Review

Condition-Based Monitoring and Maintenance: State of the Art Review

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Abstract: Manufacturing firms face great pressure to reduce downtime as well as maintenance costs. Condition-based maintenance (CBM) can be used to effectively manage operations and maintenance by monitoring detailed machine health information. CBM policies and the development of the mathematical models have been growing recently. This paper provides a review of the theoretical and practical development in the field of condition-based maintenance and its current advancements. Standard CBM platform could make it effective and efficient in implementation and performance improvement.

Keywords: maintenance; condition-based monitoring; artificial intelligence

1. Introduction

Condition monitoring is the process of observing a set of parameters and/or variables that indicate that the state of the system under investigation. It plays a significant role in the maintenance, management, and sustainable operations of various sectors, such as manufacturing industries [1–4], transportation [5,6], energy [7–9], natural resources [10–13], both natural and human-made disasters [14,15], and healthcare [16,17]. In most cases, sensors and/or micro-controllers are widely used to perform condition monitoring [18,19]. In particular, in this paper, our focus is to provide a comprehensive review on various condition monitoring approaches and their applications in the maintenance in manufacturing industries.

In terms of manufacturing industries, condition monitoring generally recommends a set of maintenance requirements in the event of failure or malfunctioning of the vital devices or equipment of the system concerned; thus, the entire process can also be termed as condition-based maintenance (CBM) [20–22]. It can be viewed as (i) a mechanism of preventive maintenance, thus effective in planning maintenance scheduling; (ii) a comprehensive tool for assessing both of the diagnostic and prognostic conditions; (iii) an assistive method in configuring system requirements and also enhancing the capability of conducting regular evaluation and/or maintenance operations; and (iv) a technique to optimize the operational availability of devices, equipment, and modules of various systems [23,24]. In general, it provides several advantages, such as (i) reducing downtime and maintenance expense by eliminating unnecessary maintenance; (ii) providing an early failure detection to increase asset availability, avoiding unnecessary downtime; (iii) supporting continuous improvement ensuring accurate and consistent response to developing conditions; (iv) providing better decision making for operations, engineering, and maintenance staff; (v) providing integration of control, safety, and maintenance environments; (vi) facilitating the opening of an operator's time to manage assets; (vii) enabling an organization to turn data into actionable and valuable information; (viii) evaluating the equipment activities

and statistics, not normally maintained in repair logs; (ix) providing a repository to capture the conditions, rules, and other tacit knowledge; (x) allowing the organization to retain intellectual property as the workforce changes; (xi) supporting safety and security to avoid major catastrophic disasters; and (xii) improving morale of the workforces and users [25–27]. Despite the above-mentioned advantages, it has some drawbacks, such as (i) the initial installation costs being even higher than the system under monitoring, and (ii) uncertainty associated with the failure of the condition monitoring devices [27–29].

The concept of CBM was developed in the 1940s; however, its significant utilization has been observed since the late 1990s [30]. It is also related to the technological advancements (in particular to electronics and communication) in the condition monitoring devices and propagation of the information to the system analyst [31,32]. It has become increasingly more important along with the progress in the field of automation engineering [33]. In order to synthesize the progress of CBM, we provide a literature review in Section 2, CBM-related research activities in the post-secondary institutes in Section 3, and finally concluding remarks and future research in Section 4.

2. Literature Review

The implementation of CBM is to be found in various applications, such as vibration modeling, sensor performance, signal processing, noise control, thermodynamic performance monitoring, lubricant oil, corrosion monitoring, non-destructive test, and inspection techniques (e.g., magnetic particle inspection, alternating current potential difference, ultrasonic, eddy current, radiography, acoustic emission) [34–37]. The selection of an appropriate CBM (and its optimization techniques) is always challenging and highly depends upon the system. We provide description of some of the commonly used such optimization techniques in CBM in the following sub-sections.

In general, a generic CBM system consists of three basic components: (i) data acquisition, (ii) data processing, and (iii) decision-making process [27,38]. Data are usually acquired by means of various sensors (e.g., electrical, electronic, mechanical, electromechanical). The acquired data are then processed in order to determine the health of the system under investigation. Numerous techniques are available, including the use of wavelet, neural network, feature recognition, statistical approaches, signal processing, and artificial intelligence [39]. Upon processing the data, it is then used in the decision-making process, such as in determining/predicting (i) remaining useful life, (ii) the confidence level, (iii) failure analysis, (iv) proactive maintenance steps, (v) cost/benefit analysis, (vi) downtime reduction, (vii) performance improvement strategy, (viii) maintenance scheduling, and (ix) health condition [40,41]. In some of the instances, a CBM system may not be effective, e.g., (i) unavailability of the data required in assessing the state of the system, and (ii) in some cases, the acquired data may be qualitative rather than quantitative in nature, which makes the assessment more complex.

