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REVIEW ARTICLE

Yanrong LI, Shizhe PENG, Yanting LI, Wei JIANG

A review of condition-based maintenance: Its prognostic and operational aspects

Abstract Condition-based maintenance (CBM) detects early signs of failure and dictates when maintenance should be performed based on the actual condition of a system. In this paper, we first review some of the recent research on CBM under various physical structures and signal data. Then, we summarize several kinds of prognostic models that use monitoring information to estimate the reliability of complex systems or products. Monitoring information also facilitates operational decisions in production planning, spare parts management, reliability improvement, and prognostics and health management. Finally, we suggest some research opportunities for the reliability and operations management communities to fill the research gap between these two fields.

Keywords condition-based maintenance, prognostics, operational decision-making, reliability

1 Introduction

Significant advances have been achieved in sensor technology, allowing manufacturers to collect product condition and other relevant information easily. Condition-based maintenance (CBM) emerges with the application of this technology in the manufacturing process and the after-sales market. CBM is a maintenance strategy based on the condition of products to minimize the costs associated with parts, personnel, tools, and so on. The key to CBM is performing maintenance actions proactively before failures occur, without suspending product use. However, developing monitoring and maintenance solutions based on real-time sensor information is a huge challenge.

Three major challenges exist in the field of CBM. The first challenge at the most fundamental level is designing the system structures and the sensor networks. The second challenge is producing reliable diagnostics about the future states of a product and estimating its remaining useful life. The last challenge is utilizing prognostic information to support decisions, such as maintenance, replacement, product life cycle analysis, and procurements. Numerous works have been proposed to deal with these three challenges.

Focusing on the first challenge, many studies have proposed various models to describe the structures and relationships of different components to estimate the reliability of multi-component systems. We summarize the literature considering different kinds of multi-unit systems, such as two-unit and series-parallel systems, to recognize the impact of their CBM structures and compare them with single-component systems. Monitoring different components, that is, collecting and analyzing different types and structures of monitoring data may be a technical challenge. To facilitate data analysis, we classify the data by different criteria as discussed in Section 2.2.

A popular means of addressing the second obstacle is finding a proper condition-based model to estimate reliability. Three kinds of assessment approaches could be adopted. The most common condition is the degradation lifetime of products. On the basis of the continuity of products' states, estimation models can be divided into two categories: Continuous- and discrete-state models. In practice, degradation is continuous in most cases and can be modeled directly as a continuous stochastic process, such as the Wiener (Zhang et al., 2018), inverse Gaussian (Wang and Xu, 2010), and gamma processes (Cheng et al., 2018; Zhao et al., 2018b). Furthermore, degradation can also be approximated through a discrete-state degradation

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Yanrong LI, Shizhe PENG, Wei JIANG (✉)
Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai 200030, China
E-mail: jiangwei@sjtu.edu.cn

Yanting LI
School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200030, China

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process using Markov chains. Predicting the remaining useful life of products based on degradation modeling is also one of the most popular topics (Zhao et al., 2018a). Moreover, usage-based models treat usage rate as a general factor, which is always considered in the reliability estimation of products. In this case, the failure rate of a product is used as an index to find the influence of usage in the model (Walter and Flapper, 2017; Verbert et al., 2018). In addition to the two kinds of models above, many papers have investigated other event conditions, such as internal jumps, external shocks, periodic backups, and some special events in particular areas.

To solve the last problem, considerable research has been devoted to the use of prognostic models for operational decisions. Condition monitoring can improve the efficiency of planning and operational decision-making. For example, using real-time sensor information, manufacturers can predict the remaining life of a product and further optimize operational decisions, such as maintenance and spare-part replacement. Moreover, the monitored condition provides more flexibility for manufacturers and facilitates proactive maintenance activities to obtain operational and logistical benefits. Now, the question of how prognostic information can be appropriately used naturally arises. Many papers specify thresholds for determining product failures. With such thresholds, maintenance actions can be initiated (Wang et al., 2016; Chehade et al., 2017). In addition to maintenance, condition monitoring has a wide variety of applications in inventory management, production planning, and other contexts of operations management. Moreover, the potential value of condition monitoring is also considered, such as advance demand information and real-time equipment control has been studied in many works (Zhou et al., 2010; Shi and Zeng, 2016).

