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On condition based maintenance policy

Jong-Ho Shin[a], Hong-Bae Jun[b,*]

[a]Department of Design and Human Engineering, UNIST, Ulsan, South Korea
[b]Department of Industrial Engineering, Hongik University, Seoul, South Korea

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Abstract

In the case of a high-valuable asset, the Operation and Maintenance (O&M) phase requires heavy charges and more efforts than the installation (construction) phase, because it has long usage life and any accident of an asset during this period causes catastrophic damage to an industry. Recently, with the advent of emerging Information Communication Technologies (ICTs), we can get the visibility of asset status information during its usage period. It gives us new challenging issues for improving the efficiency of asset operations. One issue is to implement the Condition-Based Maintenance (CBM) approach that makes a diagnosis of the asset status based on wire or wireless monitored data, predicts the assets abnormality, and executes suitable maintenance actions such as repair and replacement before serious problems happen. In this study, we have addressed several aspects of CBM approach: definition, related international standards, procedure, and techniques with the introduction of some relevant case studies that we have carried out.

Keywords: Condition-based maintenance; Predictive maintenance; Prognostic and health management

1. Introduction

In general, maintenance is defined as all technical and managerial actions taken during usage period to maintain or restore the required functionality of a product or an asset. There have been various classifications of maintenance policies. Simply, maintenance policies can be divided into breakdown maintenance and preventive maintenance. Some references, e.g. Erbe et al. [11] identified maintenance types in detail. In our study the maintenance policy is classified into three types: breakdown maintenance (corrective maintenance), preventive maintenance, and Condition-Based Maintenance (CBM). In the breakdown maintenance, the maintenance action is taken after some problems such as breakdowns in a product are found while the preventive maintenance periodically checks a product with a certain interval in order to prevent the abnormality of the product. The CBM may be similar to the preventive maintenance in the sense that its goal is to prevent product abnormality in advance before abnormality occurs. Note that some previous works put the CBM method under the preventive maintenance policy with the Time-Based Maintenance (TBM) method. However, the CBM approach is different from the time-oriented approach of preventive maintenance. It focuses on the prediction of degradation process of the product, which is based on the assumption that most abnormalities do not occur instantaneously, and usually there are some kinds of degradation process from normal states to abnormalities [12]. Hence, unlike breakdown maintenance and preventive maintenance, the CBM focuses on not only fault detection and diagnostics of components but also degradation monitoring and failure prediction. Generally, CBM can be treated as a method used to reduce the uncertainty of maintenance activities and is carried out according to the requirements indicated by the equipment condition [27]. Thus, the CBM enables us to identify and solve problems in advance before product damage occurs. In industry systems, any product damage can lead to serious results. In this respect, the CBM is very attractive method for the industry operating high-valued assets.

Until now it has been difficult to achieve effectiveness of maintenance operations because there is no information visibility during product usage period. However, recently, with emerging technologies such as Radio Frequency IDentification (RFID), various sensors, Micro-Electro-Mechanical System (MEMS), and wireless tele-communication, and Supervisory Control And Data

*Corresponding author.

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Acquisition (SCADA), Product Embedded Information Devices (PEID) are expected to be rapidly used for gathering and monitoring the status data of products during their usage period. Advancements in information technology have added accelerated growth in the CBM technology area by enabling network bandwidth, data collection and retrieval, data analysis, and decision support capabilities for large data sets of time series data [29]. Under the new environment, we can gather the product status and usage data related to distributing route, usage conditions, failure, maintenance or service events, and so on. These data enable us to diagnose the degradation status of the product in a more exact way. Therefore, using this information gives us new challenging issues for improving the efficiency of product maintenance operations. We can make a diagnosis of product status, predict products abnormality, and execute proactive maintenance, i.e. do CBM.

Since a critical failure or degradation of the product during its operation can seriously damage the belief of customers on the product reliability, the maintenance enhancement for preventing this kind of failure or degradation in advance has precedence over any other things in a company. For this purpose, recently lots of manufacturing companies are trying to adopt new technologies and get more accurate real-time information regarding product status during its usage period. As diverse information becomes available, the CBM approach to use them for preventing a critical failure or degradation in advance has been highlighted. Although most machine maintenance today is still either purely reactive (fixing or replacing equipment after it fails) or blindly proactive, world-class companies are moving forwards towards 'predict-and-prevent' maintenance [19], which is very similar to the goal of CBM. From this perspective, this study will deal with several aspects of CBM. Although there have been some literature review works on CBM, this study has some different features compared to previous works: First, this study deals with various aspects of CBM based on the survey of relevant previous works. It contains its definition, advantage and disadvantage, procedure, related standards, diagnostics and prognostics methods, and so on. Second, this study refines the definition of CBM considering several aspects of CBM, e.g. procedure and its advantage, and clarifies the difference between diagnostics and prognostics. Finally, this study addresses some discussion issues when implementing CBM based on several CBM case studies that we have carried out.