2.1. Analytical Hierarchical Approach

The analytical hierarchical approach (AHP) is a structural approach that is one of the frequently used techniques. For example, (i) Bevilacqua and Braglia [42] developed an AHP in determining the maintenance strategy selection in an Italian oil refinery with five possible possibilities of preventive, predictive, condition-based, corrective, and opportunistic maintenance. The best maintenance policy was selected for each facility of the plants including sensitivity analysis to improve the effectiveness. Due to the subjectivity associated with AHP, it might fail to capture detailed uncertainties of the system. (ii) Li and Brown [43] showed an approach to minimize the weighted average system reliability index (WASRI) by ranking maintenance tasks on the basis of their marginal benefit-to-cost ratios, wherein the benefit was defined as improvement in WASRI. A prioritizing approach was used to achieve component and system reliability. (iii) Waeyenbergh and Pintelon [44] demonstrated a framework for integrating all of the available information within a company, including experience of maintenance workers to capture data through modern information

and communication technology (ICT) by considering both of the computerized information and knowledge. However, the details about both the implementation and validation of the proposed framework were not described. (iv) Swanson [45] reported the relationship between maintenance strategies and performance and used factor analysis for developing maintenance strategies. Lastly, (v) Wang et al. [46] developed a two-stage prognosis model for optimum maintenance strategies that is based on a fuzzy AHP to evaluate different maintenance strategies (i.e., corrective maintenance, time-based preventive maintenance, condition-based maintenance, and predictive maintenance) for different types of equipment. In general, the applicability of AHP might be useful in selecting the maintenance process but limited in predicting the uncertainty associated with the system under surveillance.

2.2. Markov Chain

In general, failure is random in nature, and thus it is quite challenging to model. In this context, one of the most frequently used techniques is to employ the Markov chain (MC) method, which is even effective in modelling failure where such indications are not clear in the historical dataset. It is often used in different applications where greater uncertainties are generally expected. In [47], a semi-Markov decision process (SMDP) was developed for the maintenance policy optimization of condition-based preventive maintenance problems, demonstrating that the deterioration rate at each failure stage was the same, thus suggesting an optimal policy was a sort of dynamic threshold-type scheme. In [48], a MC-based algorithm was proposed for a deteriorating system for simultaneous optimization of parameters of condition-based preventive maintenance with an accumulated deterioration random failure. In a similar study, Hontelez et al. [49] developed optimum CBM policies using a discrete Markov decision method. In [50], a MC-based model using relevant condition predictor was proposed for reliability prediction for systems under condition-based maintenance.

2.3. Feature-Based (Signal Processing) Approach and Wavelet and Model-Based Approaches

Complex structures and/or systems often undergo damage/failure profiles that require non-stationary analysis techniques in order to be capable of detecting them [51–53]. It is of critical interest to monitor these dynamic signals from inherent structural energy changes and vibration that reflect due to the damage/failure itself. Traditional Fourier series analysis models are not appropriate since they require stationary data. Multi-scale, time-frequency analysis techniques such as wavelets can be applied to provide a robust framework for efficient analysis of such non-stationary processes [54,55]. Wavelet transforms have been studied since the 1950s by mathematicians, but it has only been in the last 10 years that they have made huge advancements in the engineering and signal processing community [6]. The wavelet transform is an operation that transforms a signal of interest with scaled and delayed from original signal to threshold signal [51]. Wavelet transformations are used for time-frequency representation of the signals for uncertainly/non-stationary using respective sampling theory. In signal monitoring and analysis, wavelet is also a very useful tool for failure prediction. On the basis of the signal from the sources, the different models could be realized for failure prediction. Wavelet and model/feature-based approaches are commonly used for failure prediction/condition-based monitoring and maintenance on the basis of the sensor and/or controller data.

In another application of wavelet, an innovative scheme for the machinery condition monitoring was presented on the basis of the wavelet modulus maxima representation [56]. Signal decomposition technique is applied to extract gear motion signal, and then wavelet transform modulus maxima is utilized to define fault growth parameter (FGP). CBM with the vibration management enhancement program is used by the U.S. Army National Guard, U.S. Army Special Operations, and U.S. Army TMDE demonstration program [57]. In another study, Wang et al. developed robust health evaluation of gearbox for tooth failure with wavelet decomposition. A study was conducted for CBM in punching–blanking of sheet metal using statistical, artificial intelligence (AI), and model-based approaches [58,59].

Special attention was given to inherent assumptions and other sources of inaccuracy, demonstrating how the signature of the force–displacement relation changes significantly with increasing tool wear in a typical configuration of sheet steel blanking. Kuravsky et al. [60] shows capability of wavelet transforms including relaxation neural networks for technical diagnostics and monitoring.