In the CBM area, several review papers summarized the existing research. As for the modeling of deteriorating systems, Si et al. (2011) focused on statistical-data-driven methods to predict the remaining useful life of products. The authors divided the statistical methods based on whether the state process are directly observed or not and listed numerous classical models from the literature. Alaswad and Xiang (2017) presented a review of the CBM literature with emphasis on mathematical modeling and optimization criteria, such as inspection frequency and inspection quality. For maintenance policy, Olde Keizer et al. (2017a) reviewed different condition-based maintenance policies for systems with multiple dependent components. The authors classified dependence as structural dependence, stochastic dependence, resource dependence, economic dependence, and so on, and summarized the model in different dependencies in detail. However, coordination is still lacking between degradation estimation and operations management, which can lead to increased inventory costs and production disruptions. Therefore, in this work, we aim to bridge the gap between these two topics and verify the efficiency of condition monitoring on designing the maintenance policy. In addition, the influence of physical structures on CBM modeling and different monitoring data processing methods is considered. The main contributions of this work are the summarization of the diagnostics methods based on monitored conditions and the discussion of several related prognostic models.

We review recent works related to the three challenges of CBM, with emphasis on efforts on developing prognostics methods and optimization models. Figure 1 illustrates the structure of this work, and the remainder of this paper is organized as follows. Sections 2 and 3 respectively present reviews of different system structures and data types and the modeling efforts to measure product conditions. Section 4 summarizes some operational problems pertaining to CBM. Section 5 concludes the work and highlights directions for further research.

2 Structural analysis and data monitoring

2.1 Structural analysis

Before developing methods for estimating the reliability of operation systems and complex products, we should always determine the structure of the systems or complex products and analyze the correlation among the different components in the systems. Thus, the first important task is recognizing and defining the physical structure. Physical structures always influence the performance of systems and products, and many works have estimated the reliability of systems from this perspective. Some research traditionally established reliability estimation models based on single-component systems (Byon and Ding, 2010; Kurt and Kharoufeh, 2010). Compared with single-unit systems, multi-unit systems have different kinds of structures (Alaswad and Xiang, 2017). According to the recent literature, we summarize different kinds of typical structures as follows.

A popular topic in multi-unit systems is the evaluation of the relationships of different components. For systems with multiple components that share a pool of spare parts, Lin et al. (2017) modeled the degradation process as a Markov chain. Given the replacement policy upon failure, they studied the effect of condition information on spare parts supply. Olde Keizer et al. (2017b) jointly optimized the replacement decision and the ordering quantity and showed through simulation that the optimal replacement and ordering policies depend on the entire system's condition, such as the state of each component and the on-hand inventory. Zhang et al. (2020) considered the maintenance issues for a k-out-of-n deteriorating system under periodic inspection. The authors believe that the failure dependence of different components may cause a momentary and transient shock to the system. For each