This study is organized as follows. First, in Section 2, we address the definition, related international standards, and previous studies associated with CBM. Furthermore, we introduce relevant case studies that we have carried out until so far. In addition, we make a discussion about the implementation of CBM approach. Finally this study is concluded with the discussion on contributions and limitations in Section 3.

2. Several aspects on condition based maintenance approach

2.1. Definition

The term, CBM, is often used with other terms such as Predictive Maintenance (PdM), Prognostic and Health Management (PHM), on-condition maintenance which comes from the U.S. Department of Defense and Department of Energy, online monitoring, or risk based maintenance. Actually, the concept of CBM was first introduced by the Rio Grande Railway Company in late 1940s and initially it was called predictive maintenance [29]. There are various definitions on the concept of CBM. Bengtsson [3] shortly described it as preventive maintenance based on performance and/or parameter monitoring and the subsequent actions. According to British Standard, CBM is defined as the maintenance policy carried out in response to a significant deterioration in a machine as indicated by a change in a monitored parameter of the machine condition. According to the definition of Kothamasu et al. [21], CBM is a decision making strategy where the decision to perform maintenance is reached by observing the condition of the system and/or its components. These definitions address the goal of CBM, but they have the limitation in describing the CBM procedure. On the other hand, Butcher [4] defined CBM as a set of maintenance actions based on real-time or near real-time assessment of equipment condition, which is obtained from embedded sensors and/or external tests & measurements taken by portable equipment. This definition includes technical aspect of CBM compared to previous ones, but lack of the descriptions on CBM goal.

In this study, we define CBM as a maintenance policy which do maintenance action before product failures happen, by assessing product condition including operating environments, and predicting the risk of product failures in a real-time way, based on gathered product data.

2.2. Advantage and disadvantage

In general, there are lots of stakeholders during asset lifecycle. For example, owner of asset, operators (users), external agents (maintenance service provider), regulators related to health and safety (government), and so on. From each viewpoint, the interests and objective of CBM will be different.

We can think of what the advantages and disadvantages of CBM approach are. Until so far, there are lots of advantages of CBM reported in previous works or from industries. Amongst them, first and foremost, the CBM gives us prior warning of impending failure and increased precision in failure prediction. Thus, it can effectively reduce the product failure compared to other approaches. From the viewpoint of product safety management, the CBM is useful for the product types where safety is considered important since it can increase safety by detecting problems in advance before serious problems occur, which leads to the improvement of customer satisfactions due to the high quality assurance. Hence, the CBM makes maintenance service providers avoid the risk cost due to the dissatisfaction of product quality. In general, by the maintenance contract, a maintenance service provider usually has the responsibility for keeping the quality of product in a customer during the warranty period. Hence, the CBM is very attractive for the maintenance service provider.

Furthermore, it allows end users to perform better planned maintenance, reduce or eliminate unnecessary inspections, and decrease time-based maintenance intervals with confidence [6]. The use of CBM systems in industry has been reported to be one way of decreasing maintenance budgets [3]. It can reduce costs by avoiding unnecessary maintenance and enabling maintenance to be scheduled more efficiently [30]. According to Lee [24], annually savings from widespread deployment of CBM technology in the United States alone is estimated at $35 billion.

In addition, the CBM can optimize the production process and improve its productivity. It provides the ability for the system to continue operating as long as it is performing within predefined performance limits [29]. It also aids in diagnostic procedures as it is relatively easy to associate the failure to specific components through the monitored parameters. It can be linked to adaptive control thus facilitating process optimization.

However, in spite of these benefits of CBM, it has some limitations. According to Hashemian and Bean [15], nearly 30% of industrial equipment does not benefit from CBM. First of all, the investment cost for CBM is usually high. To implement the CBM, it is prerequisite to install and use monitoring equipment and to develop some level of modeling or decision making strategy. Also, to implement the CBM, not only investment of hardware but also training on staff is required. It will cause fairly expensive cost. Furthermore, savings potential with CBM approach seldom shows from the management viewpoint. In addition, the technologies and technical methods for the CBM approach are still in their infancy. It means that there are some limitations in ensuring the accuracy of diagnostics and prognostics.