Different types of signal processing are also used for data processing from the sensor system. A comparative study of various classification algorithms was carried out for fault diagnosis of electric motors using different types of signals [61]. Experimental evaluation with the relative performances of five classifiers using five types of steady-state signals were conducted on the basis of three kinds of performance evaluation strategies: training-test, cross-validation, and similar measure. The raw signals are collected, and features are extracted from the collected signals; the extracted features are classified using the five classification algorithms, and an overall comparison of the five classifiers is discussed. In another study, a multi-criteria decision model is presented to determine inspection intervals of condition monitoring based on delay time analyses to simultaneously determine inspection intervals for condition monitoring regarding the failure behavior of equipment to reduce cost and downtime [62]. A decision model application in an electric power distribution company was presented. This application highlighted the suitability and practicality of the model. A tool condition monitoring approach is demonstrated in an end-milling operation based on the vibration signal collected through a low-cost, microcontroller-based data acquisition system [63]. Marinescu et al. used a time-frequency acoustic emission (AE)-based monitoring technique to identify work piece surface malfunctions in milling with multiple teeth cutting simultaneously [64]. New methods for supervising cutting processes were proposed with multiple teeth cutting simultaneously by use of AE signals backed-up by force data. Sometimes, hybrid approaches are used since single approach might not represent all uncertainties/non-stationary processes of the system or product. These wavelet-based models are very powerful in terms of modelling failure behavior if the proper signal could be collected with necessary accuracy.

2.4. Artificial Intelligence

Since failures involve uncertainties/non-stationary processes, various artificial techniques (i.e., neural network, genetic algorithm, fuzzy logics, expert systems) are frequently used for condition assessment and decision making. Applications of artificial intelligence to CBM to widen the scope of expert systems and to use it for machine diagnosis have been presented [65], and when administered properly through AI, can prevent accidents and increase the resale value of machines.

Hasan et al. [66] proposed an explainable AI-based approach for bearing fault diagnosis under variable speed and load conditions. A five-stage scheme is suggested to identify faults in the observed bearing signals: fast discrete orthogonal Stockwell transformation (FDOST) wrapper-based feature selector—Boruta, the Spearman's rank correlation coefficient (SRCC), the k-nearest neighbor (k-NN) algorithm, and the Shapley additive explanation (SHAP) for model interpretation.

Garcia et al. [67] provided the SIMAP Intelligent System for predictive maintenance to the health condition monitoring of a wind-turbine gearbox by taking account the information coming in real time from different sensors and other information sources. It is concluded that artificial intelligence and modelling techniques are adequate for reaching the main goals of the predictive maintenance strategy. Kothamasu et al. [68] presents an approach for incorporating population characteristic information and suspended condition trending data of historical units into prognosis using a feed-forward neural network, Kaplan–Meier estimator, and a degradation-based failure probability density function (PDF) estimator. The comparative model is used with a conventional time series prediction model to predict more accurately further ahead than similar methods that do not include population characteristics and/or suspended data in prognosis. In another combinational modeling (qualitative physics and product modeling) for product maintenance, model-

based maintenance in terms of inspection, monitoring, diagnosis, and planning based on functional, behavioral, and state-of-the-art models are discussed. Effective integration on AI in CBM will enhance usability and predictability of the failure systems. Jiang et al. [69] proposed a novel method based on improved convolution bearing fault diagnosis using neural network and transfer learning. The transfer learning (TL)-based framework can save a significant amount of time in the course of task completion [70,71]. This method was adopted by Hasan et al. [72] to identify bearing faults under certain fault sizes. Zheng et al. [73] used multi-synchro squeezing S-transform for fault diagnosis in rolling bearings.

Genetic algorithms and fuzzy logic are used to model uncertainties/non-stationary processes. Since there are lot of uncertainties in the maintenance systems and sometimes the systems are not well structured, the fuzzy techniques would be more applicable for failure prediction and condition assessment [74,75]. Optimizing maintenance and repair policies were presented with a combination of genetic algorithms and Monte Carlo simulation within the context of plant logistic management on the choice of maintenance and repair strategies for an industrial plant, in the face of reliability and economic constraints. Monte Carlo simulation was used for economic analysis [76]. In another study, Marseguerra et al. came up with a similar hybrid technique with stress-dependent degradation processes for load sharing components and of a reduced number of maintenance workers available on site [77]. Sharma uses an approach based on fuzzy linguistic modeling to select the most effective and efficient maintenance strategy with three input parameters (historical data, present data, and competence of data). Although it uses a fuzzy set and rule-based system, it may not provide a complete scenario [78]. A fuzzy multiple criteria decision-making (MCDM) evaluation methodology is used for the cost-effective maintenance approach [79]. A neuro-fuzzy modelling approach for CBM to focus on model comprehensibility with effective decision aid for domain experts with Kullback–Leibler mean information to evaluate and refine tuned rules with a couple of real-world applications in bearing failure and aircraft engine failure [66]. A condition-based preventive maintenance arrangement was presented for thermal power plants using a hybrid Petri net modelling method coupled with fault-tree analysis and parameter trend to perform early failure detection and isolation [80]. In a similar study, a procedure for diagnosis and CBM was provided for power transformers [81]. Recurrent neural nets and the neuro-fuzzy systems approach were developed for managing the CBM of a combined-cycle power plant at a medium-sized Italian refinery. In some situations, genetic algorithms and/or fuzzy logic could be used for condition mentoring and maintenance. There are no certain guidelines when it should be used. Although artificial intelligence is used frequently for condition monitoring and prediction, there are some reservations in applications [82]. To improve the anti-noise performance of the fault diagnosis model and the denoising performance, ref [83] studied a joint learning mechanism. Researchers have relied on several signal processing techniques, such as fast Fourier transformation (FFT) [84], empirical mode decomposition (EMD) [85], energy entropy (EE) [86], wavelet packet decomposition (WPD) [87], empirical wavelet transformation (EWT) [88], variation mode decomposition (VMD) [89].

