



An overview of time-based and condition-based maintenance in industrial application [☆]

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ABSTRACT

This paper presents an overview of two maintenance techniques widely discussed in the literature: time-based maintenance (TBM) and condition-based maintenance (CBM). The paper discusses how the TBM and CBM techniques work toward maintenance decision making. Recent research articles covering the application of each technique are reviewed. The paper then compares the challenges of implementing each technique from a practical point of view, focusing on the issues of required data determination and collection, data analysis/modelling, and decision making. The paper concludes with significant considerations for future research. Each of the techniques was found to have unique concepts/principles, procedures, and challenges for real industrial practise. It can be concluded that the application of the CBM technique is more realistic, and thus more worthwhile to apply, than the TBM one. However, further research on CBM must be carried out in order to make it more realistic for making maintenance decisions. The paper provides useful information regarding the application of the TBM and CBM techniques in maintenance decision making and explores the challenges in implementing each technique from a practical perspective.

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1. Introduction

Over the last few decades, maintenance functions have drastically evolved with the growth of technology. Maintenance is defined as a set of activities or tasks used to restore an item to a state in which it can perform its designated functions (Dhillon, 2002; Duffuaa, Raouf, & Campbell, 1999). Maintenance strategies can be broadly classified into Corrective Maintenance (CM) and Preventive Maintenance (PM) strategies (Duffuaa, Ben-Daya, Al-Sultan, & Andijani, 2001).

Corrective maintenance, also known as run-to-failure or reactive maintenance, is a strategy that is used to restore (repair or replace) some equipment to its required function after it has failed (Blanchard, Verm, & Peterson, 1995). This strategy leads to high levels of machine downtime (production loss) and maintenance (repair or replacement) costs due to sudden failure (Tsang, 1995). An alternative to the CM strategy is the PM strategy. The concept of PM involves the performance of maintenance activities prior to the failure of equipment (Gertsbakh, 1977; Lofsten, 1999). One

of the main objectives of PM is to reduce the failure rate or failure frequency of the equipment. This strategy contributes to minimising failure costs and machine downtime (production loss), and increasing product quality (Usher, Kamal, & Syed, 1998).

In the industry, application of the PM strategy can be generally performed through either experience or original equipment manufacturer (OEM) recommendations, and is based on a scientific approach. The application of PM through experience is a conventional PM practice. In most cases, it is performed at regular time intervals, T (Canfield, 1986; Nakagawa, 1984; Sheu, Griffith, & Nakagawa, 1995). Through experience, no standard procedures are followed, thus knowledge from technicians and engineers for maintenance purposes is a valuable asset to the company. Technicians and engineers in this setting learn from previous mistakes and, based on their experience, are able to detect the abnormal conditions of a machine by sense. They can then decide the appropriate PM actions to apply in order to avoid machine breakdown. The main drawback of PM through experience, however, is that the company may face difficulties when the experienced person leaves the company. Moreover, such persons may be not present in production lines round-the-clock to solve maintenance problems.

Through OEM recommendations, PM is carried out at a fixed time, for example every 1000 h or every 10 days, based on recommendations. However, this PM practice is not usually applicable when attempting to minimise operation costs and maximise machine performance. Labib (2004) listed three reasons for this:

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First, each machine works in a different environment and would, therefore, need different PM schedules. Second, machine designers often do not experience machine failures and have less knowledge of their prevention compared to those who operate and maintain such machines. Finally, OEM companies may have hidden agendas, that is, maximising spare parts replacement through frequent PMs. This is supported by Tam, Chan, and Price (2006), who stated that PM intervals based on OEM recommendations may not be optimal because actual operating conditions may be very different from those considered by the OEM. As such, actual outcomes may not satisfy company requirements.

The area of operational research introduced the application of PM based on a scientific approach in 1950. The scientific approach involves specific processes and principles that employ various analytical techniques, such as statistics, mathematical programming, artificial intelligence, etc. The main advantage of PM practice based on the scientific approach is that decision making is based on facts acquired through real data analysis. In the literature, PM based on the scientific approach can be classified into two techniques: comprehensive-based and specific-based techniques. The comprehensive-based technique also known as maintenance concept development, which can be defined as a set of various maintenance interventions (experience-based, time-based, condition-based, etc.) and the general structure in which these interventions are foreseen (Pintelon & Waeyenbergh, 1999). According to Waeyenbergh and Pintelon (2002), maintenance concept development forms the framework from which installation-specific maintenance techniques are developed and is the embodiment of the way a company thinks about the role of maintenance as an operational function. Some examples of maintenance concepts are reliability-centred maintenance (RCM), business-centred maintenance, risk-based maintenance, total-productive maintenance (TPM), and the centre for industrial management maintenance concept development framework. The specific-based technique, as its name implies, is a specific maintenance technique that has unique principles for solving maintenance problems. Examples of specific-based technique are time-based maintenance (TBM) and condition-based maintenance (CBM).

This paper presents an overview of the application of TBM and CBM, both of which have been widely reported in the literature. Although some papers that discuss TBM and CBM (e.g., Mann, Saxena, & Knapp, 1995) are available, an overview of their application and comparison from a practical perspective remains lacking. Thus, this paper has two main objectives. The first objective is to explore how each of these maintenance techniques works toward maintenance decision making. The second objective is to discuss their effectiveness from a practical point of view. The paper is presented as follows: Brief reviews of the concepts, general processes toward maintenance decision making, and recent applications of TBM and CBM are described in Sections 2 and 3, respectively. A comparison of the maintenance techniques from a practical point of view is presented in Section 4. Finally, conclusions are made in Section 5.

2. Time-based maintenance (TBM)

Time-based maintenance, also known as periodic-based maintenance (Yam, Tse, Li, & Tu, 2001a, 2001b) is a traditional maintenance technique. In TBM, maintenance decisions (e.g., preventive repair times/intervals) are determined based on failure time analyses. In other words, the aging (expected lifetime), T , of some equipment is estimated based on failure time data or used-based data (Lee, Ni, Djurdjanovic, Qiu, & Liao, 2006). TBM assumes that the failure behaviour (characteristic) of the equipment is predictable. This assumption is based on hazards or failure rate trends, known as bathtub curves, as shown in Fig. 1.

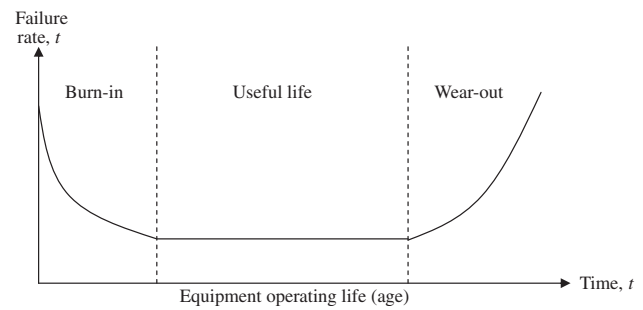


Fig. 1. Bathtub curve.



Fig. 2. General TBM process.

Failure rate trends can be divided into three phases: burn-in, useful life, and wear-out (Ebeling, 1997). The TBM technique assumes that equipment experience decreasing failure rates early in their life cycle (burn-in), followed by a near constant failure rate (useful life). At the end of their life cycles (wear-out), equipment experience increasing failure rates. The general process of TBM can be presented in two steps, shown in Fig. 2.

The first process of TBM starts with failure data analysis/modelling. The basic purpose of this process is to statistically investigate the failure characteristics of the equipment based on the set of failure time data gathered. The detailed process of failure time data analysis/modelling is systematically shown in Fig. 3.

Once a set of failure time data has been gathered, it will be analysed further through statistical/reliability modelling to identify the failure characteristics of the equipment, including mean time to failure (MTTF) estimation and the trend of the equipment failure rate based on bathtub curve process. Statistical/reliability modelling can be carried out using various statistical tools, the most popular of which is through reliability theory using the Weibull distribution model (Ghodrati, 2005; Jóźwiak, 1997). The Weibull distribution model has been widely used to model the failures of many materials and in numerous other applications due to its ability to model various aging classes of life distributions, including increasing, decreasing, or constant failure rates (Bebbington, Lai, & Zitikis, 2007). A detailed discussion of the Weibull distribution model is given in Ebeling (1997).