2.3. Literature review

There have been several previous works related to the review of CBM. For example, Bengtsson [3] investigated standards and standardization proposals related to CBM and described several organizational aspects considered when deciding to implement CBM. Jardine et al. [17] reviewed the research on diagnostics and prognostics of mechanical systems implementing CBM with an emphasis on models, algorithms and technologies for data processing and maintenance decision-making. Kothamasu et al. [21] reviewed the philosophies and techniques of system health monitoring and prognostics. They surveyed health monitoring paradigms and looked into the details of health monitoring tools. In addition, they introduced previous case studies in system monitoring and control. Furthermore, Grobal et al. [13] introduced the initial architecture for CBM framework, which was being realized in a joint project with SAP research. They mentioned several aspects of CBM: identification of indicators, measurement of indicators, modeling of indicators, forecasting of indicators, and decision making. In addition, Dragomir et al. [10] analyzed and discussed the prognostic process from different points of view: the concept, the measures and the tools. They defined a frame to perform (and develop) real prognostic systems, and also described the concept of 'prognostic' in detail and did analysis of the tools used in prognostic and prediction. The Machinery Information Management Open Systems Alliance (MIMOSA) proposed and facilitated conventions, guidelines and recommendations that promote cost-effective unification of machine information, condition assessment and control technology [22]. Recently, Hashemian and Bean [15] classified CBM techniques into three categories based on their data source: (1) the existing sensor-based maintenance technique; (2) the test-sensor-based maintenance technique; and (3) the test signal-based maintenance technique. Prajapati et al. [29] have provided a brief overview of CBM plants. Dieulle et al. [8] proposed a mathematical model for determining a CBM policy efficiently using renewal processes theory. In their model, they regarded preventive replacement threshold and inspection schedule as decision variables. Koç and Lee [20] addressed the concept of web-enabled predictive maintenance in an intelligent e-maintenance system which is implemented via Internet and showed its system elements. Furthermore, Hirable et al. [16] described the schema and requirements for the part agent that makes a recommendation on the part maintenance based on the gathered information from Internet and historical data. They mentioned that the part agent could calculate the cost for replacement based on deterioration of spare parts and their replacement fees. Deuteranopic et al. [9] proposed the framework of watchdog agent for predictive condition-based maintenance by realizing multi-sensor assessment and prediction of machine or process performance. The concept of watchdog agent based its degradation assessment on the readings from multiple sensors that measure critical properties of the process or machinery under a networked and tether-free environment. The watchdog agent is an embedded system that has algorithms to autonomously assess and predict the performance degradation and remaining life of machines and components. Yan et al. [37] presented a prognostic method for machine degradation detection, which can both assess machine performance and predict the remaining useful life. In their model, real time performance is evaluated by inputting features of online data to the logistic model. And the remaining life is estimated using an ARMA model based on machine performance history. In addition, Fu et al. [12] proposed a predictive maintenance framework for hydroelectric generating unit. They presented three key elements for the predictive maintenance such as monitoring and forecasting, diagnosis and prognosis, and decision-making. In addition, Bansal et al. [2] described a real-time predictive maintenance system for machine systems. The aim of the proposed system is to localize and detect abnormal electrical conditions in order to predict mechanical abnormalities that indicate, or may lead to the failure of a motor. They used a neural network approach to predict parameters of a machine. Recently, Lee et al. [25] introduced the emerging field of e-maintenance and its critical elements. They also introduced performance assessment and prediction tools such as neural networks, fuzzy logic, logistic regression, hidden mark models, and Bayesian belief networks for continuous assessment and prediction of a particular products performance. Recently, Gruber et al. [14] suggested a CBM framework that is based on system simulations and a targeted Bayesian network model.

They analyzed the robustness of various CBM policies under different scenarios throughout simulations, and developed an explanatory compact meta-model for failure prediction with Bayesian model.