2.5. Remaining Useful Life

Remaining useful life (RUL) is used both in theory and applications. Engineers use it mostly when they have to decide whether to perform maintenance or to delay it due to production requirements [90]. Most often, RUL is used for later life of equipment in wear-out period. Condition assessment is used commonly to predict remaining useful life (RUL) of the equipment or systems. A prognostic approach is presented to estimate the remaining useful life of gas turbine engines before their next major overhaul based on historical health information [91,92]. A combined regression including both linear and quadratic models is proposed to predict the remaining useful life. Two-stage prognostic model is used for the life of a piece of production equipment, with the first stage as the normal working stage and the second stage as the failure delay period [93–96]. With the help of condition monitoring, the equipment hidden defects may be detected for maintenance planning purposes; the

prediction of the second stage; and, more importantly, the residual life. Artificial neural network-based prediction methodology has been developed for remaining useful life of rotating machinery [97]. Tian et al. developed a neural network approach for remaining useful life prediction, utilizing both failure and suspension histories of age and condition-monitoring data from the equipment [98]. In another methodology, Technical Condition Index (TCI) is used for remaining useful life of natural gas export compressors [99]. There are greater challenges to select or develop appropriate prediction algorithm since it is on a case-by-case basis and environment-related.

2.6. Deteriorating Systems

Deterioration is a process where a system deteriorates continuously due to usage or age. Important parameters of the system gradually worsen if left unattended, and the process leads to deterioration failure [100]. Since deterioration is unpreventable, an efficient maintenance policy can reduce the system failure. Many studies have been conducted for condition-based maintenance in deteriorating systems. Much of the focus of these investigations has been in the failure prediction using different methodologies. A CBM policy for stochastically deteriorating systems was proposed to focus on analytical modelling of a condition-based inspection/replacement policy for the same [101]. A mathematical model was derived for the maintained system cost, supported by the existence of a stationary law for the maintained system state. In another study, a condition-based maintenance policy for a two-unit deteriorating system was presented [102]. Each unit's gradual deterioration and monitoring was based on sequential non-periodic inspections with a stochastic model for optimal maintenance performance. Closed-form expressions of system availability are derived when the device undergoes both deterioration and Poisson failures with a polynomial to solve for the optimal inspection interval [103]. A quantitative approach for maintenance inspection scheduling and planning was presented with three main modules: risk estimation module, risk evaluation module, and maintenance planning module [104,105]. A condition-based replacement and spare provisioning policy is presented for deteriorating systems with uncertain deterioration to failure with a simulation method and the genetic algorithm for minimizing the cost rate. A case study is provided for optimizing the maintenance scheme of haul truck motors and the order of the spare motors at Cardinal River Coals in Canada. Lin et al. [106] presented a simulation model for maintaining equipment performance with integrated equipment CBM and field activity of an elevator service provider. A simulation modelling of repairable multi component deteriorating systems was developed for on-condition maintenance optimization [107] to minimize the expected total system cost over a given mission time. A non-repairable single component, subjected to stochastic degradation, was first considered, and the degradation model was then generalized to multi-component repairable systems. The modeling techniques of failure prediction are varied on the basis of the rate of the failures and surrounding parameters. Although a statistically based methodology is commonly used, the integrated modeling approach with different methods might be more suitable to address real-world uncertainties.

2.7. Oil Condition Monitoring

Oil condition monitoring is used to measure engine oils, lubricating oils, and other fluids for detection of lubricant engine wear and related problems to reduce downtime [108]. Continuous oil condition monitoring in machineries and rotary systems is one of the rapidly growing areas for both predicting and preventing their failure. Ahmadi and Mollazade [109] demonstrated the effectiveness of oil condition monitoring techniques in determining the best oil for Dump Truck HD325-5 (used in transportation of minerals). Similar oil condition monitoring systems are available in the literature [110–112]. Du and Zhe [113] used a high-throughput inductive pulse sensor for online oil debris monitoring. In another study, Xia and Huo [114] developed oil monitoring methods based on information theory.

Mackos et al. [115] developed a fluid quality sensor to monitor the oil quality applicable for commercial, military, and off-highway vehicles.