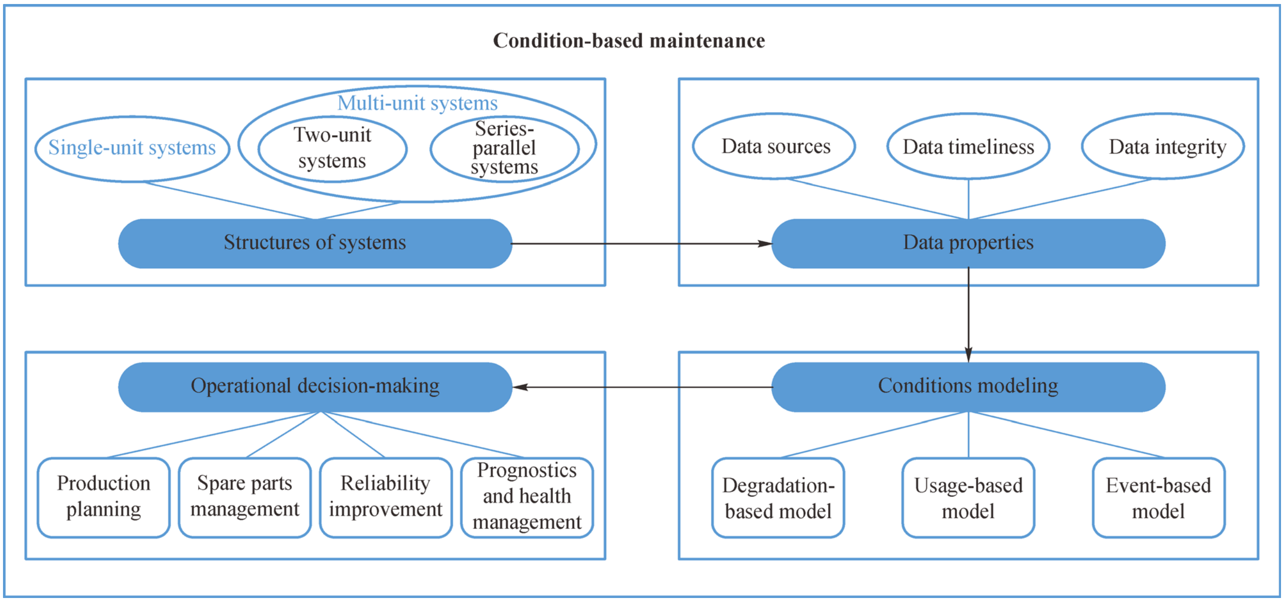

Fig. 1 Framework of CBM research.

surviving component, the shock will cause a random degradation magnitude. Meanwhile, in the multi-unit system literature, the following two typical types of structures are introduced in detail.

Two-unit systems have received significant attention in recent research. Fitouhi et al. (2017) proposed a two-machine continuous flow manufacturer system with a finite capacity buffer. They divided the state of each machine into discrete states and characterized the performance parameters. They discussed the trade-off between preventive maintenance and buffer. Similarly, Do et al. (2019) designed a model for a two-unit system to incorporate the stochastic and economic dependencies of these two components. In their model, the degradation variation of component i is defined as $\Delta X_t^i = \Delta X_t^{ii} + \Delta X_t^{ji}$, where ΔX_t^{ii} is the degradation level itself, and ΔX_t^{ji} is the influence of the other component j on i. Ma et al. (2020) investigated the reliability analysis and maintenance optimization approaches of a two-unit warm standby cooling equipment. These two components have a significant influence on temperature, and at least one is working normally. The system is in the normal state; otherwise, the system's temperature rises sharply. The reliability function of the system is formulated based on this setting, and a condition-based maintenance policy is developed based on the temperature monitoring information.

Another kind of system is series-parallel systems. Olde Keizer et al. (2018) considered the trade-off between redundancy and maintenance for a parallel system and obtained the optimal policy that minimizes the long-run average cost. Yahyatabar and Najafi (2018) proposed a maintenance policy for series-parallel systems using a proportional hazards model and a novel hybrid meta-heuristic algorithm constructed using the parallel generic algorithm.

2.2 Data monitoring

Signal data contain abundant information about system conditions. Therefore, signal monitoring is critical in reliability estimation and prediction. Our work considers different criteria of data classification. In terms of data sources, we have two types of data, namely, direct and indirect data. In terms of whether or not to receive data as a continuous flow, we have real-time and offline data (Aizpurua et al., 2017). In terms of data integrity, we have incomplete (Gössinger et al., 2017) and finite sample data (Cipollini et al., 2018).

2.2.1 Data sources

According to Wang and Christer (2000), direct data refer to signals that can directly reflect the reliability of products or systems. For example, wear and crack size data are considered direct data (Zhang et al., 2017). With this type of data, we can forecast the remaining useful life, degradation level, and health index of products or systems.

In practice, direct data are difficult to observe or monitor, and only indirect data could be used most times. However, indirect data can only partially indicate the reliability of systems. For a more reliable estimation, indirect data are often analyzed with additional information about the products and systems. According to Si et al. (2011), vibration- and oil-based monitoring are considered examples of indirect data.

2.2.2 Data timeliness

Maintenance decisions should be made based on the prognostic information of the system. According to Aizpurua et al. (2017), offline models provide a basis for online models, with the latter focusing more on regularly updating the model with data related to the prognostic results and criticality evaluation of assets.

2.2.3 Data integrity

In reality, complete information is nearly impossible to obtain. Hence, manufacturers must fuse finite data. Song and Liu (2018) designed a statistical degradation model by combining extracted features and sensor signals. They constructed a health index for estimating the degradation process. Similarly, Kim et al. (2019) proposed a model for collecting multiple sensor signals and derived the optimal weight for each selected sensor. Song et al. (2019) proposed a generic framework of a multi-sensor degradation model, which can be transformed into a supervised classification problem.

Limited data sample is another problem in reliability prediction. When few labeled samples are available, we can use supervised and unsupervised learning techniques for CBM that require few data to achieve satisfactory performance. Cipollini et al. (2018) made a supervised data analysis of a vessel system with limited diesel-electric and gas propulsion plant data. To simplify data collection, the authors focused on methods allowing minimal feedback from naval specialists.