2.4. Related international standards

There are several international standards related to CBM approach. Table 1 shows the international standards. Some are the condition monitoring and diagnostics standards for machinery industry, e.g. ISO 13372, ISO 13373, ISO 13380, and ISO 13381. In particular, ISO TC 108 deals with mechanical vibration and shock. As a result, ISO 13374 addresses the MIMOSA OSA-CBM representing formats and methods for communicating, presenting, and displaying relevant information and data. There are also standards related to the issues of integration and data sharing among manufacturing facilities for CBM, e.g. ISO 18435 (MIMOSA OSA-EAI). Recently, not only machinery industry but also plant engineering industry, e.g. petroleum, petrochemical and natural gas industry, starts to have more interest in the CBM policy, as you see in the ISO 14224.

2.5. Techniques for CBM

There are various kinds of techniques to be applied in data processing, diagnostics, and prognostics for implementing CBM as shown in Table 2. In CBM, there are three kinds of approach: (1) Data-driven approach, (2) Model-based approach, and (3) Hybrid approach [23]. According to Caesarendra [5], data-driven approach has the ability to transform high-dimensional data into lower dimensional information. It is also known as the data mining approach or the machine learning approach, which uses historical data to automatically learn a model of system behavior [30]. However this approach has the dependency on the quality of the operational data and there is on physical understanding of target product. On the contrary, model-based approach has the ability to incorporate physical understanding of the target product. It relies on the use of an analytical model (set of algebraic or differential equations) to represent the behavior of the system, including degradation phenomenon [36]. But, it has the limitation in the point that it can only be applied to specific types of products. Table 3 shows several techniques for each approach.

2.6. Procedure

The CBM can be done by (1) gathering product status data and monitoring; (2) making a diagnosis of a product status in a real-time way; (3) estimating the deterioration level of the product, its repairing cost which depends on the deterioration level, or its replacement cost, and so on; (4) predicting the time of products abnormality; and (5) executing appropriate actions such as repair, replace, left to use as it is, and disposal.

To implement the CBM approach, it is required to resolve several research issues related to data gathering, analyzing,

Table 2
Survey of condition-based maintenance techniques.

Phase	Techniques
Data processing	– Kalman filtering – Time–frequency/time–frequency moments – Wavelet analysis – Autoregressive (AR) model – Fourier analysis – Wigner–Ville analysis – Fuzzy logic – Artificial Neural network – Genetic algorithms – Statistical pattern recognition – Hidden Markov model – Support Vector Machine – Decision tree induction
Diagnostics	– Logistic regression – Artificial Neural network – Reliability theory – Statistical analysis (e.g. Regression) – Time series data analysis
Prognostics	– Case Based Reasoning (CBR) – Renewal theory – Math programming – Simulation
Maintenance operation	– Multi-Criteria Decision Making (MCDM)

Table 1
Survey of international standards.

Standards	Subject
IEEE 1451	Smart transducer interface for sensors and actuators
IEEE 1232	Artificial Intelligence Exchange and Service Tie to All Test Environment
ISO 13372	Condition monitoring and diagnostics of machines—Vocabulary
ISO 13373-1	Condition monitoring and diagnostics of machines – Vibration condition monitoring—Part 1. General procedures
ISO 13373-2	Condition monitoring and diagnostics of machines—Vibration condition monitoring – Part 2. Processing, analysis and presentation of vibration data
ISO 13374	MIMOSA OSA-CBM formats and methods for communicating, presenting and displaying relevant information and data
ISO 13380	Condition monitoring and diagnostics of machines—General guidelines on using performance parameters
ISO 13381-1	Condition monitoring and diagnostics of machines—Prognostics, general guidelines
ISO 14224	Petroleum, petrochemical and natural gas industries-collection and exchange of reliability and maintenance data for equipment
ISO 17359	Condition monitoring and diagnostics of machines—General guidelines
ISO 18435	MIMOSA OSA-EAI diagnostic and maintenance applications integration
ISO 55000	Asset management

Table 3
Survey of condition-based maintenance techniques.

Classification	Techniques
Model driven approach	– Physics based – Classical AI techniques (rule-based expert systems, finite-state machines, qualitative reasoning) [28] – Conventional numerical algorithms (linear regression, Kalman filters) [28] – Statistical approach (multivariate statistical method, state space models, regressive model) [27]
Data driven approach	– Machine learning (neural networks, decision trees, support vector machines) [28] – ANN based, Bayesian network, Hidden Markov Model, Principal component analysis, Gray model [27]
Knowledge-based approach	– Expert systems [27] – Fuzzy logic [27]