2.8. Early Warning

Early warning system is used to send warnings for the problem at the beginning or at more serious stages. Such a system can have an enormous impact where higher safety is involved, e.g., nuclear power plants. Some examples include: (i) Zhang et al. [116], who developed an early warning system using "asymptotical local" approach and applied it to a CBM system. It was based on characterizing a system through an identified model and then monitoring its changes. This approach demonstrated its effectiveness for detecting small changes, and also its robustness with respect to the bias of nominal model identification. However, sometimes it would not be possible to have knowledge about the system parameter to detecting changes; thus, a nominal model could be employed instead. (ii) A robust condition monitoring for early detection was developed of broken rotor bars in induction motors [117]. (iii) A statistical approach was used in process control as part of early defect identification [118,119]. (iv) Early warning systems using failure modes analysis was used for dam safety monitoring [120–122], etc.

2.9. K-Out-of-N System

K-out-of-N is used when there is uncertainty of the lifetime. If at least K numbers of components are in good condition out of N components in a system, this is known as a K-out-of-N system. Smidt-Destombes et al. [123] suggested maintenance operation if the quantity of good components were less than K, wherein all of the components were identical and repairable as well. Another study focused on the methodology of a condition-based preventive maintenance as part of the overall asset management strategy. A maintenance monitoring system subject to false alarms and failure to alarm used K-out-of-N systems with multiple dependent monitors on the basis of the probability matrix being weak MLR (weak multivariate monotone likelihood ratio) [124]. On the basis of their optimal procedure of a monitoring system, a K-out-of-N system can identify an optimal decision quickly. There have been studies conducted for maintenance, spare part inventories, and repair capacity with their interaction for a K-out-of-N system with wear-out [125]. Order-restricted hypothesis tests are considered for making the decision about the usual K-out-of-N model or the general sequential K-out-of-N model for given data [126]. Simultaneous maximum likelihood estimation is considered for the model parameters and the distribution parameters with a flexible location-scale family. Many researchers have extended the concept of binary K-out-of-N system to multi-state K-out-of-N systems.

2.10. Reliability-Centered Predictive Maintenance

Reliability-centered maintenance (RCM) is a systematic approach to ensure effective and efficient use of the assets in the designed operating conditions. It focuses on effective and cost-efficient preventive and predictive maintenance programs. A reliability-centered predictive maintenance (CBPM) policy is proposed for a continuously monitored system subject to degradation due to the imperfect maintenance [127]. It is assumed that the system hazard rate is a known function of the system condition and then can be derived directly through CBPM. A hybrid hazard rate recursion rule based on the concept of age reduction factor and hazard rate increase factor is built up to predict the evolution of the system reliability in different maintenance cycles. The optimal reliability threshold is determined by minimizing the cumulative maintenance cost per unit time in the residual life of the system, which is based on simulation. In another study, a reliability-centered maintenance strategy was used on the basis of maintenance-free operating period philosophy and total lifetime operating cost analysis for the aero industry [128]. RCM can also address the life cycle cost. A design of operational vehicle maintenance program based on life cycle cost and reliability-centered maintenance is proposed in military applications [129]. The cost-based performance measured was used in another study wherein a prototype cost model of

functional check decisions was used in reliability-centered maintenance [130]. RCM is more commonly applied, being oriented with large number of details of personal involvement.

2.11. Web and Wireless in CBM

Web-enabled remote monitoring is also used for condition-based maintenance [131]. It can collect data through sensors remotely and transfer the critical information for further processing and analysis. XML and web technology could be used to integrate remote equipment, devices, installations, etc., for data transfer and decision making. Ali et al. [132] introduced the emerging field of e-maintenance and its critical elements. Furthermore, performance assessment and prediction tools are introduced for continuous assessment and prediction of a particular product's performance, ultimately enabling proactive maintenance to prevent a machine from breakdowns. Kwon et al. [133] discussed the current trends in industry, which include an integration of information and knowledge-based network with a manufacturing system, which coined a new term, e-manufacturing, and focused on the accessibility to a remotely located system and having the means of responding to a changing environment. Within the framework of the web-enabled robotic system, it focuses on the remote maintenance schemes with an emphasis on condition-based maintenance strategies with mathematical modelling of system availability in the subsystems of the robot. Marquez et al. [134] developed algorithms to detect gradual failure in railway turnout with an RCM2 approach to the management of switch and crossing maintenance and demonstrated the approach using data from tests on a commonly found point mechanism by adopting a Kalman filter for pre-processing the data collected during tests. In the same year, Pedregal et al. [135] used RCM2 predictive maintenance of railway systems based on unobserved component models. Tiwari et al. [136] developed a wireless sensor network for machinery condition-based maintenance (CBM) in small machinery spaces using commercially available products. A LabVIEW graphical user interface is used for signal processing, including FFT, various moments, and kurtosis using a wireless CBM sensor network on a heating and air conditioning plant. Tiwari et al. [137] presented a wireless sensor network for machinery CBM using commercially available products, including a hardware platform, networking architecture, and medium access communication protocol on a Heating and Air Conditioning plant. Djurdjanovic et al. [138] developed an infotronics based prognostic approach for product performance degradation assessment and prediction. They called it "Watchdog Agent", and it is used for multi-sensor assessment and prediction of machine or process performance and can be utilized to realize predictive CBM, CPLM, and identification of components with significant remaining useful life. All the related work on web and remote systems is limited with a firewall of information since different applications need different types of protocols for communication. Since sensors have the limited of transferring data, web-sensors might be helpful to transfer data from source location to remote decision maker location. These kinds of web sensors might have a large impact in monitoring, especially in environment-related condition monitoring.