While researchers have developed many models to fit real data and ensure the convergence of the estimated coefficient to its true valve, the main difficulty in data processing is to find appropriate methods to deal with data from different sources and structures, especially data fusion. Because noise always exists, finding the optimal methods or functions to screen out non-informative sensor signals is always necessary.

3 Condition modeling

The conditions considered in the prediction of system reliability fall into three categories. Figure 2 presents a framework of the specific methods in each category.

3.1 Degradation-based condition

To measure the reliability of products or systems, one of the most popular methods is considering the residual lifetime up to failure given the failure time. For example, Kim et al. (2019) and Song et al. (2019) proposed the reliability analysis of an aircraft gas turbine engine using the residual lifetime because the exact failure time is known. Otherwise, a comprehensive index is proposed to represent the lifetime state of products or systems. Bae et al. (2019) proposed the temperatures in inlet steam as the

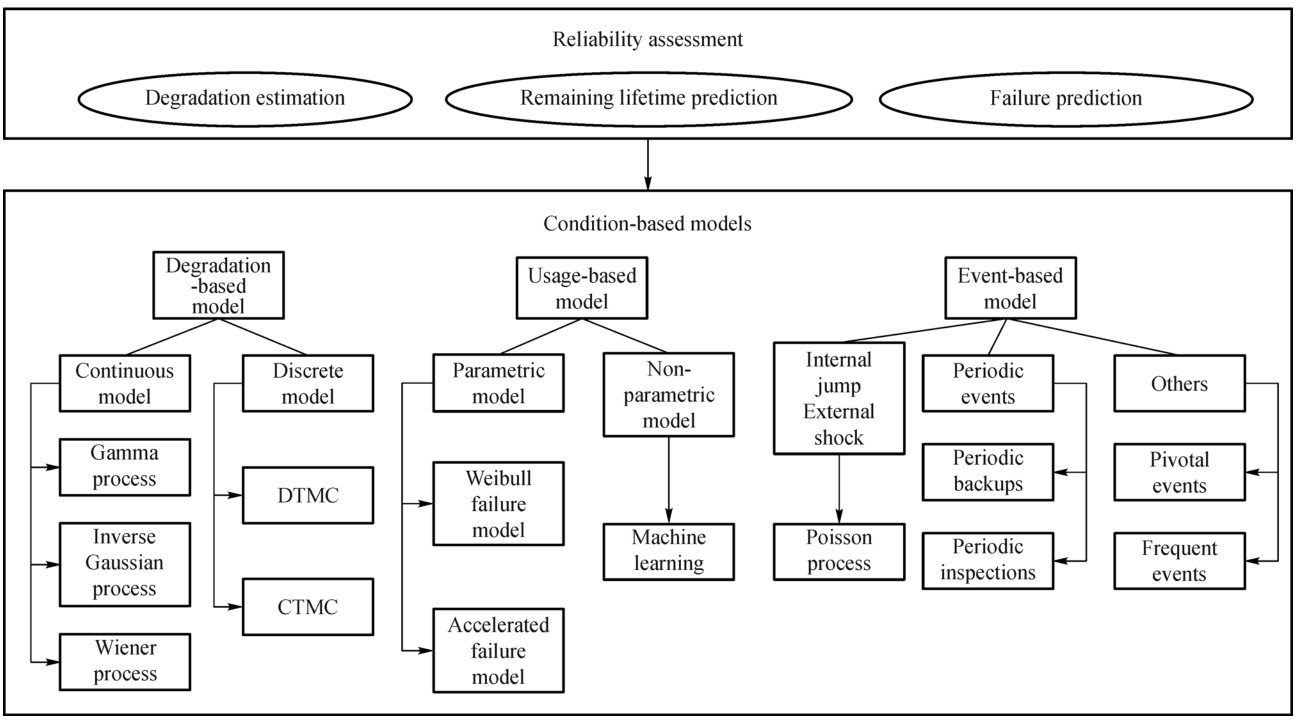

Fig. 2 Framework of CBM models summarized in this work.

pivotal monitoring condition to represent the degradation process of turbine generators. Jahani et al. (2020) used battery resistance as the index to measure the degradation level of lead-acid batteries. According to the work of Lee and Whitmore (2006), we can find the relationship between the remaining lifetime T and the degradation process $X(t)$ as follows: $T = \inf\{t : X(t) \geqslant X_f | X(0) < X_f\}$, where $X(t)$ is the degradation level at time t, and X_f is the threshold. Therefore, both cases can be transformed into each other.