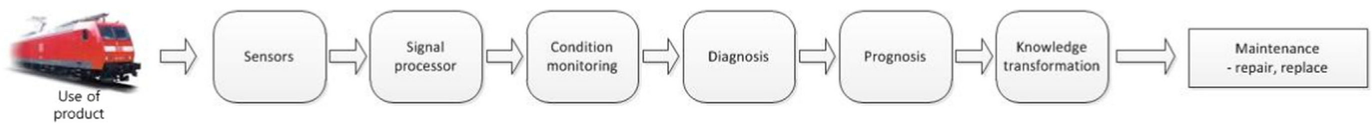

Fig. 1. Procedure for CBM approach.

decision, and actions. In the data gathering level, large amount of field data were collected by various data acquisition methods using sensors, wired and wireless techniques, and stored in a database [29]. Before data gathering, it is necessary to identify which data should be gathered during asset usage period for CBM. For the analyzing, it is required to develop an algorithm that assesses the behavior and degrading level of an asset, and predicts its remaining life time.

Analyzing has two parts in CBM: diagnostics and prognostics. Diagnostics consists of fault detection, fault isolation determining the location of the fault, and fault identification determining the fault mode [28,14]. To this end, diagnostics requires data pre/post-processing, data interpretation, data fusion, and several statistics methods with asset specific knowledge. On the other hand, prognostics corresponds to the estimation of the time to failure and the risk for one or more existing and future failure modes based on anticipated future usage [28,36]. To this end, prognostics deals with estimation of system health index and predictions of Remaining Useful Life (RUL) [6]. Prognostics is a word newly coined by the scientific community to address the combination of diagnosis and prognosis [1]. For more detailed understandings of prognostic, please refer to Dragomir et al. 's work [10]. Prognostics is employed by integrating sensor data and prediction models that enable in situ assessment of the extent of deviation or degradation of a product from an expected normal operating condition [34]. It is critically important to assess the RUL of an asset while in use since it has impacts on the planning of maintenance activities, spare parts provision, operational performance, and the profitability of the owner of an asset [33].

In the decision making level, first, there are some decision issues to be made [35]: selecting the parameters to be monitored; determining the inspection frequency; and establishing the warning limits. Furthermore, it is also necessary to develop a decision method that selects the best cost-effective maintenance operation telling us which maintenance option is the best under a given situation in terms of maintenance costs. Depending on cases, there are several maintenance options related to what, when, and how to do maintenance. For each option, it is required to build up maintenance cost models. Comparing cost models will allow us to select the best cost effective maintenance schedule. In the action level, it is requisite to design action plans for all possible scenarios. Finally, it is necessary to develop a framework for integrating these four issues.

Regarding the procedure of CBM, first of all, we should look into the MIMOSA Open Standard Architecture Condition Based Maintenance (OSA-CBM) architecture. OSA-CBM is designed by MIMOSA which is an organization involved in the development of the standards for CBM. OSA-CBM is a standard for information flow to help realize an end-to-end CBM system [29]. According to MIMOSA Open Standard Architecture Condition Based Maintenance (OSA-CBM), there are six layers needed to implement the concept of CBM: Data Acquisition, Data Manipulation, State Detection, Health Assessment, Prognostics Assessment, and Advisory Generation.

Fig. 1 shows the generic procedure for implementing CBM approach based on the OSA-CBM architecture.

2.7. Introduction of related case studies

In this section, we briefly introduce several case studies related to CBM approach that we have carried out. Table 4 shows the summary of our case studies.

2.7.1. Oil analysis: Truck engine

The first case study [18] has dealt with a CBM method of estimating the change time of engine oil of a vehicle (truck). Oil debris analysis is one popular technique in the CBM domain. According to Prajapati et al. [29], some automobile companies like GM has deployed a CBM system to detect the oil quality based on the life of oil components. In this case study, we have developed a predictive algorithm to determine a suitable changing time of engine oil by analyzing its degradation status with mission profile

Table 4
Classification of case studies.

Target product	Concerning variable	Application area	Objective
–Engine	–Engine oil quality	–Commercial vehicle	–RUL estimation
–Lift arm	–Crack	–Heavy load vehicle	–RUL estimation
–Locomotive	–Fault event data	–Locomotive	–RUL estimation and fault analysis
–Compressor	–Vibration	–Offshore plant equipment	–RUL estimation

data. In most cases, engine oil changes are typically performed according to mileage or calendar schedules, i.e. time-based preventive maintenance. However, this strategy is not efficient because the oil change interval usually depends on the usage mode of a vehicle which can be identified by its mission profile data during its usage period. Depending on the type of a vehicle and its usage objective, the usage mode (hereafter called mission profile type) will be different. Some vehicles may be frequently used in a highway, while some could also be mainly used in an urban. Diverse mission profile types make the degradation process of engine oil different. Thus we should apply different time intervals to change engine oil considering the specific mission profile type of a vehicle. It is the main idea of this case study.