2.12. Cluster-Based

Almomani et al. [139] advanced a cluster framework for planning preventive maintenance actions using the Group Technology (GT) concept. Gong et al. [140] used cluster analysis (CA) to establish the qualitative analysis models on the basis of the two-channel and differential dielectric spectroscopy (TD-DES) data and Fourier transform infrared (FTIR) spectroscopy data of the in-service lubricants. Da-Silva et al. [141] utilized most of CA techniques while clustering the chemical analysis of lubricant. In a recent study, CA was utilized to confirm fuel dilution in an engine oil [142]. A fuzzy clustering approach was proposed as a lubricant system fault diagnosis framework using fuzzy sets theory on the system characteristics [143].

2.13. Standardization of CBM Systems

Although CBM systems are well known and are used in many applications with significant improvement, there is no consensus about universal standard. There are barriers in platform, industry sectors, IP issues, etc., to coming up with an open system. Thurston and Lebold [144] discussed the development of open system architecture for CBM and defined the requirements for a general CBM architecture and the framework of the distributed architecture. It was also being evaluated for transition by both Army and Nany programs. The changing role of maintenance is presented from the perspective of life cycle management and identified technical issues of maintenance [145]. A generic model was presented with the total productive maintenance (TPM) and CBM basics, in conjunction with ecology-oriented manufacturing (EOM) and 5S f in attaining organizational equipment maintenance goals [146]. A systematic implementation framework coupled with the standard tools, techniques, and practices has been designed in a large semiconductor manufacturing company. Another generic CBM architecture was developed across different domains with a combined data fusion/data mining-based architecture [147]. Data fusion is extensively used in defense applications with an automated process of combining information from several sources in order to make decisions regarding the state of an object. Whereas data mining seeks unknown patterns and relationships in large datasets, the methodology is used to support data fusion and model generation at several levels. In the architecture, methods from both these domains analyze CBM data to determine the overall condition or health of a machine. This information is then used by a predictive maintenance model to determine the best course of action for maintaining critical equipment. Banjevic et al. [148] used Cox's PHM (prognostic and health management) with a Weibull baseline hazard function, and time-dependent stochastic covariates are used to describe the failure rate of the system with proposed structure of the decision-making software EXAKT. Sundberg [149] provides the economical aspect of condition monitoring and the strategically important considerations inside the maritime industry. Web and agent technologies in condition monitoring and the maintenance of mechanical and electrical systems are presented [150]. The OSA-CBM (Open System Architecture Condition-Based Maintenance) layers are used for the analysis of the reviewed work. Different architectures, methodologies, and tools are proposed by the researchers for the development of agent systems. Few findings report the use of mobile devices. Since the mobile/handheld devices spread markets recently, the effectiveness of those types of equipment for CBM to reduce downtime is unaddressed. The limited methodologies are available for the applications of mobile devices. There is a great potential to use handheld device injunction with web-based system for wider integration and effective use for decision making. It might give easy access remotely since the technologies are evolving faster than ever. Web-sensor open platform could be application also.

3. University Research Related to CBM

As people around the world are becoming increasingly more aware of the applications of CBM, they are taking interest in developing new technologies and strategies and are coming up with new management tools related to CBM. Most of this research around the world takes place in universities and defense. In the United States, the Department of Defense (DoD) has invested a large amount in the field of CBM. Their main focus is to meet the warfighter expectation while making every effort to conduct cost-effective sustainment operations. Thus, on 7 November 2007, DoD established a policy for CBM+, which provides an integrated strategy for deployment of enabling technologies, processes, and procedures that focus on a broad range of weapon system sustainment improvements. CBM+ was originally developed as a DoD initiative to provide a focus for a broad variety of maintenance improvements that would benefit both the maintainer and the warfighter [151]. It was established to expand upon condition-based maintenance (CBM) and encompasses other technologies, processes, and procedures that enable improved maintenance and logistics practices. The CBM+ Action Group developed a "CBM+ DoD Guidebook" as an

information reference and tool to assist logistic managers with CBM+ project development, implementation, and execution.