The Weibull distribution model is usually presented with two parameters: the scale parameter, θ , and the shape parameter, β . The scale parameter shows the lifetime (age) of the component, while the shape parameter presents the characteristics of the component lifetime, whether with a decreasing, constant, or increasing failure rate. The types of failure rates based on the Weibull distribution model can be presented by β , as shown below:

$\beta < 1$, represents a decreasing failure rate

$\beta = 1$, represents a constant failure rate

$\beta > 1$, represents an increasing failure rate

The value of the MTTF can then be determined using

$$MTTF = \theta \Gamma \left(1 + \frac{1}{\beta} \right) \quad (1)$$

where $\Gamma(x)$ is the gamma function

Referring to Fig. 3, only the equipment that has an increasing failure rate is considered for the next process (decision making

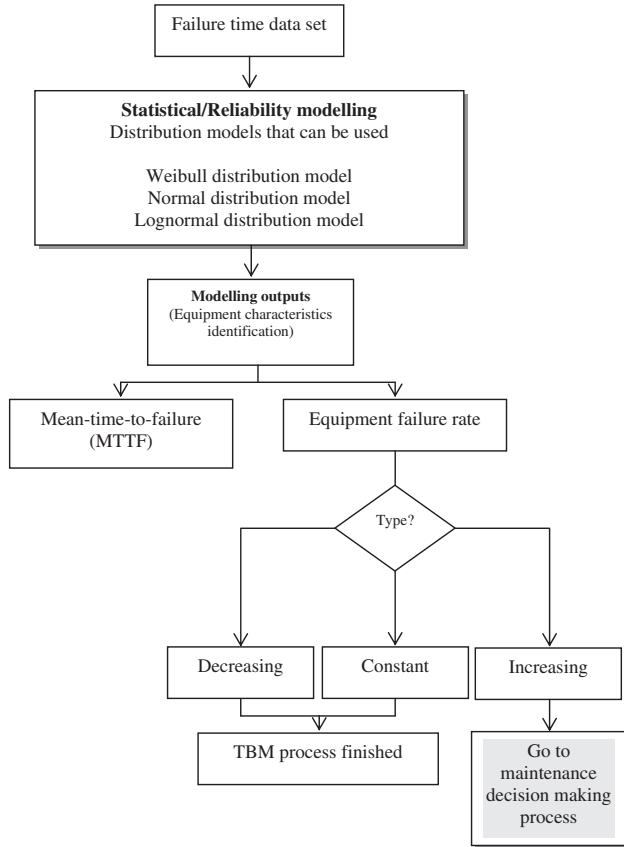


Fig. 3. Failure data modelling process.

process). This is because the optimal PM exists only if the equipment has an increasing failure rate distribution (wear-out stage).

The next process of TBM is the maintenance decision making process. The main objective of this process is to determine the optimal maintenance policies that aim to provide optimum system reliability or availability and safety performance at the lowest possible maintenance cost (Pham & Wang, 1996). Details of the maintenance decision making process are systematically shown in Fig. 4.

Referring to Fig. 4, the maintenance decision making process is composed of two main assessments. The first is the operational cost assessment. The aim of this assessment is to calculate the two types of operational costs: failure cost and PM cost. These costs can be calculated as follows:

$$TC_{fc} = C_m + C_r + C_{dt} \quad (2)$$

$$TC_{pm} = C_m + C_{dt} \quad (3)$$

where TC_{fc} is the total failure cost, TC_{pm} the total PM cost, C_m the maintenance cost, C_r the product reject cost, and C_{dt} is the down-time cost.

The next step in the maintenance decision making process is the equipment mechanism assessment. The aim of this assessment is to classify the structure type of the equipment as either non-repairable or repairable. The definitions of these structure types are as follows:

“Repairable equipment is defined as one that can be repaired to recover its functions after each failure rather than be discarded (Crow (1974))”

After the structure of the equipment has been identified, the appropriate maintenance policy can be selected or developed. For non-repairable types, the replacement policy is used. One of the

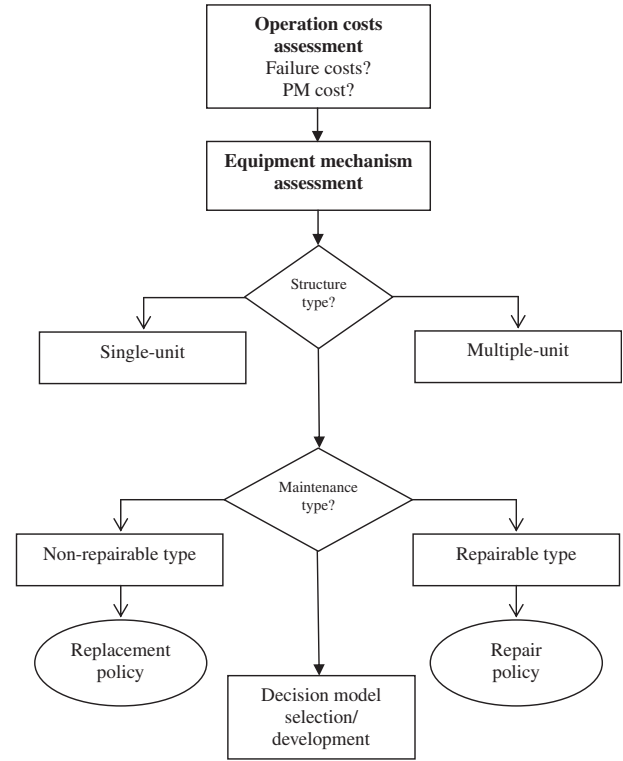


Fig. 4. Maintenance decision making process.

replacement policies is an age-dependent policy. Under this policy, a unit is always replaced at its age, T , or failure, whichever occurs first, with the replaced equipment assumed to be ‘as-good-as new’. The most popular decision model under this policy in the literature is the age replacement model (ARM) (Aven & Jensen, 1999; Handlarski, 1980). The general mathematical model of ARM, which was developed by Barlow and Hunter (1960), is presented in Eq. (4). The main objective of this model is to determine T by minimising the cost function $C(T)$.

$$\min : C(T) = \frac{C_f F(T) + C_p R(T)}{\int_0^T R(t) dt} \quad (4)$$

where $C(T)$ is the cost function at time, T , T the optimum time of replacement, C_f the cost of failure replacement, C_p the cost of preventive replacement, $F(T)$ the cumulative distribution function, and $R(T)$ is the reliability function

For repairable equipment, a repair policy (also known as minimal repair policy) is applied. This policy addresses the appropriate times to perform repairs and replace equipment. The basic repair policy model was first given by Barlow and Hunter (1960), as shown in Eq. (5), where $gm(t)$ is the long-run expected cost per unit time, $N(t)$ is the expected number of failures at time t (minimal repair function), and C_m is the cost of minimal repair. The policy recommends that the equipment be replaced after t hours, and any failure that occurs before t hours is restored with minimal repairs. This minimal repair model assumes that the cost of minimal repairs is less than the cost of preventive replacement.

$$g_m(t) = \frac{C_m N(T) + C_p}{t} \quad (5)$$

Since the introduction of TBM, its application has been extended to many different cases, such as non-repairable to repairable units and single-unit to multi-unit systems. As a result, some reasonable assumptions or concepts have been introduced. One of the most

popular concepts discussed in the literature is the concept of imperfect maintenance introduced by Chaudhuri and Sahu (1977). Imperfect maintenance refers to the effect of maintenance activities, where, after maintenance (repair or replacement), the equipment is not assumed to be good-as-new, but is supposed to be younger (Pham & Wang, 1996). Thus, the challenge of imperfect maintenance is to measure how much younger the equipment is after maintenance is carried out. The extensive discussions regarding imperfect preventive maintenance models are given by Ben-Daya, Duffuaa, and Raouf (2000), Nakagawa (2005), Osaki (2002), and Pham (2003).

On the other hand, many maintenance policies have also been introduced for specific maintenance problems and cases. For example, the periodic PM policy is introduced for non-repairable and repairable multi-unit systems. Under this policy, a group of units is preventively maintained (replaced or repaired) at fixed time intervals. Two decision models of this policy have been introduced: the block replacement model and the block repair–replacement model. Other maintenance policies include the failure limit, sequential PM, and repair limit policies. Under the failure limit policy, PM is performed only when the failure rate or other reliability indices of a unit reach a predetermined level, and intervening failures are corrected by repairs. Under the sequential PM policy, a unit is preventively maintained at unequal time intervals. Finally, under the repair limit policy, repairs are undertaken if the estimated cost of failure is less than a predetermined limit; otherwise, the unit is replaced. A comprehensive review of various maintenance policies is given by Wang (2000).

