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Real-time prediction of remaining useful life and preventive opportunistic maintenance strategy for multi-component systems considering stochastic dependence

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ABSTRACT

This paper presents a dynamic opportunistic condition-based maintenance strategy for multi-component systems. The strategy is based on real-time predictions of the remaining useful life under the simultaneous consideration of economic and stochastic dependence. First, the effect of a component's degradation level on the remaining useful life of other components is considered. The remaining useful life of components that have a stochastic dependence on one another is predicted using stochastic filtering theory. Given the condition monitoring history data, we model the effect of a component's degradation level on the remaining useful life of other components. And a penalty cost evaluates the additional cost of shifting the maintenance time. This allows us to determine the optimal trade-off between reducing the remaining useful life of some components and decreasing the set-up cost of maintenance. An optimization model is then established by choosing the dynamic opportunistic maintenance zone and optimal group structure that minimizes the long-term average maintenance cost of the system. A numerical example including three multi-component systems is presented. The results show that our proposed method maximizes production efficiency on the premise of ensuring system reliability, and reduces the system operation and maintenance costs.

1. Introduction

Maintenance activities play a major role in improving the availability, reliability, and security of industrial systems, and can also reduce their lifecycle costs. Condition-based maintenance (CBM) decisions are scheduled according to the condition of single or multiple components (Ahmad & Kamaruddin, 2012; Jardine, Lin, & Banjevic, 2006). CBM has been extensively studied and widely applied, such as in enabling real-time sensor information to be received from a component's degraded state (Zhao, Tian, & Zeng, 2013). Another efficient and systematic approach for evaluating the reliability of a system in its actual operating condition is Prognostics and Health Management (PHM), which predicts the progression of any failures and mitigates operating risks via management actions. PHM gives advance warning of impending system failures, thereby assisting maintenance decisions and preventive actions (Le Son, Fouladirad, Barros, Levrat, & Iung, 2013; Si, Wang, Chen, Hu, & Zhou, 2013).

The estimation of remaining useful life (RUL) is a key component of PHM and CBM (Si, Wang, Hu, & Zhou, 2011). Studies on RUL have mainly focused on prediction models. Most existing prediction models can be divided into three main categories: physics-based methods (Zhao et al., 2013), models based on expert knowledge (Biagetti & Sciubba, 2004; Ma, Chen, & Xu, 2006), and statistical data-driven methods (Si et al., 2011, Si, Wang, Hu, & Zhou, 2014; Vališ, Žák, & Pokora, 2015). Among these RUL prediction methods, we focus on statistical data-driven approaches based on stochastic filtering. Methods based on stochastic filtering are more suitable for CM data, and estimate the RUL by fitting the available data under probabilistic and mathematical properties, without relying on any physics or engineering principles. By applying statistical analysis to CM data, the probability density function (PDF) of RUL is derived based on Bayesian theory, and no critical failure threshold is required. This is one of the most appealing features of this approach, because the failure threshold is difficult to determine (Si et al., 2013).

When the prediction of RUL and preventive maintenance are considered, most models mentioned above focus only on the single

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Acronyms

CBM	condition based maintenance
CM	condition monitored
RUL	remaining useful life
OM	opportunistic maintenance
PDF	probability density function
PSO	particle swarm optimization
AIC	Akaike information criterion
ML	maximum likelihood

Notation

t_i	time of the ith monitoring point
$z_i^{(k)}$	monitoring information of component k at t_i
$f_i^{(k)}\left(t\middle\vert s_i^{(k)}, s_i^{(j)}, j \in D_k\right)$	PDF of component k at time t_i
$T_i^{(k)}$	RUL of component k at time t_i
C_p	cost of preventive maintenance
C_f	cost of failure replacement
C_h	penalty cost
S	fixed set-up cost
t_R^*	optimal replacement date of single component
N_w	time window
$C_{\min}^{(\eta)}$	minimum average cost rates of the single component η
$S_i^{(k)}$	CM history of preventive maintenance
$f_0^{(k)}(t)$	initial PDF of a new component
$g^{(k)}(z^{(k)}\vert t, s^{(j)})$	degradation status information PDF of component k
$g^{(j)}(z^{(j)})$	degradation status information PDF of component j
q_i	cost saving of dynamic OM based on CM information until t_i
q_T	saved cost preventive OM strategy over a long-term period T
Q	average saved cost rate
$\Delta t_0^{(\eta)*}$	optimal OM zone threshold of component η
Q_T	average saving cost over the long-term period T