In many studies, product usage is considered a stochastic degradation process because of some uncertain covariates and random factors. In this work, we divide the degradation process into two categories because the change in reliability states could be continuous or discrete over time.

The continuous-state model defines reliability degradation as a continuous stochastic process. In the literature, the most widely used processes are the Wiener, gamma, and inverse Gaussian processes.

The Wiener process is a stochastic process with continuous-time parameters and state spaces. According to Elwany and Gebraeel (2008) and Peng and Tseng (2009), the Wiener process is defined as $X(t) = X(0) + vt + \sigma B(t)$, where $X(0)$ is the degradation level at time 0, and v and σ are the draft and diffusion parameters, respectively. However, draft is more likely to appear with nonlinear forms over time in practice. Some papers define degradation level as $X(t) = X(0) + \alpha \int_0^t u(\tau;\ \beta) \mathrm{d}\tau + \sigma B(t)$, where $\alpha \int_0^t u(\tau;\ \beta) \mathrm{d}\tau$ is the average accumulated degradation level. In addition to the linear and nonlinear models, Zhang et al. (2018) summarized the multi-source variability, covariates, and multivariate in the Wiener process.

The gamma process is a stochastic process with density function $f_{X(t)}(x) = Ga(x|\alpha(t),\ \beta)$, where $\alpha(t)$ is the shape parameter, and the derivative of $\alpha(t)$ reflects the average degradation rate at time t, which also describes the relationship between the degradation level and the system age (Ellingwood and Mori, 1993). The parameters in this function are solved by moment estimation (Cinlar et al., 1977) and maximum likelihood estimation. The gamma process is also used to describe the diffusion process (Cheng et al., 2018) of the production system. Huynh et al. (2017) proposed a homogeneous gamma process to estimate the stress corrosion cracking in the propagation phase of systems.

Inverse Gaussian is a common stochastic process related to the Wiener process. According to the analysis of Ye and Chen (2014), given threshold Λ and a linear Wiener degradation process, the first time to achieve the threshold Λ follows inverse Gaussian processes, which are useful for predicting the remaining life. Wang and Xu (2010) used the Expectation-Maximization (EM) algorithm to obtain the maximum likelihood estimators of the parameters in the model and the bootstrap to assess their variability. Xu and Wang (2013) used the Bayes method to establish the adaptive inverse Gaussian model and the evidential reasoning method of data fusion to estimate the parameters more precisely.

Many other cases are considered in the CBM area, such as nonlinear drifting (Lee and Whitmore, 2006), change point detection (Wang, 2007), jump (Tang et al., 2014; Zhang et al., 2017), and diffuse volatility (Ghamlouch et al., 2017).

The continuous-time Markov chain (CTMC) and the discrete-time Markov chain (DTMC) are also appropriate for modeling the age-based condition. Discrete-state spaces and transition matrices are defined first. Then, Markov chain theories are used to approximate the real degradation process. Zhang and Revie (2017) presented a semi-Markov decision process for machine maintenance. Wang and Xu (2010) proposed a degradation model, focusing on incorporating the proportional hazards model into the CTMC. As for the DTMC, de Jonge (2019) presented an approach to discretizing the stationary continuous time and state for degradation processes. From this work, we know that discrete-time and state models have a better analytical performance when combined with a continuous model. The author also proposed a gamma process as a special case to be discretized and transferred into the DTMC.

3.2 Usage-based condition

In large-scale systems, usage-based conditions are commonly used in practice. Given that usage-based conditions consider time and usage rate, high-dimensional data must be processed. However, analyzing high-dimensional usage data is a significant challenge due to the degrees of correlation between different variables. The methods in the literature for overcoming this challenge can be grouped into parametric and nonparametric models.

Parametric models for quality estimation and control, such as the Weibull failure model (Attardi et al., 2005) and the accelerated failure time model (Ye and Murthy, 2016), are among the most popular topics in recent years. Other methods for reducing data dimension include the application of domain knowledge in finding an intermediate variable to replace original variables (such as failure time and failure usage) (Huang et al., 2017). Statisticians also use copulas appropriately to deal with multivariate distributions (Wu, 2014).

Nonparametric methods generally rely on big data analytics and machine learning, such as support vector regression (Wu et al., 2009) and logistic regression (Skordilis and Moghaddass, 2017). For example, Kontar et al. (2018) proposed a nonparametric method for predicting the condition-based remaining useful life.