2.1. An overview of TBM application

In this section, an overview of TBM application for solving maintenance problems reported in the literature from year 2000 is given. This overview focuses on the application of TBM in solving two main maintenance problems that is related in the real industry practice; replacement and repair–replacement problems.

In industry, replacement of production equipment/system is one of the maintenance problems commonly faced by maintenance management. The main focused of this problem is to determine the best replacement time by minimising/maximising some interest criteria such as downtime, failure and maintenance costs, reliability, availability etc. The complexity of the replacement problem depends on the structure of targeted equipment/system such as single-system, multi-systems, parallel and series structure. For example, Das and Acharya (2004) studied the replacement problem of single-component. Two replacement policies based on age replacement policy were proposed. The authors claim that the proposed policies are appropriate for complex process plants, where the tracking of the entire service life of each component is difficult. Castro and Alfa (2004) also considered replacement policy for the case of single-unit system based on the lifetime of the unit. Two replacement models, namely Model I and Model II were developed, where Model I required to replace the unit by a new one when the unit attains a predetermined lifetime, while Model II is to close repair facility when the lifetime of the unit attains a predetermined quantity.

The application of TBM for solving replacement problem for the case of multi-components system is considered by some researchers. For instance, Nakagawa and Yasui (2005) studied replacement problem for the case of multi-systems towards parallel structure. Two replacement models were proposed by considering two cases where a system was replaced only at scheduled times and each unit failed only by shocks. The aim of the paper was to obtain an optimal number of units and replacement times that minimised the expected costs. Some numerical examples were given to validate the proposed models. Childress and Durango-Cohen (2005) also studied a replacement problem on a parallel machine case. A

stochastic version of the problem was formulated and the structure of the optimal policies under general classes of replacement cost functions was analysed. In addition, the authors illustrated how the structural results could be used to reduce the computational effort required to find optimal replacement policies. Meanwhile, Maillart and Fang (2006) studied the replacement problem for multi-systems towards series structure. Age-replacement policy was applied, where optimal replacement time is determined subject to a budget constraint and throughput requirement. Laggoune, Chateaufneuf, and Aissani (2009) studied the optimisation of replacement for a multi-component series system subjected to random failures, where the cost rate is minimised under general lifetime distribution. The proposed optimisation model for the component replacement is validated for the hydrogen compressor in an oil refinery. Scarf and Cavalcante (2010) also investigated the replacement problem for a multi-component system in series structure. The hybrid models of block replacement and inspection policies were developed and the case study of traction motor bearings was used for model validation. Laggoune, Chateaufneuf, and Aissani (2010) studied the opportunistic replacement policy for multi-component systems in the context of data uncertainty, where the expected total cost per unit time was minimised under a general lifetime distribution. A replacement model was developed by applying the Bootstrap technique in order to model the uncertainties in parameter estimates, while the Weibull parameters were considered as random variables rather than just deterministic point estimates. A solution procedure to determine the optimal replacement time was proposed based on Monte Carlo simulations. Wu, Ng, Xie, and Huang (2010) considered the replacement problem for finite lifecycle multi-state systems that is subject to both degradation and Poisson failures. A threshold on the current system state and a threshold on the residual life cycle are two control parameters used for replacement decision. The procedure towards determination optimum time of replacement was proposed. The related paper discussed the replacement problem on series–parallel equipment is given by Hartman and Ban (2002). In their paper, a multiple machine replacement problem in which assets work in both parallel and series was investigated. The application of integer programming and dynamic programming to determine optimal purchase, salvage, utilisation and storage decisions for each asset over a finite horizon were investigated.

In real operation environment, the production equipment/system may expose with particular effect such as the effects of different failure modes or “shock” condition, thus the replacement problem become more complicated. The application of TBM in solving replacement problem subject to shocks condition is highlighted by many researches. For example, Satow, Teramoto, and Nakagawa (2000) considered a replacement policy for the case of a unit suffers two kinds of damage which occurs either by shocks or increases with time. The aim of proposed replacement policy is to prevent failure, where the damage is checked when each shock occurs and a unit is replaced before failure when the total damage exceeds a threshold level k . Sheu and Griffith (2002) studied the replacement problem of a system is subject to shocks. The extended block replacement policy with shock models and used items were developed. Sheu and Chien (2004) considered a generalised age-replacement policy of a system subject to shocks with random lead-time. A model was developed for the average cost per unit time and is based on the stochastic behaviour of the assumed system and reflects the cost of storing a spare as well as the cost of system downtime. Hsieh (2005) investigated replacement problem towards the state-dependent maintenance policy of a multistate deteriorating production system with standby redundancy. A model of a maintenance policy that considered aging and random shocks was developed. The aim of the study was to determine the optimal operating state for component

replacement and the optimal number of standby key components that maximised the annual net profit of the production system. Numerical examples were given to illustrate the proposed maintenance policies using different transition probabilities in the deterioration process. Lai and Chen (2006) applied the periodic replacement model for solving replacement problem for a two-unit system with failure rate interaction between units. A model of the long-run expected cost per unit time by introducing relative costs as a criterion of optimality was derived. Chien, Sheu, Zhang, and Love (2006) focused the replacement problem for a system subject to shock towards two types of failure; type I (minor failure) and type II (catastrophic failure). A generalised replacement policy was proposed, where a system is replaced at the n th type I failure or first type II failure or at age T , whichever occurs first. Lai, Shih, and Tang (2006) proposed a discrete replacement policy model to solve replacement problem for a single-unit system subjected to external shocks. The authors considered two types of external shocks, namely non-lethal and lethal, depending on their effect to the system. An optimisation model towards long run expected cost per unit time was formulated by introducing relative costs and derived as a criterion of optimality. Rangan, Thyagarajan, and Sarada (2006) studied the replacement problem for system warranty analysis application for the case of the system due to shocks occurrence frequency. A replacement policy called N -policy was adopted by which the system was replaced after the N th failure. Montoro-Cazorla, Pérez-Ocón, and Segovia (2009) investigated the replacement problem of a system subject to shocks based on a general model where the replacements are governed by a discrete phase-type distribution. Chien (2009) considered a number-dependent replacement policy for a system with two failure types that was replaced at the n^{th} type I (minor) failure or the first type II (catastrophic) failure, whichever occurred first. A model for the average cost per unit time based on the stochastic behaviour of the system and replacement, storage, and downtime costs was developed. Sheu, Chang, Chen, and Zhang (2010) proposed a periodic replacement policy for a system subjected to shocks. As these shocks occurred, the system experienced one of two types of failures: a type-I failure (minor), rectified by a minimal repair; or a type-II failure (catastrophic), which called for a replacement. A generalised model for determining the optimal replacement policy with minimal repair based on a cumulative repair-cost limit was developed. Some numerical analyses were presented to study the unique features of the developed model.

In relation, the application of TBM in solving replacement problem based on traditional replacement policy may require unrealistic assumptions (e.g. failure distribution of the equipment/system must be known), where in real cases it may not practical to be applied. In the application of TBM, some researchers have modified traditional replacement policy to be more realistic and appropriate to be used in real practice. For instance Coolen-Schrijner and Coolen (2007) proposed more realistic replacement policy called adaptive replacement strategy. The motivation of adaptive replacement strategy is that instead of assuming complete knowledge of a unit's failure time distribution (assumption used for traditional replacement strategy), one uses information from the process to learn about this distribution. An adaptive age replacement with a one-cycle criterion within the nonparametric predictive inferential framework was presented. Meanwhile, Jamali, Ait-Kadi, Cléroutx, and Artiba (2005) considered more efficient solution of replacement problem by proposing an optimal periodic replacement strategy. From the results reported, the authors claims that the propose strategy seems more efficient than the basic block replacement strategy and it is also easy to implement.

The other recent references that related with TBM application for solving replacement problem is given by Jung, Han, and Park (2008), where the optimal replacement policies of a system following the

expiration of warranty is studied. Determination of optimal replacement period is based on overall value function, which is established based on the expected downtime and the expected cost rate combined. Jiang (2009) studied the replacement problem of the equipment based on sequential age replacement policy for a finite-time horizon. An optimisation model that provided an accurate approximation to find an approximate optimal solution is presented. The author claims that the proposed approximation is computationally simple and suitable for any failure distribution. Zhang and Wang (2010) studied the replacement problem for a multistate degenerative simple system. An optimal model of replacement policy that minimised the average cost rate was proposed. The authors claim that the proposed policy is convenient policy from the managerial point of view.

