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Assessment of diagnostic and prognostic condition indices for efficient and robust maintenance decision-making of systems subject to stress corrosion cracking

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ABSTRACT

Seeking condition indices characterizing the health state of a system is a key problem in condition-based maintenance. For this purpose, diagnostic and prognostic models have been unceasingly developed and improved over the past few decades; nevertheless none of them explains thoroughly the impacts of such indices on the effectiveness of maintenance operations. As a complement to these efforts, this paper analyzes the effectiveness of some well-known diagnostic and prognostic indices for maintenance decision-making. The study is based on a system subject to competing risks due to multiple crack paths. A periodic inspection scheme is used to monitor the system health state. Each inspection returns the perfect diagnostic information: the number of cracks, corresponding crack sizes, and the system failure/working state. Based on this information, two kinds of prognostic condition indices are predicted: the average value and probability law of the system residual useful life. The associated condition-based maintenance strategies and cost models are then developed and compared with the ones whose maintenance decisions are based on diagnostic condition indices. The comparison results allow us to conclude on the performance and on the robustness of these strategies, hence giving some suggestions on the choice of reliable condition indices for maintenance decision-making.

1. Introduction

Condition-based maintenance (CBM) program has nowadays attracted a great deal of interest among organizations, because of the significant economic impact to companies and environmental impact to society [1]. Within this maintenance program, condition monitoring (CM) information, such as vibration level, acoustic emission signal, temperature, pressure, humidity, etc., is collected and, through that knowledge, indices characterizing the health state of systems are synthesized for maintenance decision-making purposes. Such indices, called *condition indices* [2], may be the result of real-time diagnosis of impending failures or prognosis of future system health. In reality, diagnosis and prognosis are two essential aspects of a CBM program, and a lot of contributions have been developed in this field over the past few decades. Pusey and Roemer provide in [3] a broad overview of the development in diagnosis and prognosis applicable to high-performance turbo-machines until 1999. Jardine et al. give in [4] an interesting survey of the different diagnostic and prognostic approaches and associated CBM strategies for various machines up to 2005. Lee et al. [5] provide a comprehensive review of various methodologies and techniques in prognostics and health management research. More recently, Ahmad and Kamaruddin [6] and Shafiee et al. [7] systematically review maintenance decision-making methods based on the system health diagnostic and prognostic information. Other recent developments in this field can be found in [8–15]. A common remark drawn from these existing works is that different problems related to a CBM program, such as deterioration monitoring and health status assessment, remaining useful life (RUL) prediction, and maintenance decision-making, have been separately considered. This may lead to shortcomings in assessment of a whole CBM program. Furthermore, most efforts have been focused on improving the quality of diagnosis and prognosis processes; and the question on how to

Acronyms: CBM, condition-based maintenance; CM, condition monitoring; SCC, stress corrosion cracking; HPP, homogeneous Poisson process; HGP, homogeneous Gamma process; DTS, degradation-threshold-shock; RUL, residual useful life; MRL, mean residual life; PR, preventive replacement; CR, corrective replacement; pdf, probability density function; cdf, cumulative distribution function