3.3 Event-based condition

Many internal or external factors can influence the reliability of production systems or products, especially in industrial companies. Here, we present a brief summary of the events that influence the degradation process or the remaining lifetime.

The most common events include internal jumps and external shocks. Ghamlouch et al. (2017) proposed a degradation model that describes the internal jump factor as $\xi_J \mathrm{d}N(t)$, where ξ_J is the amplitude, and $N(t)$ is the standard Poisson process of the jump. For external shocks, Wei et al. (2019) considered a binary-state deteriorating system under zoned shock effects, and the random shocks are adopted by a homogeneous Poisson process $\{N(t), t \geqslant 0\}$, where $N(t)$ is the total number of shocks during $(0, t]$.

Periodic backup is another kind of event that is related to system reliability. Levitin et al. (2017) considered an integrated model, which considers the effects of periodic backups, and used the model to monitor the first failure time and find an optimal maintenance strategy. Liu et al. (2017a) analyzed the signals of the degradation from monitored periodic inspections and proposed a method for finding the optimal maintenance policy to minimize the long-run cost.

Moreover, other events are also considered in the literature. Pivotal events not only have a significant impact on industrial companies but also influence the quality of products. Li et al. (2014) established an event-based method of finding optimal production improvement opportunities using online production information. Li et al. (2017) proposed a systematic method of predicting the negative impact of CBM stoppage events on production in a multistage manufacturing system. In addition to pivotal events, general and frequent events can also be regarded as signals in condition monitoring. Wan et al. (2018) proposed a maintenance model to discuss whether maintenance is needed when monitoring the time between failure occurrences with a control chart of time among events.

Most of the above research consider only a single factor or event, and few has discussed condition monitoring with more than one factors simultaneously. In practice, the interactions between different factors need more attentions. For example, internal jumps and external shocks may occur at the same time. Ghamlouch et al. (2017) and Wei et al. (2019) developed models for deteriorating systems considering internal jumps and external shocks, respectively. The interactions between the two events can be analyzed in the future.

4 Operational decision-making

4.1 Production planning

Production decisions affect the deterioration rate of a production system. Thus, manufacturers must determine the production lot size, adjust the production rate, and schedule the production of multiple types of products to optimize maintenance costs and production revenues. The recent development of sensor technology allows the remote monitoring of a system's condition and real-time decision-making on maintenance. Maintenance actions are taken based on condition information to increase equipment availability and hence production efficiency. Some works concerning the interaction between production and CBM have been conducted and are reviewed in the following.

Manufacturers usually carry out an inspection at the end of each production run to gather condition information. Different equipment conditions correspond to different production and maintenance plans. Jafari and Makis (2015) used the proportional hazards model to optimize the production lot sizing and the failure rate level for replacement. The authors (Jafari and Makis, 2016) further considered a setting where condition monitoring can provide partial information about the hidden state of a production system. Peng and van Houtum (2016) incorporated CBM into lot sizing decisions using renewal theory. In their model, predictive maintenance is performed according to a control limit policy, and corrective maintenance requires a random repair time. Jafari and Makis (2019) considered a stochastic Poisson demand arrival process in the joint optimization of CBM and manufacturing quantity. Cheng et al. (2018) analyzed the implications of condition information on preventive maintenance and overhauls for a system with both reliability and quality degradations. uit het Broek et al. (2019) developed a production planning model in which the deterioration of a single-unit system is production-dependent. The manufacturer can dynamically adjust the production rate of the system and control equipment usage to maximize production revenues. For a production system with stochastic reliability, Khatab et al. (2019) found the optimal threshold level and inspection cycle based on economic manufacturing theory.

In a multi-product, single-equipment production system, equipment condition affects the yield of each product. Sloan and Shanthikumar (2000) decided whether to suspend production to clean equipment and, if not, which product to manufacture. Kazaz and Sloan (2008) modeled multiple products that have different profits, processing times, and deterioration probabilities. They introduced the concept of critical ratio to obtain the optimal production choice in each machine state. Batun and Maillart (2012) reconsidered this problem and presented a revised first-come-and-first-serve approach. The literature on production planning also considers resource constraints (Liu et al., 2019), quality control (He et al., 2017; Bahria et al., 2019), and demand forecasts (Wang et al., 2019).

More complex and realistic settings considered in the maintenance literature should be incorporated in production planning, such as stochastic deterioration processes, multi-unit systems, imperfect CBM, periodic inspections, and various structures of repair costs. Moreover, more efforts could be made toward the integration of statistical quality control/CBM and production planning to address how condition monitoring leads to quality improvement in production systems.