On the other hand, repair-replacement problem is another maintenance problem that occurs in real industry practice. Repair-replacement problem deals with determination of when appropriate time to repair and replacement the targeted equipment/system. Like replacement problem, the repair-replacement problem becomes more challenging when some particular cases (e.g. parallel, series and multiple units, shocks condition, etc.) are considered. Leung and Fong (2000) studied the repair-replacement problem of gearbox based on geometric approach. Seven types of gearbox were used in their study and the optimal maintenance policy based on minimising the long-run average cost per day was determined for each type of gearbox. Moustafa, Maksoud, and Sadek (2004) investigated repair-replacement problem for a multi-state deteriorating system. Two approaches were developed to obtain the optimal maintenance policy that minimises the expected long-run cost rate.

Meanwhile, the application of TBM in solving repair-replacement problem based on imperfect maintenance concept has been reported by many researchers. It is because the imperfect maintenance concept is more realistic assumption in actual practice. Dohi, Ashioka, Osaki, and Kaio (2001) studied the repair-time limit replacement problem of a system with imperfect repair. An optimisation model based on graphical method was developed to determine the optimal repair-time limit which minimises the expected total discounted cost over an infinite time horizon. Sheu, Lin, and Liao (2005) applied periodic PM by considering imperfect and perfect PM types to three repair models: major repaired, minimal repaired, or fixed until perfect PM upon failure. Each of the models was developed to determine the optimum PM time to minimise the total cost rate. A numerical example was given to discuss the features of the developed models. Zequeira and Bérenguer (2006) also applied a periodic PM policy based on the imperfect maintenance concept for two categories of competing failure modes: maintainable and non-maintainable. A model to study equipment condition improvement (improvement factor) as a function of the time of the PM action was presented. The main objective of the model was to minimise the cost rate for an infinite time span. Wang and Pham (2006) proposed maintenance policies for a series system with n constituent components under the general assumption that each component was subject to correlated failures and repair, imperfect repairs, shut-off rules, and arbitrary distributions of times to failure and repair. In this study, two classes of maintenance cost models and system maintenance cost rates were proposed and modelled. In relation to this, models to optimise system availability and/or system maintenance costs were developed, and optimum system maintenance policies were discussed through a numerical example. Lai (2007) studied the repair-replacement problem by considering a periodical replacement model based on a cumulative repair-cost limit, where the concept uses the information of all repair costs to decide whether the system is repaired or replaced. A model to obtain optimal time of replacement based on repair cost limit and minimising long-run expected cost was developed. Aven

and Castro (2008) presented a new dimension to the minimal repair–replacement theory by introducing two types of failures. The main objective was to determine an optimal planned replacement time, T that minimised the expected discounted costs under the safety constraints. Castro (2009) modelled the imperfect PM for a system under the assumption that system failures can be grouped into two categories or modes: maintainable (repairable) and non-maintainable (non-repairable). The objective was to determine an optimal length between PM actions and the optimal number of PM actions between replacements of the system. Yeo and Yuan (2009) investigated a model that incorporated imperfect repairs, where the focus was given under two system replacement strategies: periodic maintenance before and after warranty. The optimal maintenance period and optimal level of repair based on the structures of the cost and failure rate functions were derived. Bartholomew-Biggs, Zuo, and Li (2009) studied the repair–replacement problem of scheduling some equipment based on imperfect PM concept, where focus was given to the way such schedules were affected by the choice of aging model used. An approach was presented to minimise a performance function that allowed for the costs of minimal repair and eventual system replacement, as well as for the costs of PM during the equipment's operating lifetime. Jack, Iskandar, and Murthy (2009) discussed the application of a repair–replace strategy for the manufacture of a product sold with a two-dimensional warranty. The strategy was based on a specified region of the warranty defined in terms of age and usage with the first failure in the region rectified by replacement and all other failures being minimally repaired. A new model of the repair–replace strategy was formulated to be more appropriate for these types of warranty. Soro, Nourelfath, and Ait-Kadi (2010) investigated the repair–replacement problem for multi-state degraded systems with minimal repairs and imperfect PM. A model for evaluating the availability, production rate, and the reliability function of multi-state degraded systems subjected to minimal repairs and imperfect preventive maintenance was developed. A numerical example was given to illustrate the proposed model.

The application of TBM in solving repair–replacement problem for equipment/system subject to shocks is also considered by some researchers. For example, Sheu et al. (2010) studied the repair–replacement problem for a system subject to shocks by applying a periodic maintenance policy. A periodic replacement model based on cumulative repair-cost limit was proposed. A numerical example of a system followed Weibull distribution model is used to validate the proposed model. The other related references concerned to repair–replacement problem subject to shocks are given by Delia and Rafael (2011) and Chang, Sheu, Chen, and Zhang (2011). Meanwhile, a recent review of TBM application given by Das and Sarmah (2010) focused on optimisation model application for the repair/replacement/inspection of components/assemblies/subsystems in heavy process industries. On the other hand, Jardine and Tsang (2005) in their book (see Section 2) discussed a number of industrial applications such as boiler plan, bearing and compressor equipment replacement problems based on TBM.

3. Condition-based maintenance (CBM)

Condition-based maintenance, also known as predictive maintenance is the most modern and popular maintenance technique discussed in the literature (Dieulle, Berenguer, Grall, & Roussignol, 2001; Han & Song, 2003; Moya, 2004). CBM was introduced in 1975 in order to maximise the effectiveness of PM decision making. According to Jardine, Lin, and Banjevic (2006), CBM is a maintenance program that recommends maintenance actions (decisions) based on the information collected through condition monitoring process. In CBM, the lifetime (age) of the equipment



Fig. 5. General CBM process.

is monitored through its operating condition, which can be measured based on various monitoring parameters, such as vibration, temperature, lubricating oil, contaminants, and noise levels. The motivation of CBM is that 99 per cent of equipment failures are preceded by certain signs, conditions, or indications that a failure is going to occur (Bloch & Geitner, 1983). Therefore, CBM is needed for better equipment health management, lower life cycle cost, catastrophic failure avoidance etc.

The heart of CBM is the condition monitoring (CM) process, where signals are continuously monitored using certain types of sensor or other appropriate indicators (Campos, 2009). Thus, maintenance activities (e.g., repairs or replacements) are performed only 'when needed' or just before failure (Andersen & Rasmussen, 1999). In general, the main goal of CBM is to perform a real-time assessment of equipment conditions in order to make maintenance decisions, consequently reducing unnecessary maintenance and related costs (Gupta & Lawsirirat, 2006). Fig. 5 presents two important processes of CBM.

Monitoring is defined as: 'An activity which is intended to observe the actual state of an item' (SS-EN 13306, 2001, p. 16). In other words, CM is a tool used to indicate the condition of equipment in a system (Hameed, Hong, Cho, Ahn, & Song, 2009). In general, the purpose of the CM process is twofold. First, it collects the condition data (information) of the equipment. Second, it increases knowledge of the failure causes and effects and the deterioration patterns of equipment.

The CM process can be carried out into two ways: on-line and off-line. On-line processing is carried out during the running state of the equipment (operating state), while off-line processing is performed when the equipment is not running. In addition, CM can be performed either periodically or continuously. Typically, periodical monitoring is carried out at certain intervals, such as every hour or every working shift end, with the aid of portable indicators, such as hand-held meters, acoustic emission units, and vibration pens. The CM process also includes evaluations based on human senses to measure or evaluate equipment conditions, such as degree of dirtiness and abnormal colour. As for continuous monitoring, as its name suggests, monitoring is performed continuously and automatically based on special measurement devices, such as vibration and acoustic sensors.

Jardine et al. (2006) stated that two main limitation of continuous monitoring exist: it is expensive because many special devices are required and inaccurate information may be obtained because the continuous flow of data creates increased noise. In contrast, the main limitation of periodic monitoring is the possibility of missing some important information of equipment failure between monitoring intervals.

As stated by Bloch and Geitner (1983), most equipment failures are preceded by certain signs, conditions, or indications that such a failure was going to occur. Many CM techniques can be used to monitor equipment conditions, several of which are discussed below.

