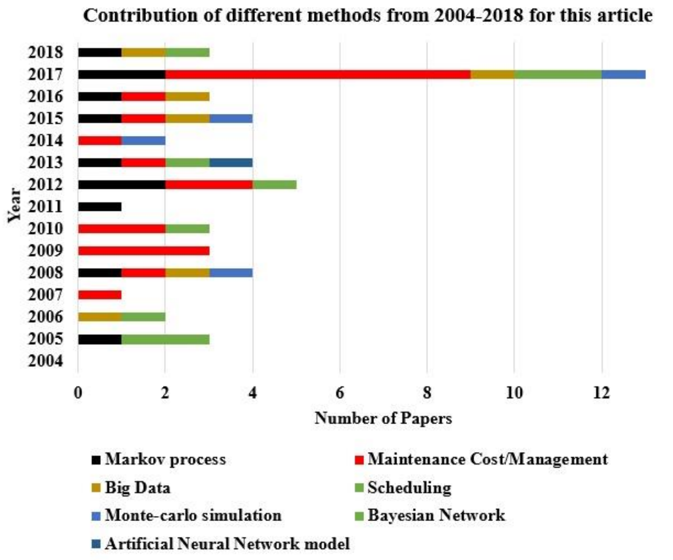

Fig 2: Contribution of journal papers in given methods found from 2004-2018

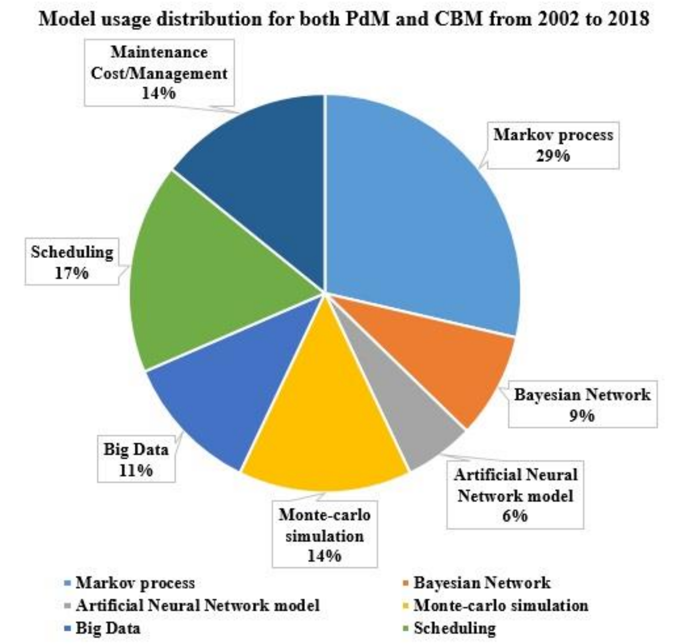

Fig 3: Focus of journal papers regarding certain methods from 2004-2018

Complex methodologies, multi-stage operations, reliability, sustainability & maintenance costs are pressing issues in PdM & CBM. Data analysis, hierarchical statistics methods, simulation etc. mathematical analysis with various methods are being examined in recent years. After digging down into those domains they found out maximum papers are published on Maintenance cost and Scheduling under PdM and CBM. Then gradually most to least other methods are Markov process, Artificial Neural Network, and Big Data. In 2017, the highest number of researches are done in PdM and from maximum to minimum other years are 2015 (6 papers), 2012/2013 (5 papers), 2005/2008 (4 papers) and 2006. CBM policy is a recent research topic where 2017 has almost maximum papers in it (7 papers). We further analyzed that year and found that China has most published paper on both PdM and CBM (6 papers). Other countries are Netherlands, Sweden etc.

5. Discussion

Due to growing industrial sectors and pressing issues on maintenance all over the world researchers have changed their concepts from Corrective/Preventive maintenance to PdM. In the 90s when the need of minimizing cost and maximizing the efficiency of production increased scientists have formulated many methods like Markov process, Bayesian network to estimate failure rate, deterioration of components, the breakdown of machines and effective scheduling to overcome problems. After that in 2000s new IoT technology, Data mining, online simulation is introduced together with CBM. As industries have a different product, different methodology and different process not all types of mathematical models are efficient for all types of the manufacturing process.

System reliability and sustainability require the proactive judgment of possible unforeseen degradation thereby any preventive action may be done to increase machine useful life. Many countries have adopted the probabilistic approach and numerical models to estimate time horizon in between each maintenance program. Since multi-stage production has replaced single stage production, the parallel manufacturing process has become a leader in manufacturing. Therefore, Markov, Semi-Markov, Hidden-Markov all these algorithms are placed in the study to predict failure rate, aging factor, residual life and optimize scheduling cost. These concepts are still being used since the 2000s. They described some papers from 2004 to 2018 where these methods have modified due to the introduction of advanced technical analysis. Markov processes are also being used in CBM where experimental data is taken in different cases to optimize costs. Performance-based real-time data acquisition needs to evaluate for judging PdM schedule that might help to reduce cost significantly. Hence Reliability centered condition criteria with given parameters, loggers, signals are essential to predetermine deterioration age of machines and proper decision-making policy can be obtained. H-MOIA, MIDOS, RCM, AHP these are common techniques used by engineers for the last 15 years.

Bayesian techniques are also integrated through these models that are described before in this paper. Different case studies have been seen in recent years where predictive inspections, data collection, and analysis is done to find near accurate maintenance policy that will help us to forecast future accidents. Moreover, simulation-based maintenance policy like Monte-Carlo simulation, ANN, and Data mining approaches have become a popular research area when historical data are present to work with them. Moreover, machine condition, maintenance redundancy, remaining useful life, life-cycle management etc. can be evaluated through data mining, ARMA model, prognostic model, hazard model. These models are modified from the 2000s and we can see from 2012 to till now these are rapidly used in various research papers. Although Bayesian Network and ANN were a pioneer in PdM (2004-2008), later Markov Process, Monte-Carlo Simulation, and Big Data approach has prevailed those methods from the 2010s.

Although Condition-based Predictive maintenance was a new topic starting in the 2000s but frequently became core topic after 2010s. We identified more than 20 journal papers focusing on this topic that was published after 2010 and we

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explained how CBM policy has superseded among scientists in the literature reviews. Considerably we can understand that CBM programs will grow more with new modified models such as Machine Learning, Dynamic statistical process control, Knowledge management, complex systems. Big data, data mining, advanced data processing is quite new in this arena. Starting from 2012, many authors have introduced these topics that might be future research models where more accuracy can be obtained in CBM.

6. Conclusions and Outlook

In this paper, we summarized some selective papers in the last 15 years and tried to show scopes of Condition-based Predictive Maintenance that is evolving in manufacturing. The use of methods has validated through different analysis, compared with one another and bring out most advantages in Condition-based Predictive maintenance. However, we could not explain all processes instead speculate major applications that may be helpful to understand the present situation. From 2002 to 2018, many researchers are still working on going for better component life expectancy, cost minimization, effective scheduling and improved productivity. From Corrective to CBM the journal papers have taught us that a combination of PdM and CBM is also possible and in fact, some papers have already given notion about it. In the future, this domain will flourish with more pragmatic research, possible solutions regarding machine life, scheduling and cost. Future research will be a broad understanding of mixed, multi-phased maintenance model which will lead us to predict more accurate result considering each case or condition while necessary.

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