4.2 Spare parts management

To guarantee quick response to unexpected machine failures, manufacturers must store spare parts in warehouses. Inventory decisions for spare parts must be carefully made to balance the costs of holding inventory (due to parts deterioration) and shortages. Real-time condition monitoring offers vast opportunities to deal with this issue. Sensors continuously monitor the condition of a functioning device. We can predict the remaining useful life of a device and initiate maintenance jobs when the predicted remaining life reaches a certain threshold based on sensor readings. Then, the demand for spare parts, as an input to inventory models, is derived based on maintenance schedules. The ultimate aim is to build a just-in-time inventory system.

Harris (1990) addressed traditional economic manufacturing quality theory in inventory optimization. Some researchers have used Bayesian approaches to update uncertain parameters of the distribution of the time to failure because the common practice is to periodically record condition signals. Aronis et al. (2004) determined the optimal parameter S of an $(S-1, S)$ ordering policy to meet the desired service level during the lead time. Elwany and Gebraeel (2008) proposed a sense-and-respond architecture to improve logistical decisions. In the sensing stage, they first used signal values to update the random parameters of the linear and exponential degradation models and then predicted the remaining life distribution of individual components. In the response stage, following Armstrong and Atkins (1996), they optimized the replacement and spare parts ordering times to minimize the total cost rate per renewal cycle.

Li and Ryan (2011) proposed a framework to capture the relationship between machinery fault diagnosis and spare parts management. They modeled machine degradation as a Wiener process with either known or unknown drift parameters. Then, they derived the demand distribution for spare parts in a Bayesian manner and proposed a base-stock inventory control policy that depends on some subsets of the observed condition monitoring information. Louit et al. (2011) determined the optimal ordering time for a single spare part so that the interval between the identification of a potential failure and the occurrence of failure is larger than the random lead time. Under this policy, stocking a spare is unnecessary. Given imperfect demand information due to imperfect predictions, Topan et al. (2018) allowed the return of inventory to the supplier and partially characterized the structures of the optimal ordering and return policy. Zhu et al. (2020) incorporated an on-condition maintenance task as advance demand information for spare parts.

Zhang and Zeng (2017) jointly optimized the replacement decision and ordering quantity for a multi-unit system. Given preventive and opportunistic maintenance thresholds, they incorporated opportunistic maintenance at periodic inspection times and ordered spare parts to meet the safety inventory level for the next inspection. Yan et al. (2020) considered imperfect maintenance for a multi-unit system. Kian et al. (2019) described a mathematical programming model of the spare part management problem for a vessel engine.

Note that monitored signals are multi-dimensional in many applications. How to incorporate predictions of statistical models into inventory models would be an interesting direction for future research. Also, different policies of CBM imply different demand distributions of spare parts and in turn lead to different inventory policies. Although we conjecture that the base-stock policy and its variants would still be optimal in most cases, a further potential avenue of research would be to design novel ordering policies of spare parts in the setting of CBM. Finally, more works can be done with respect to inventory networks. For example, the risk pooling of spare parts among warehouses or companies has not been studied yet. Such practices are common in the airline industry.

4.3 Reliability improvement

CBM helps improve system reliability and reduce operating costs. Based on the real-time information obtained from condition monitoring, researchers have developed inference-based approaches or stylized models to capture the degradation process of a system. Various CBM policies have also been proposed in the literature. For example, under a threshold-based CBM policy, maintenance actions are recommended when the degradation level exceeds a certain maintenance threshold. The literature on CBM is rich, and readers are referred to Alaswad and Xiang (2017) and de Jonge and Scarf (2020) for recent overviews.

Three operational actions are usually involved in managing a degrading system: Replacement, preventive maintenance, and doing nothing. Wang and Christer (2000) established a preventive maintenance and replacement model where system conditions cannot be obtained directly. Makis and Jiang (2003) derived an optimal preventive replacement strategy for a system with unobservable operational states. Information that is stochastically related to the system state is obtained through condition monitoring at equidistant inspection times. Zhou et al. (2007) considered imperfect maintenance and optimized the reliability threshold using a hybrid hazard rate function. Liu et al. (2013) optimized the maintenance threshold level for a degrading system with multiple failure modes. Liu et al. (2017b) showed that a monotone control-limit policy is optimal for a repair-replacement model with an age- and state-dependent operating cost. Si et al. (2018) proposed a framework for degradation modeling and used maximum likelihood estimation to determine the optimal replacement time of a system.