In this case study, our goal is to determine the appropriate time for changing engine oil based on the analysis of mission profile data. If we are truck drivers, at a specific time T, we want to know whether we should change engine oil or not. How do we determine the appropriate time of engine oil change without direct analysis of engine oil, just only by using the mission profile data gathered at T? This was the problem that we wanted to solve in this case study.

To resolve this problem, we have proposed a predictive algorithm based on gathered vehicle operation data via on-board diary equipment in a vehicle. Since there was no direct sensing mechanism for identifying engine oil quality, we used indirect sensing measures (e.g. RPM, the number of engine starts, etc.) gathered by on-board diary equipment built in a truck. We identified the relationship between indirect measures and direct measures for engine oil quality (e.g. TAN, TBN, Viscosity), and used it for the algorithm for estimating the suitable engine oil change interval. In the proposed algorithm, we used several statistical methods such as discriminant and classification analysis, factor analysis, and multiple regression analysis. First, based on historical data, it is necessary to identify main factors of mission profile indicators and oil quality indicators. Then, analysis of mission profile data gathered for prediction is done to get the information of mission profile type of a truck. After identifying mission profile type of the truck, we can identify the relations between main factors of mission profile indicators and oil profile indicators for each mission profile type. Based on them, we could predict the quality of engine oil and decide whether the change of engine oil is needed or not.

2.7.2. Crack propagation analysis: lift arm structure of TTL

The second case study [32] is about developing the CBM method for the lift arm structure of a heavy loaded vehicle, called Track Type Loader (TTL). The developed CBM algorithm focuses on the RUL estimation of the lift arm structure. It could be estimated based on the degradation state data, mission profile data, and future usage mode data.

The degradation state data is assessed by the crack propagation data measured by sensors. To assess the degradation state of the lift arm, it is necessary to use several sensors attached to different locations of structure welds. Each sensor observation provides the measurement value related to the degradation state of each location. The sensor provides the information at each ligament breaking during the time of use of the structure part. One ligament breaking corresponds to 8.33% of sensor damaging. The sensing data could be transmitted to a central server via RFID and wireless communication technology. To estimate the RUL in a more exact way, it is necessary to understand the concept of mission profile. The mission profile data consist of operation data and working environment data. The operation data indicates usage behavior data generated from product consumers or operators under a specific usage mode and collected by various sensors attached to the TTL during its operation: e.g., engine Revolution Per Minute (RPM), mileage, operation hours, the number of engine starts, and several loading conditions such as hydraulic cylinders pressure measurement, pin load sensors measurements, and hydraulic cylinders displacements measurements. The working environment data are related with working places where the product is usually used. As working environment data, geographical data in the product working site such as humidity, temperature, and soil type could be collected. The future usage mode data are the predefined working conditions for future use, e.g. economic mode or sport drive mode in a car. For the TTL case, as the future usage mode, the following can be considered: waste transfer, forestry, road construction, quarry, ship hold, demolition (building), house construction, and so on. To select the future use mode of the structure part means to decide at the present instant what future mission will be realized.

Without the detailed identification and segmentation of the mission profile, and the selection of future usage mode, it is difficult to estimate the RUL in an exact way. Some TTLs are used in the harsh environment or under strict usage operations while others are used in the mild environment or under loose usage operations. Thus, depending on environmental and operational conditions, the degradation will be different, which indicates that the RUL estimation should be done considering mission profile data and future usage mode data. Based on the selected usage mode, a typical segmentation of mission profile data is established and each one is stored in the mission profile database for reuse. When the future usage mode is identified, the corresponding mission profile data can be retrieved from the mission profile database and used for the RUL estimation. For example, loading condition data is used for a Finite Element Analysis (FEA). Using these loading conditions and a CAD model of the lift arm, the FEA allows to retrieve the future local stress history at each location of the structure, and in particular at the sensor measurement point. When the future local stress profile is found, the remaining number of applied stress cycles can be calculated by the fracture mechanics theory based on current degradation state data by sensors and so the local remaining life time can be estimated by the crack propagation method based on fracture mechanics.