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Nomenclature

Notation

N_t	number of appeared cracks up to time t
T_i	arrival time of the i-th crack
λ	intensity of the HPP $\{N_t\}_{t\geq 0}$
$f_{T_1,\ldots,T_k\mid N_t}$	joint pdf of k first arrival times $\{T_1, \ldots T_k\}$ given N_t
$1_{\{\cdot\}}$	indicator function
$X^i_{\Delta t}$	length of the i-th crack at Δt units of time after its initiation
α, β	shape, scale parameters of the HGP $\{X^i_t\}_{t\geq 0}$
m, σ^2	average rate, variance rate of $\{X^i_t\}_{t\geq 0}$
$f_{\alpha\Delta t,\beta}$, $F_{\alpha\Delta t,\beta}$	pdf, cdf of $X^i_{\Delta t}$
$\Gamma(\cdot)$, $\Gamma(\cdot,\cdot)$	gamma function, incomplete gamma function
X_t^S	sum of all crack increments up to time t
$X_t^S\mid N_t$	sum of all crack increments in the time intervals $[0, t]$ given N_t
$X^S_{[t,t+u]}\mid N_t, N_{t+u}-N_t$	sum of all crack increments in the time intervals $[t, t+u]$ given N_t and $N_{t+u}-N_t$
$f_{X_t^S\mid N_t}$, $F_{X_t^S\mid N_t}$	pdf, cdf of $X_t^S\mid N_t$
$F_{X^S_{[t,t+u]}\mid N_t, N_{t+u}-N_t}$	cdf of $X^S_{[t,t+u]}\mid N_t, N_{t+u}-N_t$
L, N	critical degradation threshold, limited number of cracks
Z, Y	failure times of the *unmaintained* system and of the *maintained* system
$\rho(t\mid X_t^S, N_t)$	conditional RUL of the system at time t given X_t^S and N_t
$R(t+u\mid X_t^S, N_t)$	conditional reliability of the system at time $t+u$ given X_t^S and N_t
$\mu(t\mid X_t^S, N_t)$	conditional MRL of the system at time $t+u$ given X_t^S and N_t
T, τ_j	inspection period, j-th inspection time
M	PR threshold associated with the sum of crack sizes
N_p	PR threshold of associated with the number of cracks
μ_p	PR threshold of associated with the conditional MRL of the system
R_p	PR threshold of associated with the conditional reliability of the system
PR^N	PR due to an excessive number of cracks over the threshold N_p
PR^X	PR due to an excessive level of crack size over the threshold M
CR^N, CR^X	CR due to cracks number, CR due to sum of crack sizes
$Q_{\tau_j^-}$, $Q_{\tau_j^+}$	values of the quantity Q at the time just before, and just after τ_j
$C(t)$	total maintenance cost including the downtime cost up to time t
C_∞	long-run expected maintenance cost rate
C_i, C_p, C_c	cost per inspection, cost per PR, cost per CR
C_d	downtime cost rate
S_1	first replacement time of the system
$P_{p,k}(kT)$, $P_{c,k}(kT)$	probabilities of PR and CR at time kT
$W_{d,k}(kT)$	system downtime in a renewal cycle
MTTF	mean time to failure of the system
$\eta(X_t^S, N_t)$	either $\mu(t\mid X_t^S, N_t)$ or $R(t+T\mid X_t^S, N_t)$
η_p	either μ_p or R_p
M_k	minimum value of sums of crack sizes x such that $\eta(x, k)\leq \eta_p$
ϵ_p	relative error of PR decision parameters
ϵ_C	relative increase in C_∞ when the decision parameters are different than their optimal values

design and to use the best condition indices for maintenance decision-making remains an open and challenging issue. Faced to this situation, the present paper focuses on building a generic and complete framework to quantify the performance and robustness of CBM strategies built from some typical diagnostic and prognostic condition indices, and hence aims at providing suggestions on the choice of reliable indices for maintenance decision-making.

From an economic viewpoint, we define the *performance* of a maintenance strategy as its capacity to save maintenance costs under its optimal configuration, and its *robustness* as its ability to keep its cost saving close to the optimum when it is out of its optimal configuration. Classically, we can assess the maintenance strategy performance through its *long-run expected maintenance cost rate* [16]. Such a cost criterion can be analytically evaluated on the basis of (semi-)regenerative stochastic techniques [17,18]. In reality, the performance assessment based on the long-run expected maintenance cost rate is a key problem in the reliability and maintenance field, and it motivates many works on maintenance modeling and optimization in the literature [19]. Contrary to the problem of performance assessment, the robustness of maintenance strategies has not attracted much attention, especially for CBM strategies. As far as we know, only the authors of some recent papers [20–24] study the robustness of CBM strategies, and the assessment is mainly performed on the basis of the so-called *relative increase in long-run expected maintenance cost rate* [25]. By combining both above criteria, this paper proposes an approach to jointly quantify the performance and the robustness of CBM strategies, and thus to determine reliable condition indices for maintenance decision-making as follows.

- developing a degradation and failure model for the considered system,
- synthesizing diagnostic and prognostic condition indices on the basis of the developed degradation and failure model,
- building diagnosis and prognosis-based maintenance strategies, and developing the associated cost models,
- assessing the performance and robustness of the considered strategies to find out reliable indices.

This approach allows exploring the complete CBM processing chain for a system, from deterioration monitoring and health status assessment, to remaining useful life estimation, right through to maintenance decision-making. It also constitutes a generic and complete framework to choose appropriate condition indices for CBM decision-making.

More precisely, we develop our degradation and failure model based on the operating feedback data-set described in [26]. This data-set consists of the initiation times and the crack length measurements in the propagation phase which appear on different components of nuclear power plants. The two-stage cracks behavior is thus modeled by two stochastic processes: a homogeneous Poisson process (HPP) for the incubation phase, and a homogeneous Gamma process (HGP) for the propagation phase. While such a use of these processes is quite classical [27], the way to define the competing failures of the system is new and original. Four condition indices are considered: sum of crack sizes, couple of sum of crack sizes and number of cracks, conditional mean residual life (MRL) of system, and system conditional reliability. The two first indices are directly gathered by inspection operations, while the two latter ones are synthesized using also the developed degradation and failure model. These indices represent respectively the *partial* and *complete* information about the current system heath, and the *average* type and *quantile* type information of the future system heath. These representative indices are then incorporated into maintenance decision-making. To maintain coherence with CM strategies recently implementing to obtain the operating feedback data-set [26], four quite simple periodic inspection and replacement strategies have been built. Note that the prognostic-based maintenance strategies proposed here are rarely considered in the literature. The mathematical