Defense Acquisition University, which provides learning and consulting for acquisition programs and projects, provides training on CBM+ business case analysis [152]. The Condition-Based Maintenance plus (CBM+) module provides the learner with an overview and introduction to Depot Maintenance Management and Operations needed in DoD systems [153]. The Applied Research Laboratory at the Pennsylvania State University (ARL Penn State) is using a systems approach for CBM. This is done by using a hierarchical architecture for developing and implementing health assessment systems. Here, in this hierarchy, a system is considered right from the top level to the lowest level of components where the failure originates. This hierarchical architecture consists of six levels: material, element, component, subsystem, system, and plant platform. They have been working in this field since 1994 and have established themselves as the world leader in CBM mechanical systems. Their projects cover various CBM issues from materials to decision support. The Systems and Operations Automation (SOA) Division of the ARL Penn State addresses the emerging fields of condition-based maintenance (CBM) and advanced sensing and control. The division provides valuable research and development efforts to support the U.S. Department of Defense and U.S. industry. It uses a number of specialized tools and facilities focused on condition-based maintenance such as mechanical diagnostic test bed, diesel-enhanced mechanical diagnostic test bed, lubrication system test bench, bearing prognostics test rig, torsional test rig, ball and V-ring test stand, battery prognostics test bench, complex systems monitoring features toolbox, and systems integration and technology transfer (SITT) facility [154].

A lot of research is being done at the University of South Carolina (USC), in which emphasis has been given to collect and warehouse data and formulate requirements for a move towards CBM. Their CBM Research Centre has supported the U.S. Army by conducting research to support a timely and cost-effective aircraft maintenance program. The CBM program at USC combines comprehensive research with a multi-faceted methodology to strive towards continued success by the U.S. Army's aviation division. The CBM test facilities include a full-scale drive train test that stands capable of testing several platforms such as the U.S. Army Apache, Blackhawk, and Chinook helicopters [155]. At the University of Toronto, Canada [156], the research and development in the Vibration Monitoring, Signal Processing and CBM Laboratory focuses on the development of effective fault detection and diagnostic schemes on the basis of analysis and modelling of vibration data for CBM purposes. Moreover, CBM software developed at the University of Toronto, EXAKT, is quite well known in the industry for maintenance optimization. Furthermore, at their Centre for Maintenance Optimization and Reliability Engineering (C-MORE), they employ proportional hazards modelling to pinpoint the risk factors that threaten the health of the asset from all signals obtained during health monitoring. This hazard estimate (the conditional probability of failure) is then blended with economic considerations to establish optimal CBM decisions. A large amount of research on maintenance, predictive failure, e-manufacturing, and industry applications with embedded system are conducted at the NSF Industry/University Cooperative Research Center on Intelligent Maintenance Systems with multi-campus collaboration (University of Cincinnati, University of Michigan-Ann Arbor, and Missouri University of Science and Technology).

At the Robotics Research Group at the University of Texas at Austin [157], researchers are working on a method for automatic condition-based maintenance (CBM) that is based on decision-making criteria. This is to enhance the reliability, safety, and maintainability of robot actuators or other variable duty cycle machines and to reduce the cost of their overall maintenance. They are currently developing a decision making CBM (DM/CBM) to overcome the problems of modern model-based CBM. They have created a software test that plays an important part in the development of decision-making software that also will be used as a guideline for future students who will perform CBM-related research. At the Centre for Operational Research and Applied Statistics (CORAS) of the University of

Salford, Greater Manchester University, United Kingdom, the research team is working on CBM [158], having concentrated their attention to date on developing models of the decision aspect of condition monitoring with the aim of optimizing a criterion function of interest. They have used stochastic filtering and hidden Markov models to model predictions of the residual life of monitored engineering systems, and hence to provide cost effective decision support. The conditional residual life formulation using semi-deterministic stochastic filtering is perhaps the first of this kind in condition-based maintenance modelling, which has been followed by many others since. The research has closely collaborated with industry users and engineering departments at other universities [159].

Other than the above-mentioned universities, the following is a list of a few universities wherein over the past few years, CBM/reliability-related work has been conducted:

1. Intelligent Systems Laboratory, Department of Mechanical, Industrial, and Nuclear Engineering, University of Cincinnati, Cincinnati, OH, USA.
2. Automation and Robotics Research Institute, Ft. Worth, Texas, USA.
3. Zhejiang University, China.
4. Luleå University of Technology, Sweden.
5. Malardalen University, Sweden.
6. University of Groningen, Groningen, The Netherlands.
7. Wichita State University, USA.
8. National Institute of Technology, Tiruchirappalli, India.
9. Reliability Engineering Centre, Indian Institute of Technology, Kharagpur, West Bengal, India.
10. Department of Agricultural Machinery, Faculty of Biosystems Engineering, University of Tehran, Iran.
11. Vaxjo University, School of Technology and Design, Sweden.
12. School of engineering, Cranfield University, Cranfield, England, United Kingdom.
13. Division of Industrial and Information Systems Engineering, Ajou University, South Korea.
14. Queensland University of Technology, Brisbane, Queensland, Australia.
15. Federal University of Rio Grande do Norte, Rio Grande do Norte, Brazil.
16. University of Teeside, Middlesbrough, United Kingdom.
17. Department of Industrial Engineering, University at Buffalo (SUNY), Amherst, USA.
18. NSF I/U Center for Intelligent Maintenance System, University of Cincinnati, University of Michigan-Ann Arbor and Missouri University of Science and Technology, USA.
19. Dipartimento di Energetica, Universita Politecnica delle Marche, via Brecce Bianche, Ancona, Italy.
20. Universidad Pontificia Comillas, Instituto de Investigacion Tecnologica, Santa Cruz de Marcenado, Spain.
21. School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China.
22. University of Wisconsin, Milwaukee, USA.
23. Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong.
24. Rensselaer Polytechnic Institute, Troy, New York, USA.
25. The Logistics and Maintenance Applied Research Center (LandMARC), Georgia Tech.
26. Reliability and Maintainability Center, University of Tennessee, Knoxville.
27. Center for Risk and Reliability (CRR), and The Center for Advanced Life Cycle Engineering (CALCE), University of Maryland College Park.
28. The Industry/University Cooperative Center for Quality and Reliability Engineering Research with Rutgers University, Arizona State University, and University of Arizona.
29. University of Iowa, USA.
30. Wind Energy Center, University of Massachusetts Amherst, USA.