3.1. Vibration monitoring

The most popular CM technique used in the CBM program, especially for rotating equipment (e.g., bearing and gearbox), is vibration monitoring (Al-Najjar, 1997; Carnero, 2005; Higgs et al., 2004). The vibration monitoring technique refers to the use of

in situ non-destructive sensing and analysis of equipment characteristics. This means that the health of the equipment is tested or determined *in situ* (or in place) with the aid of special devices, such as vibration sensors, to detect changes that may indicate damage or degradation. Monitoring processes based on vibration measures are carried out on-line, either through periodical or continuous practice.

3.2. Sound or acoustic monitoring

Sound or acoustic monitoring is another CM technique frequently used in CBM; it has a strong relationship with the vibration monitoring technique. However, there also exists a fundamental difference between the two. While vibration sensors are rigidly mounted on the component involved to register local motions, acoustic sensors 'listen' to the equipment. Like vibration monitoring, sound or acoustic monitoring is executed on-line, either through periodical or continuous ways.

3.3. Oil-analysis or lubricant monitoring

Another CM technique is oil-analysis or the lubricant monitoring technique. In this technique, the condition (quality) of the oil is evaluated to determine whether or not the oil is suitable for further use. At the same time, the results of oil analysis can show the wear conditions of internal oil-wetted components, such as engine shafts. This technique has two general purposes: safeguarding oil quality and safeguarding the components involved. A detailed discussion of the physical test and contamination identification procedures that constitute a normal periodic oil sampling program is given by Newell (1999).

3.4. Other CM techniques

Other CM techniques include electrical, temperature, and physical condition monitoring. The electrical monitoring technique involves measuring changes in equipment properties, such as resistance, conductivity, dielectric strength, and potential. This technique can be used to detect electrical insulation deterioration, broken motor rotor bars, and shorted motor stator lamination. The temperature monitoring technique is often applied for the failure identification and monitoring of electric and electronic components. Physical condition monitoring focuses on identification of the physical changes of materials, such as cracks and corrosion. This technique is typically carried out off-line and is mostly popular in the construction industry. Another CM technique that is less well known compared to other techniques is performance monitoring. This technique basically predicts problems by monitoring changes in certain parameters, such as pressure, flow rate, and electrical power consumption.

Maintenance decision making under the CBM program can be classified into two: diagnosis and prognosis. According to Jeong, Leon, and Villalobos (2007), diagnosis is the process of finding the source of a fault, while prognosis is the process of estimating/predicting when a failure may occur (Lewis & Edwards, 1997). The main aim of diagnosis is to provide early warning signs to engineers while the monitored equipment is operating in abnormal conditions (deterioration state). Although the equipment is running in an abnormal state, it does not mean that the equipment has failed. It can probably still be used for a certain amount of time before failure occurs. To address this situation, prognosis must be done. The main aim of prognosis is to provide further warning by estimating/predicting when the equipment will fail. As such, the equipment can be fully utilised and the appropriate time to carry out PM just before it fails can be determined.

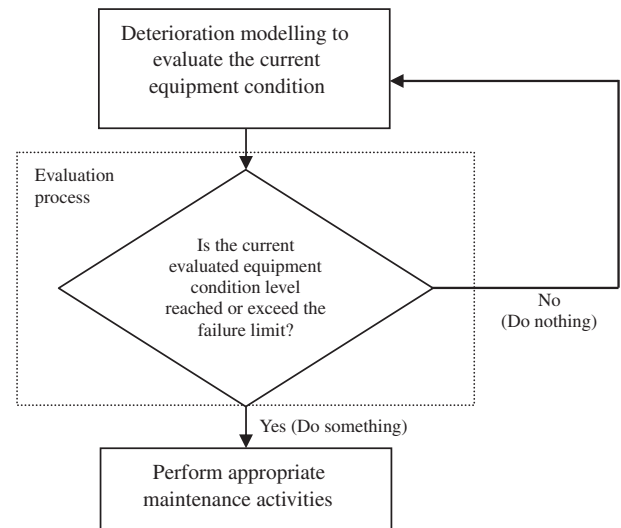


Fig. 6. Typical decision framework of the CCEB method.

From a maintenance point of view, prognostics is superior to diagnostics in the sense that prognostics can prevent unexpected failures, thus saving unplanned maintenance costs (Jardine et al., 2006). In CBM, maintenance decision making, particularly toward prognostic processes, can be achieved through equipment deterioration modelling. Decision making can be carried out based on two methods: current condition evaluation-based (CCEB) and future condition prediction-based (FCPB).

The CCEB method evaluates the current equipment condition, after which the appropriate maintenance is carried out if needed. The decision procedure for this method is illustrated in Fig. 6. Once the current related condition data are collected, the modelling process is carried out to estimate the actual equipment condition at present, which will then be compared to a predefined failure limit. If the equipment condition level reaches or exceeds the limit, the equipment will be called for maintenance. Otherwise, the equipment is assumed to be in good condition and can still be used. In most cases, this method is performed via periodic monitoring or inspection monitoring activities in order to collect current condition data.

The FCPB method is another CBM decision making method. The method predicts the future trend of the equipment condition, and, as in the previous method, the appropriate maintenance is planned and scheduled if needed. The general decision procedure for the FCPB method is presented in Fig. 7. Based on future prediction results (modelling process), if the condition of the equipment reaches or exceeds the predefined failure limit, the appropriate maintenance activities are planned and scheduled. Otherwise, the equipment is assumed to be in good condition and can still be used for operation.

In the FCPB method, the condition monitoring process can be carried out either continuously or periodically. Sensors and a data collection system may be required for continuous monitoring. Graphically, how the FCPB method works is illustrated in Fig. 8. The deterioration trend of the equipment is presented via the horizontal and vertical axes, which show the operating times and condition levels, respectively. The failure limit indicates the demarcation between the operating and failure zones. If the predicted trend reaches or exceeds the failure limit, appropriate maintenance may be planned and scheduled. The ability to predict future deterioration trends is the backbone of the FCPB method in the PM strategy.

In the literature, CBM research maybe carried out based on different platform. For example, one of the CBM platforms towards advanced technologies application is via Prognostic and Health

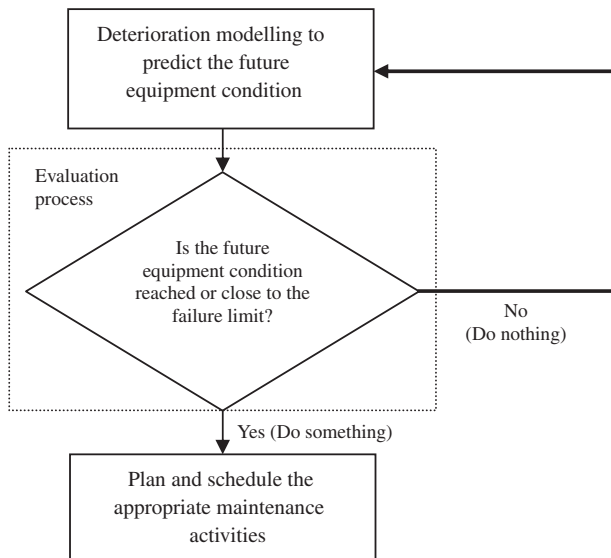


Fig. 7. Typical decision framework of the FCPB method.

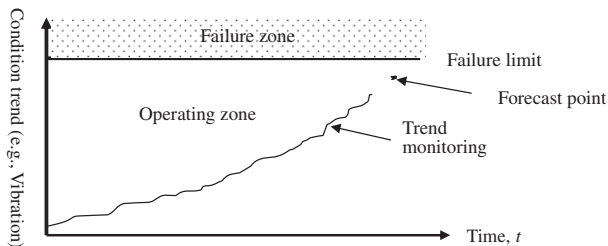


Fig. 8. The principle of the FCPB method.

Management (PHM). According to Cheng, Azarian, and Pect (2010), PHM is discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate equipment/system risk. The fundamental process of PHM is monitoring parameters and analysis of data using prognostic models. In PHM research, a large number of monitoring parameters are required to evaluate the condition/health of a product. Meanwhile, PHM relies highly on the sensor technology to obtain long-term accurate *in situ* information to provide anomaly detection, fault isolation, and rapid failure prediction. The application of PHM for specific engineering systems including rotating machinery (Chen, Craig, Callan, Powrie, & Wood, 2008), electronics component/systems (Kalgren et al., 2007), fuel system (Shen, Wan, Cui, & Song, 2010), turbines (Ashby & Scheuren, 2000), engines (Roemer, Byington, Kacprzynski, & Vachtsevanos, 2006), etc.