2.7.3. *Field operation data analysis: locomotive*

To implement the CBM, one important task is to correlate monitored product usage data with the product status. In reality, many industries gather a big amount of product usage data, but do not analyze or use them in a systematic way. In this respect, the third case study [31] focuses on how to analyze the lots of product usage data from the CBM approach viewpoint.

The case study has been done based on the operation data of a locomotive during one year. The locomotive has lots of sensors to monitor and, gather and store the usage data of components/parts into the PEID, e.g. on-board computer, during its operation. The gathered data in PEID are periodically transmitted to a central server for analysis. However, the locomotive operation company does not have any kind of effective method to use gathered product usage data in a systematic way. Although more exact failure analysis could be possible with currently obtainable usage data such as temperature, current, voltage, pressure, etc., the data monitored by sensors are just transferred to the main database located in the company and stored. Hence, it is necessary to upgrade the current maintenance policy for the efficient operation of the locomotive, e.g. CBM approach.

The prediction of product status based on the analysis on product usage data is one of the most challenging tasks to realize the CBM approach. To this end, various kinds of methods, such as logistic regression analysis, Artificial Neural Network (ANN), AutoRegressive Integrated Moving Average (ARIMA) model, and reliability analysis, and so on, have been studied and implemented.

In this case study, the ANN is applied to correlate monitored product usage data with the product status. The case study based on the locomotive operation data has been carried out to predict the next failure event by correlating the accumulated failure data of locomotive components/parts with the locomotive status with several ANN methods. To find the most suitable type of ANN model for the CBM, several types of ANN models are tested with field data collected during locomotive operations. Whenever a failure event occurs during operation, the ANN is trained using stored data in the database for each failure event type. The trained ANN is used to estimate the next failure event occurrence time and failure event occurrence rate with the currently monitored operational and environmental data.

2.7.4. *Vibration analysis: Compressor*

In this case study [7], we have introduced an algorithm predicting the next failure time of the compressor which is one of essential mechanical equipment in Liquefied Natural Gas Floating Production Storage (LNG FPSO and Offloading vessel).

Nowadays due to the fact that an accident of LNG FPSO in operation causes catastrophic damage, many studies dealt with the improvement of operating a maintenance system for high-valued assets such as LNG FPSO. The LNG FPSO is composed of lots of facilities and equipment. Among them, this case study focuses on a gas compressor equipment which is an important device in not only offshore but also onshore plants. A gas compressor is a mechanical device that increases the pressure of a gas by reducing its volume. Among several types of compressors, we choose the centrifugal compressor.

In order to monitor the status of the gas compressor and estimate the next failure time based on the gathered status data, among several status parameters of the compressor, we have focused on vibration parameter data since it is widely used in detecting the status of rotating equipment such as compressor. Relative shaft vibration and bearing vibration sensing data are usually used to evaluate the status of a compressor of the LNG FPSO. This case study has evaluated the status of a gas compressor through relative shaft vibration data.

According to ISO 7919 standard for relative shaft vibration of rotating machines, four levels of vibration limits are recommended: limit of start-up performance, limit of good vibration performance, limit for warning alarm, and limit for trip. As an evaluation criterion, this case study used the magnitude of vibration, i.e. Peak–Peak value. To do the CBM approach of a LNG FPSO compressor, this study has proposed a prognosis algorithm based on continuous time Markov model theory. In the proposed algorithm, first, after collecting relative shaft vibration history classified by status transition between the levels of vibration limits, status transition rates could be estimated. And then, the next failure time could be estimated based on the developed formula. To show the usefulness of the proposed algorithm, an example based on generated shaft vibration sensor data was described in the case study. For more details, please refer to Cho et al. [7].

3. Discussion

There are some discussion points in implementing CBM approach. First, the CBM is not always effective in all cases. Depending on product type and its lifecycle, economic benefits will be different since the degree of importance of maintenance operation will be different, which requires detailed analysis on maintenance strategy. There are various product types such as large-scaled plant, industry or consumer products with high value or low value. For the large scale plant or high valued product, the CBM could be a good solution because the product failure causes great loss. However, for mass-consumption products such as automotive, the CBM may not be effective in terms of maintenance cost. Thus, we should consider economic benefits when we apply a new maintenance strategy. To this end, it is imperative to define the business model for new maintenance operation and identify benefits and costs.