component system (Carr & Wang, 2011; Son, Zhang, Sankavaram, & Zhou, 2015) or independent multi-component system (Liu, Xu, Xie, & Kuo, 2014). However, large-scale complex systems consist of multiple components that are structurally or stochastically dependent upon one another. The optimization of a single component does not ensure optimal performance in the entire system. Interactions between these components cannot be neglected, and should be taken into account in prognostics and maintenance decisions. The problem of appropriate maintenance scheduling in multi-component systems is difficult to analyze. Nonetheless, these dependencies offer the possibility of jointly maintaining multiple components, and multi-component maintenance policies can reduce downtime losses and decrease costs (Gustavsson, Patriksson, Strömberg, Wojciechowski, & Önnheim, 2014; Nakagawa & Mizutani, 2009).

An optimal multi-component maintenance strategy considers systems of several interdependent components. The dependencies between multiple components can be classified as economic dependence, stochastic dependence, or structural dependence (Dekker, Wildeman, & van der Duyn Schouten, 1997). Many maintenance strategies for multi-component systems focus solely on the economic dependency between components, as it is simpler to describe these relationships (Bouvard, Artus, Berenguer, & Cocquempot, 2011; Koochaki, Bokhorst, Wortmann, & Klingenberg, 2012; Laggoune, Chateauneuf, & Aissani, 2010). Huynh, Barros, and Berenguer (2015) introduces a multi-level decision-making approach that combines maintenance decisions at the system level and the component level considered the economic dependence and structural dependence. However, many multi-component systems have a degree of stochastic dependence. For such systems, the assumption that components degrade independently is inappropriate (Bian & Gebraeel, 2014). Existing models consider the effect that a component's failure has on the remaining functioning components with stochastic dependence (Kvam & Pena, 2005; Nicolai & Dekker, 2008; Scarf & Deara, 2003). Li, Coit, and Elsayed (2011) presented a stochastic dependence model for multi-component systems. The stochastic dependence among component lifetimes was characterized by correlated multivariate lifetime distributions, the parameters of which vary as components fail. Carr and Wang (2010) reported a theoretical Bayesian model for RUL prediction that considers the failure of one component to induce various degradation states in other components. Zhang, Wu, Li, and Lee (2015) studies maintenance policies for multi-component systems in which failure interactions and opportunistic maintenance (OM) involve. In reality, the failure rates are unobservable, and thus cannot be used to understand the underlying physics-of-failure. In contrast, we are more concerned with modeling interactions at the level of degradation processes: the proposed approach characterizes the real-time evolution of this degradation by modeling the associated degradation signals prior to failure.

Stochastic dependence models that address component interactions in terms of system degradation states have also been studied. These include Markov models (Lisnianski & Levitin, 2003) and semi-Markov models (Chryssaphinou, Limnios, & Malefaki, 2011) in which the transition rate of each component depends on the state of the system. Nonetheless, one of the most important limitations of such models is that they do not investigate the physics-of-failure at the component level. Thus, they cannot be used to capture component interactions. Interactions between components and the overall system are determined by a pre-specified structure function, which does not necessarily consider the degradation or failure effect of one component on another. Certain qualitative models are limited to relating these interactions from a logical standpoint, and do not provide quantifiable estimates of the interaction or lifetime. In contrast, our proposed methodology can be used to predict the RUL of components by leveraging real-time CM data.

The prediction of RUL provides information that facilitates maintenance decisions. However, the development of maintenance strategies remains a core aim (Tang, Makis, Jafari, & Yu, 2015). Common maintenance planning approaches for multi-component systems include block replacement policies, grouping maintenance policies, and OM policies (Nowakowski & Werbińka, 2009). Different maintenance decision models have been established based on these three basic maintenance strategies. These models mainly discuss the determination of a satisfactory maintenance schedule that applies the relevant policy under different system structures, costs, maintenance methods, and optimization goals. Early research into block replacement maintenance policies focused on the periodic maintenance of different components to achieve the optimal system maintenance time (Scarf & Deara, 2003). The popularity of grouping maintenance policies and OM policies has increased with the development of CBM. These