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# A failure-dependency modeling and state discretization approach for condition-based maintenance optimization of multi-component systems

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ABSTRACT

Unexpected component failures in a mechanical system always cause loss of performance and functionality of the entire system. Condition-based maintenance decisions for a multi-component mechanical system are challenging because the interdependence of individual components' degradation is not fully understood and lack of physical models. Most existing literature commonly assumes that degradation and failure of individual components within a mechanical system are independent, which could lead to inaccurate diagnostic and prognostic results. In this research, state-rate dependence denoting interaction between component health condition (degradation state) and failure rate is proposed for degradation and failure analysis for a two-component repairable system. A state discretization technique is proposed to model how health state of one component affects the hazard rate of another. An extended proportional hazard model (PHM) is used to characterize the failure dependence and estimate the influence of degradation state of one component on the hazard rate of another. An optimization model is developed to determine the optimal hazard-based threshold for a two-component repairable system. A case study on a generic industrial gearbox has been conducted to show the effectiveness of the proposed model.

## 1. Introduction

Condition-based maintenance (CBM) has received serious attentions in recent years because of improvement in sensor technology and cost reduction in data collection. The majority of CBM research focuses on single-component system. As manufacturing technology advances, manufacturing system becomes more complex and the interrelations among components become more complicated. CBM in complex system becomes very challenging. In addition, the varieties and abundance of the interrelations make CBM in complex system more intractable. As to tackle the problem, the common way is to assume that component degradations or failures are independent. However, this overlooks the truth that stochastic dependence exists, e.g., Bian and Gebraeel [14] and Sun et al. [25] address the genetic gear-box as a typical mechanical system to present the existence of stochastic dependence. In their work, it has been demonstrated that the degradation of a bearing can be reflected from its own vibration amplitude and the vibration can accelerate the degradation of the coupled shaft and other bearings. As a result, the vibrations of the affected bearings increase and exacerbate the degradations and failure rates of other bearings. As to simply deal with failure or degradation dependence among components, researchers assume that the dependence level is defined with prespecified parameters or functions (Li et al. [8]; Hong et al. [9]; Zhang and Yang [18]). Although stochastic dependence exists in multiple forms, extant forms of stochastic dependence can be categorized into four types and presented in Fig. 1. Dependence, such as hazard-hazard dependence (Sun et al. [25]), state-rate dependence (Bian and Gebraeel [14], Rasmekomen and Parlikad [17]), degradation-hazard dependence (Caballé et al. [3]) and shock-degradation dependence (Song et al. [24]) are studied in different multi-component systems. One of the state-rate dependences is state-hazard dependence, which is defined that the degradation state of component influences the hazard rates of other components. State-hazard dependence is rarely studied in CBM.

In this work, an investigation is carried out on how the component states affect the hazard (failure) rate of other components (state-rate dependence) and measuring the magnitude of state-hazard dependence. We develop a method for discretizing component degradation states. We proposed a method for measuring the influence of component state on the hazard rate of other components. A replacement policy taking into account component state information and maintenance cost is developed.

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**Nomenclature**

| | |
|---|---|
| $\Delta$ | inspection interval |
| $\beta$ | shape parameter of Weibull distribution |
| $\gamma$ | weight of covariate |
| $\eta$ | scale parameter of Weibull distribution |
| $r^{(l)}_v$ | point index in segment v for observation $l$ |
| $c^{(l)}_v$ | number of failures in segment v for observation $l$ |
| $h(t, Z(t))$ | hazard rate given system age $t$ and covariate vector $\mathbf{Z}(t) = [Z_1(t), Z_2(t)]$ |
| $k_{ip}$ | the minimum positive integer number satisfying $kip \le tip$ |
| $n^{(l)}_v$ | length of segment $v$ for observation $l$ |
| $t_{ip}$ | the time that the failure risk first reaches the threshold given state vector $\mathbf{Z}(t) = [i, p]$ |
| $C_{AC}$ | average cost per unit time |
| $C_{cycle}$ | total cost in association with repair and replacement per cycle |
| $C_m(k,i,p)$ | expected repair cost due to failure given component age $k$ and covariates $i$ and $p$ |
| $C_{me}$ | cost of per minimal repair performed on component $e$ |
| $C_p$ | total cost of replacing component 1 and 2 |
| $D$, $d$ | condition-based threshold |
| $N(D)$ | number of failure repairs before replacement |
| $\boldsymbol{P}$ | covariate state transition probability matrix |
| $R(k,i,p,t-k\Delta)$ | conditional reliability function until time t given the age of the system is $k\Delta$ and $\mathbf{Z}(k\Delta) = [i,p]$ |
| $S_c$ | contrast function optimization stopping criteria |
| $T_r$ | replacement time; |
| $U(V)$ | contrast function; |
| $V$ | number of change-points |
| $W(D)$ | expected replacement time |
| $W(k,i,p)$ | expected replacement time given state vector $\mathbf{Z}(t) = [i, p]$ |
| $Z_{FT}$ | physics-based threshold (fault threshold) |
| $Z(t)$ | value of the stochastic covariate at time $t$ |
| $\mathbf{Z}(t)$ | covariate vector $\mathbf{Z}(t) = [Z_1(t), Z_2(t)]$ contains state covariates of components 1 and 2 at time $t$ |
| $\lVert\hat{\Sigma}\rVert$ | determinant of empirical covariance matrix $\hat{\Sigma}$ |