Furthermore, another challenging issue is how to implement CBM in the case of very few or no data situations. This is typical for newly commissioned systems where no observed failure data and maintenance information exists [33]. In this case, as Si et al. [33] mentioned, the quantity and completeness of data are insufficient to fit the full statistical models. Hence, it may be a better choice to develop physics-based models with the help of subjective expert knowledge from design and manufacturing. If machine learning techniques are used for diagnosis or prognosis, in the beginning of CBM implementation, the unsupervised learning approach may be better to build up the reference model identifying normal and abnormal situations. And then, supervised learning and reinforcement learning approach could be applied to make the CBM algorithms more accurate.

Another discussion point is that, as Mobley [26] mentioned, most CBM approaches treat target product as isolated unit system and not as part of an integrated system. As a result, no effort is made to determine the influence of system variables (process parameters, e.g. flow rate, temperature, load, speed, etc.) on the individual component. CBM is not just a box you can buy to integrate onto your platform or system, but is a set of integrated technologies, processes, and capabilities that together enable CBM to be realized [29]. CBM methods and practices have been continuously improved for the last decades: however, CBM is conducted at equipment level-one piece of equipment at a time, and the developed prognostics approaches are application or equipment specific [19]. However, to get the practical benefit of CBM approach, it is necessary to consider applying CBM into not only one piece of equipment but also an integrated system level.

In addition, one challenging issue is to make the closed link between product design improvement and CBM. Collecting product status data during product usage period makes a product itself or product operations improved in a various way. For example, we can consider the improvement of design as well as the optimization of maintenance operations. Despite much interests on the CBM methods over diverse domains, there has been a lack of methods to combine product usage information with design improvement in a systematic way. Although there have been some related research works, there is still the limitation in the decision framework or guidance for product design improvement based on product status information assessed by gathered product usage data during product operation. For example, the RUL value at a certain time can be compared to the theoretical remaining life time of a product calculated by the difference between the designed life time and product operating time. A comparison of these values tells us how adequately the product is being used. As a result, if the remaining life time is longer than the theoretical remaining life time, then, we can let the product go without any maintenance actions or modify the severity of mission profile for the use of more intensive applications. Otherwise, CBM operations should be done. Thus, it is needed to develop a decision support method applying product status data analyzed during CBM into supporting design improvement. Finally, it is valuable to discuss what the issues are in order to implement CBM in a real time way. In order to realize the CBM, there are some ICT challenges to be solved in a real field: sensor data quality related to gathering frequency, noise, and level of details of sensor data, data availability, wireless communication problem, frequency of diagnostics and prognostics, and so on. From the data gathering viewpoint, we should consider the scale of gathered data. In CBM, sensor measurements could be taken at regular interval or even continuously in a real time way. If we can monitor a product and gather the product status data in a real time way, it must be the best way for analyzing the product status. However, with this approach there is the heavy load of data gathering which leads to high cost. From the practical viewpoint, it is not cost-effective to gather the data of product status in a real time and continuous way. Actually, data gathering is done based on a certain time period, e.g. every five minutes, every one hour, and so on. Hence, it is necessary to decide the most suitable time period for data gathering considering the scale of gathered data. On the other hand, we should consider data transmission mechanism. In general, product status data can be gathered via various sensors and on-board computer already attached to a product via wire or wireless communication. For the data transmission between various sensors and a host computer, we can use RFID tags as transmitters or directly send gathered sensor data into the host computer via wire or wireless communication. Since there are various ways of data transmission, it is necessary to identify which data transmission type (wire or wireless) is effective in terms of cost and reliability.

4. Conclusion

There is no doubt that the CBM approach will be one important tool to industries in the era of big data. Although the concept of CBM is introduced a few decades before, recently the CBM approach has been highlighted from industries according to the development of emerging ICTs. To implement the CBM approach, first and foremost, it is required to look into what the CBM is. For this purpose, this study has reviewed the CBM approach from several viewpoints. The definition, advantages and drawbacks, related international standards of CBM were introduced. Furthermore, data, procedure, techniques for implementing the CBM approach have been addressed. In addition, various CBM case studies have been briefly introduced. Finally, some challenging issues and discussion points to realize the CBM approach have been dealt with.

Although this study tried to deal with several aspects of CBM, there are still some limitations, which could be considered future research works. First, there is the limitation in providing the more details on the technological traits on CBM. Second, since it does not contain all of relevant previous works, there may be some limitations in providing more concrete analysis on CBM approach. Despite the above limitations, we believe that it will help people understand the concept of CBM approach in more detail.

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