3.5. An overview of CBM application

This section presents an overview of CBM application reported in the literature from year 2000. Literature review reveals that CBM applications cover many problems from different fields, such as industrial machinery, building structures, and medical equipment. In this paper, an overview of CBM application is focuses on industrial machinery problem.

One of the main focused of CBM application is on condition monitoring (CM) process that typically emphasise on issues of diagnostic/fault detection on machinery equipment/system. For instance, Trutt, Sottile, and Kohler (2002) presented a CM method for induction motor windings based on a voltage mismatch technique. The

proposed method demonstrated the robust nature of the monitoring process not only under conditions of power supply imbalance but also in situations where motor construction imperfections exist and mechanical loads are unpredictable. Yang, Mathew, and Ma (2005) monitored and diagnosed rolling bearing defects at inner and outer race faults based on vibration signals. A new basis pursuit method was applied in the extraction of features from signals collected. Ocak and Loparo (2005) introduced a new bearing fault detection and diagnosis scheme based on hidden Markov modelling (HMM) utilising vibration signals. Alfayez, Mba, and Dyson (2005) applied acoustic emissions (AEs) as a CM technique for detecting incipient cavitations and the best efficiency point (BEP) of a 60 kW centrifugal pump. The results of their study showed that application of the AE technique offers early detection of incipient cavitations. The technique also demonstrated the ability to determine the BEP of a pump. Han, Yang, Choi, and Kim (2006) proposed an online CM fault diagnosis system for induction motors by combining the discrete wavelet transform, feature extraction, genetic algorithm (GA), and neural network (NN) techniques. The efficiency of the proposed system was demonstrated by motor faults of electrical and mechanical origin on the induction motors and tested using signals obtained from six induction motors under no load and full-load conditions. Orhan, Aktürk, and Celik (2006) studied and analysed the application of vibration signals to detect bearing defects on machines operated in a petroleum refinery. Three different case studies were carried out, all of which ran under real operating conditions. Their research concluded that bearing defects toward a ball bearing outer race, a cylindrical bearing outer race, and bearing looseness were successfully diagnosed. Suyi and Shuqing (2006) presented a CM process that integrated data collection and vibration signal analysis to assess equipment conditions and maintain the operational performance of hydropower turbine units. Tandon, Yadava, and Ramakrishna (2007) studied CM techniques for the detection of defects in induction motor ball bearings. These CM techniques, such as vibration, stator current, acoustic emission, and shock pulse methods (SPMs) for the detection of a defect in the outer race of induction motor ball bearings, were compared. Han, Yang, and Yin (2007) proposed a CM fault diagnosis system for induction motors based on motor vibration signals. The proposed system combined the GA and NN techniques in its diagnosis process. The performance of the proposed system was validated on a self-designed test rig and four ship motors. The results showed that the proposed system was efficient and promising for real time applications. Demetgul, Tansel, and Taskin (2009) analysed fault diagnosis of pneumatic systems with artificial neural network (ANN) algorithms. A synthetic data generation process was proposed to train and test the ANNs better when signals are extremely repetitive from one sequence to other. The results indicated that ANNs could be used for the diagnostic of even extremely repetitive automation system. Eftekharijrad, Carrasco, Charnley, and Mba (2011) investigated fault detection of rolling element bearings by using Acoustic Emission (AE) and vibration technologies. Results shows that the application of AE in defect identification was more sensitive than vibration, where it was reinforced other investigators. The other papers related with CBM fault detection is given by Wang and Zhang (2008a, 2008b), Ayaz, Oztürk, Seker, and Upadhyaya (2009), Pedregal and Carnero (2009) and Galka and Tabaszewski (2011). Meanwhile, a comprehensive review of the CBM fault detection by using acoustic emission technology for rotating equipment is given by Mba and Rao (2006).

Another CBM application reported in the literature is towards decision making process commonly focuses on prognostic/remaining useful life (RUL) estimations/predictions. For example, Wang and Zhang (2005) presented a case study where the residual life of aircraft engines was predicted based on available oil monitoring information. A set of censored life data from 30 aircraft engines

(right censored due to preventive overhaul), along with the history of their monitored metal concentration information, was used for residual life predictions. Liao, Zhao, and Guo (2006) presented estimations of the remaining useful life of individual units using the proportional hazards and logistic regression models. A case study for bearings was carried out to demonstrate the proposed approach in practical use. Dong, He, Banerjee, and Keller (2006) presented the RUL estimation using hidden semi-Markov models (HSMs). Two real-world case studies using this HSM-based methodology were carried out for a UH-60A Blackhawk helicopter. The first study involved the fault diagnosis of the UH-60A Blackhawk main transmission planetary carriers, while the second involved a hydraulic pump prognosis. Lu, Tu, and Lu (2007) proposed RUL prediction method by adopting a state-space model and Kalman filtering technology. From the proposed model, maintenance decisions were made according to the predicted degradation conditions and associated cost factors to enhance the profit produced by the system. Tran, Yang, Oh, and Tan (2008) proposed the RUL prediction method based on the one-step-ahead prediction of time-series forecasting techniques and regression trees. Real trending data of low methane compressors acquired from CM routines were used to evaluate the proposed method. The results indicated that the proposed method offers a potential for machine condition prognosis. Tran, Yang, and Tan (2009) proposed a prognosis approach to predict the future operating conditions of machines by applying regression trees and adaptive neuro-fuzzy inference systems. The proposed approach was evaluated using the real trending data of a low methane compressor. A comparative study of the predicted results obtained from CART and ANFIS models was also carried out to appraise the predictive capability of these models. The results showed that the ANFIS prediction model could track changes in machine conditions and had the potential to be used as a tool for machine fault prognosis. Herzog, Marwala, and Heyns (2009) studied a prognosis method for machines and components by applying the NN technique to predict residual life. A number of NN variations was trained and tested using two different reliability-related datasets. The first dataset was collected in the laboratory by subjecting a series of similar test pieces to fatigue loading with a hydraulic actuator. The second dataset was collected from a group of pumps used to circulate a water and magnetite solution within a plant. Heng et al. (2009) proposed a model to predict the machinery failure consisting of a feed-forward NN with training targets of asset survival probabilities estimated using a variation of the Kaplan–Meier estimator and a degradation-based failure probability density function (PDF) estimator. Pump vibration data were used for model validation. The proposed model was compared to two similar models that neglected suspended data, as well as to a conventional time series prediction model. The results showed that the proposed model could make predictions more accurately than could similar models that do not include population characteristics and/or suspended data during prognosis. Caesarendra, Widodo, and Yang (2009) proposed a method to assess the degradation and prediction of incipient failure until the occurrence of final failure of equipment by combining logistic regression and relevance vector machines. The proposed method was validated based on simulation and experimental data for bearings. Pham and Yang (2010) proposed a hybrid model to estimate and forecast the machine state based on vibration signals by applying autoregressive moving averages and generalised autoregressive conditional heteroscedasticity. The proposed model was verified using empirical results for the real system of a methane compressor in a petrochemical plant. Peng and Dong (2011) proposed a prognosis method based on age-dependent hidden semi-Markov model. A case study of a hydraulic pump was used to illustrate the procedure of the proposed prognostic methodology. For the others references regarding the RUL estimation, refer to Lee et al. (2006), Wang

(2007), Wang and Zhang (2008a, 2008b), Pecht and Jaai (2010), Gašperin, Juričić, Baškoski, and Jožef (2011). A recent review towards the techniques and algorithms applied in equipment/system prognostic is given by Peng, Dong, and Zuo (2010). Meanwhile, a review of RUL estimation based on the statistical data driven approaches is given by Si, Wang, Hu, and Zhou (2011).