4. Concluding Remarks and Future Research

This paper presents a review of different methods and applications on condition-based maintenance. The main purpose of this paper is to enlighten the field of CBM by providing

a holistic view of the global approach to CBM. Even though CBM requires sophisticated technologies, there is a large amount of research being done as people are starting to realize its importance. However, there is still much more that can be done. This includes lagging in open architecture, limited mobile applications, barrier in industry-to-industry sectors, limited censuses on unique CBM platform, etc. By only determining the states for which the unit is replaced in order to gain the maximum maintenance cost (Markov decision process) or by modelling the system deterioration, which is stochastic and continuous, people are looking at a specific part of the system, not the system as a whole. A holistic view is more important than complex models and techniques. Figure 1 shows a generic CBM platform supervisory control and data acquisition (SCADA) proposed by [160]. Figure 2 shows a generic failure prediction approach.
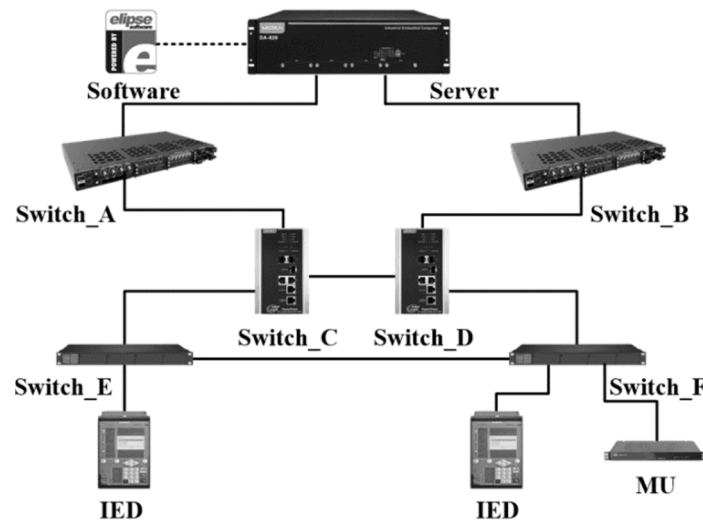
Figure 1. Schematic diagram illustrating a generalized form of CBM Platform.
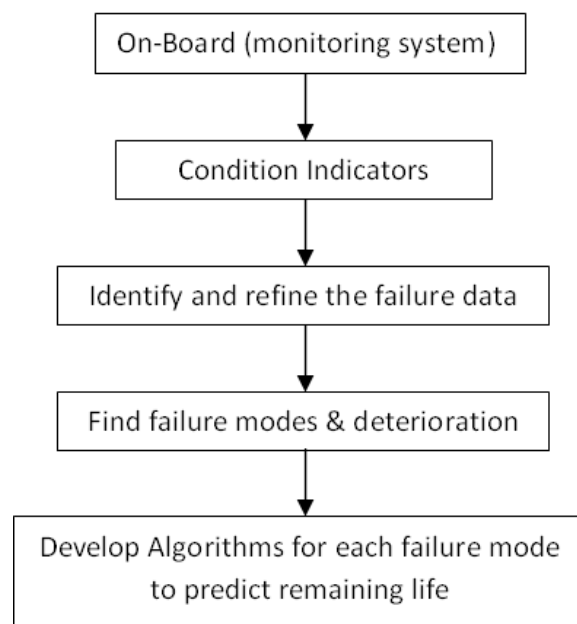
Figure 2. Failure algorithm steps.

As we go deep to the component level, we have to look it from a management point of view. A proper business case has to be developed that will take into consideration functionality, availability, economics, and reliability of the system. A proper study has to

be performed well up front to address different issues while implementing CBM. These are the issues a proper business case must address. As we are approaching the end of the first decade of the 21st century, computers are becoming faster and a highly efficient electronic equipment, such as sensors are available in the market. There is a lot that we can be used from this industry that can be well implemented in the CBM field. A more focused approach is needed towards application of embedded electronics in CBM. The advancement in web technologies allows remotely located robots to be programmed, operated upon, and monitored for maintenance. However, the findings show that e-maintenance is still in its infancy stage. Artificial intelligence offers a number of methods and techniques that provide potential benefits if harnessed properly.

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