## 2. Background literature

Review works in CMB from different perspectives are presented by researchers. Cho and Parlar [6] survey the literature on maintenance and replacement models for multi-component system. A number of models, such as repair model, group/opportunistic model, maintenance/replacement model, and inspection/maintenance model are presented. Jardine et al. [1] review machinery diagnostics and prognostics implementing CBM. The overview synthesizes the processes from degradation data acquisition and data analysis until maintenance decision-making. Techniques for dealing with different data forms, such as time-domain data, frequency-domain data and value type data, are mentioned. Alaswad and Xiang [22] present a panoramic view of CBM for single-component system. Their review work focuses on inspection performance, maintenance quality and maintenance optimization criteria. The demand of CMB for multi-component system with stochastic dependence has been emphasized.

### 2.1. CBM for single-component system

Numerous papers are published on CBM for single-component system (Banjevic et al. [4]; Banjevic and Jardine [5]; Shafiee et al. [16]; Peng et al. [19]; Vlok et al. [20]; Makis and Jardine [27]; Zhu et al. [28]). Banjevic et al. [4] propose a model known as control limit policy for maintenance decision-making. An iteration algorithm and a recursive procedure are developed in the proposed model as to obtain the optimal preventive replacement threshold. Based on the control limit policy, the research is further extended by Banjevic and Jardine [5] for remaining useful life estimation. Peng et al. [19] present their research on a single-component system suffering multiple dependent competing failure processes. The studied failure processes are competing and deemed as interdependent.

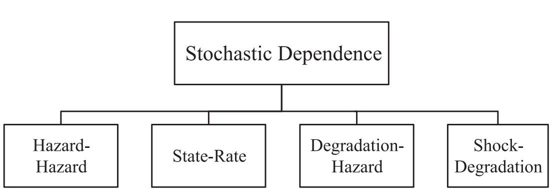


**Fig. 1.** Type of stochastic dependence.

### 2.2. CBM for multi-component system

Because of the importance and demand of CBM for multi-component system, an abundance of research investigating different forms of dependence has been published. In contrast to stochastic dependence, economic dependence is easy to manage and studied in plentiful research (Bouvard et al. [12]; Tian and Liao [30]; Tian et al. [32]). CBM in multi-component system with stochastic dependence is few due to the variety and complexity of stochastic dependence. As to make the maintenance modeling of multi-component system simple, Zhu et al. [29] assume that the studied failure modes, hard failure and soft failure, are independent. The maintenance performance with imperfect prediction signal is investigated. In fact, the assumption, that degradation processes of components in complex system are independent, is lack of justification and always results in errors in estimating system reliability or lifetime.

Golmakani and Moakedi [10] develop a model to find out optimal inspection interval for a two-component repairable system with failure interaction. Failures are classified into soft and hard, and hard failure has influencing effect on soft failure and can not affected by soft failure. Song et al. [24] propose a new reliability model for a series system subject to competing hard and soft failure processes. Shocks can cause hard failure and incremental progress on soft failure processes. Rasmekomen and Parlikad [17] propose a model with state-rate interactions. They aim at identifying the optimal inspection timing and preventive replacement threshold for each tube under multiple maintenance strategies. Zhang et al. [31] develop a mathematical model by taking into account opportunistic maintenance and environmental influence to determine an optimal maintenance policy for a multi-component system. The environmental conditions are shown to exert an influence on the component degradation processes. Caballé et al. [3] propose a CBM strategy for the system subject to two dependent causes of failure: degradation processes and sudden shocks. The studied deterioration levels of the degradation processes directly influence the sudden shock process and indirectly affect the intensity of total failure of the system. In order to study how stochastic dependence level influences maintenance strategy, copulas (Li et al. [8]; Hong et al. [9]; Zhang and Yang [18]), such as Levy copula, Gumbel copula, Clayton copula and normal copula, are proposed to model the magnitude of stochastic dependence. Stochastic dependence with different magnitudes is investigated via the marginal distribution functions (Li et al. [8]; Hong et al. [9]). A dependent latent age model for capturing reliabilities of components with multiple competing failure modes and failure interdependence is developed by Zhang and Yang [18]. A joint