Under a high sampling cost of condition information, Kim and Makis (2013) determined when such information should be collected and characterized the optimal sampling and maintenance policy using a control chart with three critical thresholds. Lam and Banjevic (2015) considered an inspection scheduling problem and obtained the myopic optimal time for the next inspection via the proportional hazards model. Some recent works have included two-unit systems (Berrade et al., 2018), partial repairs (Huynh, 2020), and hybrid policies (Poppe et al., 2018).

Degradation signals are often used to determine whether a product has failed or when the replacement of a product should be triggered. Therefore, under a threshold policy, only the action of replacement is performed when the threshold is reached, that is, a product is restored to its original condition. This is appropriate for non-repairable products. However, for repairable products, a better choice is to conduct imperfect maintenance actions. A direction for future research would be to optimize the degradation level after CBM.

4.4 Prognostics and health management

Considerable research on prognostics and health management (PHM) exists. According to the review by Lee et al. (2014), the term “prognostics” comes from the medical area and has become popular in the industrial field. For a systematic PHM design, the authors proposed an introductory summary of different components in a production system and presented several methods for identifying critical components. Vogl et al. (2016) proposed a review of prognostic capabilities for manufacturing. They emphasized the importance of PHM in reducing costs and summarized the challenges, needs, methods, and best practices of PHM in a manufacturing system.

In recent research, PHM has been considered a way to estimate reliability in the presence of regularly updated information. Kim et al. (2018) developed new algorithms based on PHM theory. Data-driven methods, such as data fusion (Song and Liu, 2018) and parameter estimation (Hanachi et al., 2018), have also been integrated into PHM. PHM is particularly suitable for complex high-end equipment. Feng et al. (2017) established PHM models under the CBM of aircraft fleets from both competitive and cooperative perspectives. Lin et al. (2018) proposed a fleet maintenance model based on fatigue structures. In addition to aircraft applications, Bae et al. (2019) used PHM and control charts in the setting of steam turbine generators.

5 Conclusions

CBM has received special attention from the industry and the academia because it is more cost-effective than traditional time-based maintenance. We present a review of the recent development of CBM, with emphasis on the modeling of product conditions and the operational applications of CBM models. Specifically, we consider different types of products’ physical structures and signal data. We summarize common statistical or stochastic models for three kinds of degradations, namely, deteriorating process, usage, and specific events. Related operational decisions can be made based on such conditioning information to maximize profits or minimize costs. Through this framework, we aim to combine the fields of reliability and operations management and build a chain that extends from past work to future directions.

Although the literature on CBM models is rich, the following research areas could be further investigated. First, degradation is usually dependent on environmental variables, not just on age and usage. Few reports on failure characteristics in other dimensions have been published. Thus, variable selection models are needed for reliability prediction. Methods for obtaining good estimations of model parameters, especially those that change over time, are also needed. For event-based conditions, the existing research has addressed the single jump and the external shock separately, while few papers have considered these two factors together.

Second, data fusion is an interesting topic in sensor networks. Data from different sources may be correlated. For example, a faulty sensor may affect the functioning of other sensors in the network, or measurement errors produced by one sensor may result in noisy data from many others. Sifting valuable information from noise is still a key issue in sensor data analysis. Therefore, developing improved methods for filtering signal is another appealing research direction.

Third, although some studies have considered the difference between various failure modes, extended analysis can help investigate the impact of customer behavior on them. Customer behavior is essential in understanding the failure modes of a product. The abundance of information regarding product use allows us to consider the human factor in reliability design. However, improving methods for updating the analysis as new customer data become available is challenging. Further efforts might be better directed to the online learning of failure characteristics to apply CBM in various modes in the system.

Finally, under a threshold policy, manufacturers often replace a product when its degradation level reaches a certain threshold. The concept of impulse control can be used to incorporate imperfect CBM into the policy. Moreover, many products undergoing CBM are covered by warranties. Limited research has been conducted with respect to their interplay. The relationship between CBM and warranty policies must be investigated. Given that CBM is scheduled for an individual product, a warranty must also be customized. This is an interesting avenue for future research.

In essence, optimization models of reliability and operations management often share similar structures. Methodologies underlying studies from these two fields can be borrowed from each other to solve new problems. Of course, necessary revisions are needed in order to incorporate their own features. In this process, new contributions can be made to the existing models and techniques.

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