On the other hand, applications of the optimisation approach in CBM maintenance decision making have also been presented by some researchers. Garcia, Sanz-Bobi, and del Pico (2006) proposed a CBM system called Intelligent System for Predictive Maintenance (SIMAP) for the health condition monitoring of a wind turbine gearbox. The authors showed that SIMAP was able to optimise and adapt a maintenance calendar for a monitored wind turbine according to its real needs and operating life, as well as other technical and economical criteria. Tan and Raghavan (2008) developed a simple and practical framework for a predictive maintenance (PdM) program to schedule the maintenance activities of multi-state systems (MSS) based on an imperfect maintenance policy. The maintenance schedules were derived from a system-perspective using the failure times of the overall system as estimated from its performance degradation trends. A statistical model was derived to analyse the system degradation and estimate the replacement time of the system. The developed framework was validated in a case study of a flow transmission water pipe system. Ambani, Li, and Ni (2009) developed a degradation model based on the continuous time Markov chain theory and a cost model to quantify the effects of maintenance on a multiple machine system. An optimal maintenance policy for a multiple machine system in the absence of resource constraints was obtained. A case study focusing on a section of an automotive assembly line was used to illustrate the effectiveness of the proposed model. Jiang (2010) developed a flexible degradation model and two cost models to optimise the alarm threshold and the sequential inspection scheme based on condition-independent and condition-dependent variables, respectively. The usefulness and appropriateness of the proposed models were illustrated by five examples. Niu, Yang, and Pecht (2010) developed a novel condition-based maintenance system that used a reliability-centred maintenance (RCM) mechanism to optimise maintenance costs, and employed a data fusion strategy for improving condition monitoring, health assessment, and prognostics. Two case studies on induction motors and low methane compressors were carried out to validate the proposed system. The others related papers is given by Jardine, Banjevic, Montgomery, and Pak (2008), Tian and Liao (2011) and Xia, Xi, Lee, and Zhou (2011). Meanwhile, the application of CBM technique in industry based optimisation approach is discussed (see Section 3) by Jardine and Tsang (2005).

4. Comparison of TBM and CBM

The previous sections presented an overview of TBM and CBM with respect to their principles, general processes toward maintenance decision making, and their recent application reported in the literature. In this section, the challenges of implementing the TBM and CBM techniques from a practical perspective that covers the issues of data required and collection, data analysis/modelling, and decision process are compared and discussed. A summary of these issues is given in Table 1.

4.1. Data required and collection

For any scientific maintenance practice, data is one of the most important requirements and collecting it is a challenging task (Waeyenbergh & Pintelon, 2002). For TBM, the basic dataset needed refers to the failure time data for the equipment of interest.

Table 1
Comparison criteria of TBM and CBM.

Comparison criteria	TBM	CBM
Data required and collection	<p><i>Theory/principle</i> Uses failure time/user-based data</p> <p><i>Practical issues</i></p> <ul style="list-style-type: none"> • The recording of failure time data is not always available • Very sensitive due to incorrect recording and censoring effects • A set of adequate failure data (time to failure) for the modelling process is difficult, time-consuming, and may be expensive to gather (Dekker & Scarf, 1998) 	<p>Uses any parameter that indicates equipment conditions (e.g., vibration, sound, heat, etc.)</p> <ul style="list-style-type: none"> • High data collection costs (sensor, training, etc.) (Kothamasu, Huang, & VerDuin, 2006) • Exposed to noise effects, especially waveform-type data
Data analysis/modelling	<p><i>Theory/principle</i> Uses the reliability theory based on Bathtub curve assumption</p> <p><i>Practical issues</i></p> <ul style="list-style-type: none"> • Unrealistic assumptions • Operating conditions are assumed constant (e.g., environmental effects) • Only effective for equipment in deteriorating state (increasing failure rate) 	<p>Deterioration modelling</p> <ul style="list-style-type: none"> • Requires large data samples • Data cleaning process is required, especially for waveform-type data, and it is a complex task
Decision process	<p><i>Theory/principle</i> Use of the optimisation approach</p> <p><i>Practical issues</i></p> <ul style="list-style-type: none"> • Difficult to model and interpret • Decision model is not always stable • Time-consuming in model development • Is more of a mathematical exercise most of the time rather than a practical application 	<p>Use of the failure estimation/prediction approach and comparison with predetermined failure limits</p> <ul style="list-style-type: none"> • Not enough time to plan maintenance if the CCEB method is applied • Low reliability of long-term prediction results if the FCPB method is applied • Determination of failure limits may be biased

It refers to the data that measure units of time/cycle such as minutes, hours, product cycle, days or working shifts. In contrast, the basic dataset used for CBM includes any possible parameters that can indicate the health (condition) of the equipment, such as vibration, sound, temperature, and current, among others.

In real practise, collecting failure time data required for TBM is very challenging. First, the data are not always available and may be very sensitive due to incorrect recording and censoring effects. For instance, machinery replacement may be recorded because of planned maintenance instead of equipment failure (e.g., recommendations from the equipment supplier). This record is not considered as a clean failure time data point but it is classified as censored (unclean) because it may affect the results of data analysis/modelling. Another challenge of collecting failure time data is that a large amount of time is required for gathering a set of adequate numbers of failure time data. For example, an engineer may require only a few years to obtain a sufficient set of data to derive tight confident intervals for analysing/modelling purposes, while others may require more or less (Dekker, 1996).

The required data and data collection process for CBM is also challenging. Although the condition data are always available, in most cases, they are expensive to collect. This is because specific monitoring equipment, such as portable sensors, vibration pens, and rotating speed and temperature indicators, are necessary. All these support monitoring tools directly involve high costs, and not all companies are willing to invest in them.

4.2. Data analysis/modelling

Data analysis refers to the process of cleaning, transforming, and modelling data with the goal of showing useful information, such as the current condition of the equipment. Once this is accomplished, the data can be used by engineers or managers to suggest plans of action and support decision making. In the data analysis process, various analytical theories and techniques are adopted.

For TBM, the basic aim in analysing failure time data is to statistically investigate the trend and characteristics of the set of failure times gathered. The analysis of the failure time data is performed based on the reliability theory with respect to the bathtub curve assumption (Fig. 2), where the failure behaviour (characteristic) of any equipment is assumed to be predictable (age-related). In real practise, this assumption is not always true for most type of equipment life cycles. According to Amari, McLaughlin, and Pham (2006), several independent studies across various industries revealed that only 15–20% of all equipment failures are age-related (based on the bathtub assumption). The other 80% to 85% of equipment failures is based on the effects of random events that happen in the machine system. The literature review reveals why one of the common assumptions of TBM application is that the failure (reliability) of the equipment is represented by certain failure distributions, such as the Weibull distribution (Chen & Feldman, 1997; Lapa, Pereira, & Barros, 2006; Sheu et al., 2005). Another practical issue in analysing/modelling failure time data is that all operating conditions (e.g., environmental effects) are assumed constant (Mann et al., 1995). However, this assumption is rarely accurate in real practice because it may not represent the actual condition of the equipment during real operations.

In contrast, the general aim of analysing/modelling CBM data is to identify and evaluate equipment conditions based on current updated data. This process is also known as the deterioration modelling process. However, the complexity of CBM data analysis/modelling is highly dependent on the type of CBM data. According to Jardine et al. (2006), CBM data can be classified into three types: value type, waveform type, and multi-dimensional type. Value type data exist in a single value, examples of which include oil analysis data, temperature, pressure, humidity, and quality scale. Waveform and multi-dimensional type data can also be referred to as signal and image forms, respectively. Examples of waveform type data include vibration and acoustic data, while image data, such as infrared thermographs, visual images and X-ray images, are examples of multi-dimensional type data. In real practise, value

type data are easier to analyse and interpret compared to the two other types of data. For example, analysing/modelling waveform data is very challenging because of noise effects, which are unwanted signals generated by other equipment. Thus, noise must be minimised or eliminated from the data. As well, the analysis and interpretation of condition data require specific computerised monitoring software and expert knowledge, respectively. These requirements directly involve large company investments, especially since such companies must buy and maintain these systems, as well as provide training for their use.

4.3. Decision process

The decision process involves follow-up actions that must be determined after useful information is obtained from the data analysis/modelling process. The general aim of this decision process is to avoid or minimise the effect of unplanned maintenance (corrective maintenance events). The maintenance decisions basically depend on the mechanism of the equipment. For example, it is either repairable or non-repairable, a single-unit equipment or a multi-unit equipment.

In TBM, the maintenance decisions are made based on the optimisation approach. Optimisation is a part of mathematical programming that aims to determine the best (optimum) point by maximising or minimising some criteria of interest. In TBM application, the optimisation approach is used to determine the optimum PM time or interval (e.g., preventive replacement time) in order to minimise or maximise certain criteria of interest, such as cost, risk, downtime, availability, and reliability. According to Dekker (1996) the use of the optimisation approach in maintenance decision making is rarely needed in practice. The main reason for this is that the optimisation approach usually exists in complex mathematical form; thus the decision models are difficult to understand and interpret. Therefore, engineers may not be interested in applying it to real cases. Another practical issue here is that the decision model developed based on the optimisation approach is not always appropriate for all cases of equipment failure. For example, the optimum time for preventive maintenance models (e.g. age replacement model) only exists if the failure rate of the interest equipment is in the increasing failure rate phase/stage. Meanwhile, the cost ratio of failure and preventive replacement costs is also affects the effectiveness of the preventive models in term of its potential cost saving. For instance, Huang, Miller, and Okogbaa (1995) proved that the larger of the cost ratio implies the more significant of potential cost saving.

In CBM, the backbone of the decision making process is failure prediction/estimation of the equipment based on current updated data, which will be compared to predetermined failure limits in order to decide appropriate maintenance. The decision procedure of CBM can be performed based on two decision methods, CCEB and FCPB, which are shown in Figs. 7 and 8, respectively. However, both of these methods have some limitations in real industrial practise. For example, if the CCEB method is applied, there may not be enough time to plan maintenance if the evaluation results show that the equipment condition has already reached or exceeded the failure limit. This is because this method evaluates current equipment conditions only when the current data is updated. Therefore, the decision process suggested via the CCEB method does not really adopt the PM concept, where maintenance is planned before failure occurs. Although this limitation can be solved by applying the FCPB method, where the idea is to predict future equipment conditions to plan appropriate maintenance, the reliability of future predictions remains debatable. In fact, the reliability of short-term predictions is higher than that of long-term ones. In other words, FCPB only useful and reliable for

short-term predictions, such as in situations where one must be one or two forward steps ahead of the prediction.

5. Future challenge and consideration of CBM

Previous section reveals that although the application of CBM is more beneficial compared to TBM from a practical point of view, further research on CBM is still necessary. This section discusses some of the challenges and considerations the future of CBM research.

The application of CBM for complex and sensitive equipment/system such as electrics, electronics and mechatronics products become one of the challenge in future CBM research. This challenge relay on the application of advanced monitoring technologies particularly on sensors technology. Build-in and multi-functions sensors are some examples of sensor technology that has high potential to be applied in equipment/system condition monitoring. As introduced in Section 3, advanced CBM research via Prognostic and Health Management (PHM) platform seems the right research direction for complex and sensitive equipment/system health monitoring. An overview regarding the benefits of PHM for electronics equipment is given by Vichare and Pecht (2006) and the others application is highlighted by some researchers, refer to Ramakrishnan and Pecht (2003), Anderson and Wilcoxon (2004), Mishra, Ganesan, Pecht, and Xie (2004), Lall, Islam, and Suhling (2005), Brown, Kalgren, Byington, and Orsagh (2005), Orsagh, Brown, Roemer, Dabney, and Hess (2005), Goodman, Vermeire, Spuhler, and Venkatramani (2005) and Kalgren et al. (2007). Meanwhile, Pecht (2008) in his book discussed in detail the application of PHM condition monitoring and prognostics for electronic system.

Another challenge and consideration of future CBM research is the development of computerised CBM oriented programme towards more friendly and practical application. From the authors' point of view, this programme is the final stage of how the CBM can be fully applied and implemented in real industrial cases. The best example is the development of CBM monitoring and decision making software by Jardine's group known as EXAKT that used for monitoring and decision making of rotating equipment (Jardine, Banjevic, & Makis, 1997). Some EXAKT application for real industrial cases has been reported in the literature (refer to Jardine, Banjevic, Wiseman, Buck, & Joseph, 2001; Jardine, Joseph, & Banjevic, 1999; Jardine & Tsang, 2005). Other examples of efforts towards development of computerised CBM oriented programme is predictive condition-based maintenance (PCBM) system developed by Lu et al. (2007), intelligent decision support system (IPDSS) developed by Yam et al. (2001a, 2001b) and intelligent system for predictive maintenance (SIMAP) for health condition monitoring of a wind turbine gearbox developed by Garcia et al. (2006).

On the other hand, some theoretical issues of CBM must takes into account in future CBM research, so that more reliable maintenance decision can be made based on real case scenario. One of the theoretical issue is the way of failure limit of the targeted equipment/system is defined and determined. This issue relates with the appropriateness of monitoring parameter(s) used to indicate the equipment/system deterioration towards failure. In the most application of CBM reported in the literature, the equipment is considered failed when the monitoring parameter level reaches or exceeds a predefined limit (failure limit), after which the appropriate maintenance action is carried out. In real industrial practice, the determination of failure limits based on certain monitoring parameters is not always able to represent the failure of the equipment because the failure of each of equipment may be defined and classified in different ways. For example, the failure of production equipment can be classified into three types. The first is

breakdown failure, where the equipment is considered failed when the function of the equipment is terminated due to physical damage (e.g., cracks, breakage, etc.). This type of failure results in the complete cessation of operation of the entire machine (sudden breakdown). The second is functional failure, where the equipment is considered failed when its performance does not reach the required level. This type of failure may not result in the cessation of operation of the equipment but its output characteristics (products), such as quality characteristics, may not satisfy requirements. Finally, a combination of functional and breakdown failure may occur, especially for multi-unit equipment. Therefore, the definition and determination of failure limits should be considered from both the entire machining process perspective (system/sub-system) and the overall output of the system (e.g., product quality characteristics). This issue supported by Arunraj and Maiti (2007), where in production machine perspective there is close relationship between maintenance and product quality, as product quality depends on equipment condition.

Another theoretical issue that may effects to the application of CBM in real practice is data availability issue. In theory by having more data/info on the targeted equipment/system better analysis and decision can be made. However, in real case although most of monitoring parameters of targeted equipment/system are naturally exists, but collecting it may not always practical. For example, wear rate is an essential monitoring parameter for machining tools monitoring towards wear and tear effect, where it may appropriate to be collected in experimental situation but not in real manufacturing process environment. Another example is the used of some monitoring parameters in condition monitoring of rotating equipment (e.g. bearing). Although some research shows that the used of acoustic signal is better than vibration signal due to its sensitivity and accuracy (see Al-Ghamd & Mba, 2006; Baydar & Ball, 2001; Tandon et al., 2007), but in practice the application of acoustic signal may not appropriate due to the significant effects of noise (unwanted signals) from other equipments. Therefore the used of others sources of data/info that available in practice (e.g. others related monitoring parameters, data based on ISO Standard, data based on original equipment manufacturer, subjective information from experience worker, etc.) become the alternative or supportive data/info towards equipment/system condition monitoring. However, how to best used these alternative data/info towards monitoring and decision making process remain a big challenge in future CBM research. Thus, the authors believe that the development of CBM framework or method that is able to deal with this data availability issue is needed in future CBM research.

6. Conclusions

This paper presented an overview of the TBM and CBM techniques with emphasis on how these techniques work toward maintenance decision making. A recent application of each technique was reviewed, followed by a comparison of the challenges faced in implementing each technique from a practical point of view. In general, it can be concluded that each of the techniques has its own unique concept/principle, processes, and challenges toward real industrial practise.

From the concept/principle point of view, the application of CBM appears more realistic compared to TBM. This is based on the fact that 99% of equipment failures are preceded by certain signs, conditions, or indications that such a failure was going to occur (Bloch & Geitner, 1983). From the issue of data required and collection, the application of CBM also has many advantages compared to TBM. Data availability and accuracy (e.g., sensor-based technology) are some of the reasons to support CBM. The issue of data analysis/modelling also reveals the advantages of CBM. CBM

data analysis/modelling has very clear objectives for evaluating equipment conditions via deterioration modelling. In contrast, TBM data analysis/modelling must follow several statistical rules and assumptions (e.g., bathtub curve assumption); this is not realistic for application in real practise. Finally, the decision process point of view also reveals that the application of CBM is simpler than that of TBM because the former is based on the optimisation approach. Simple, however, does not always mean practical and effective, thus some limitations were presented regarding CBM decision making methods. Overall, although this paper finds that the application of CBM is more beneficial compared to TBM from a practical point of view, further research on CBM is still necessary.

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