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Reliability model of a component equipped with PHM capabilities

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ABSTRACT

We propose an analytic, time-variant model that conservatively evaluates the increase in reliability achievable when a component is equipped with a Prognostics and Health Management system of known performance metrics. The reliability model builds on metrics of literature and is applicable to different industrial contexts. A simulated case study concerning crack propagation in a mechanical component is considered to validate the proposed model.

1. Introduction

In the last decade, Prognostics and Health Management (PHM) has often been proposed as an effective technology to respond to the reliability challenges posed by the modern safety-critical components and systems (e.g., nuclear power plants, oil&gas assets, etc.), in which failures can result not only in significant costs, but also in life-threatening consequences such as explosions and natural disasters.

PHM allows in principle monitoring the system health condition, predicting its Remaining Useful Life (RUL) and, ultimately, preventing catastrophic failures [1–5]. However, in practice it is important to know which are the reliability and availability of a component or system. In this respect, to the authors' best knowledge a modeling framework that allows translating the PHM contribution into the component or system reliability is still lacking.

A few works have attempted to evaluate the influence of PHM on system Life Cycle Cost (LCC, [6–11]), looking at the economic benefits of PHM in terms of increase of component or system availability. On the other hand, for safety-critical applications PHM is expected to mainly increase the component or system reliability (rather than availability). PHM helps avoiding over-estimations of the actual component RUL, which may lead to accidents with possible consequences on the asset, the environment and the public.

To evaluate the added value of the PHM technology on system reliability, it is necessary to characterize the performance of the PHM adopted. In this respect, a variety of performance metrics and indicators have been introduced for detection (i.e., the recognition of a deviation from the normal operating conditions causing such deviation, e.g., [8,12]), diagnostics (i.e., the characterization of the abnormal state, e.g., [13]) and prognostics, (i.e., the prediction of the evolution of the abnormal state up to failure, e.g., [2,14,15]). The original contribution of this work is to propose a general modeling and decision framework for linking PHM metrics of literature to the component reliability. This framework also allows accounting for the decision criterion adopted for maintenance (overhaul), which heavily depends on the risk attitude of the decision maker.

The proposed reliability model is validated by way of a simulated case study concerning the crack propagation in a mechanical component, which requires to estimate the values of the relevant PHM metrics.

Although various definitions of performance metrics exist in the PHM literature, a detailed procedure to estimate their values is still lacking, apart from a few metrics such as the MTTF [16]. For this, a further original contribution of our work is the Monte Carlo (MC) procedure proposed to estimate the performance metrics encoded in the developed reliability model.

The remainder of the paper is organized as follows: Section 2 briefly introduces the general framework; in Section 3, the impact of a PHM tool on system reliability is modeled; Section 4 illustrates a simulated case study concerning the crack propagation in a mechanical component; Section 5 validates the developed model by way of the simulated case study; Section 6 concludes the work.

2. Modeling framework

We consider a degrading component, whose degradation state is monitored every Δt units of time with respect to a continuous indicator variable (Fig. 1). The degradation process is stochastic for the degradation state and two thresholds are considered: the detection threshold, which mainly depends on the characteristics of the instrument used for monitoring the degradation variable (for example, considering that the instrument is not capable of detecting the degradation state for values

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Nomenclature

λ	Time window modifier, such that $t_\lambda = T_{pr} + \lambda(T_f - T_{pr})$; $\lambda \in [0, 1]$
λ^*	Time from which the values of the performance metrics are estimated
T_d	Time instant at which the system reaches the detection threshold
T_f	Time instant at which the system reaches the failure threshold
T_ϕ	Length of the time interval $T_f - T_d$
f_{T_d}	pdf of time T_d
f_{T_ϕ}	pdf of T_ϕ
f_{T_f}	pdf of T_f
Δt	Time interval between two successive Remaining Useful Life (RUL) predictions
DTD	Detection Time Delay, $T_{pr} - T_d$
f_{DTD}	probability density function (pdf) of DTD
P^α_λ	$\alpha - \lambda$ performance
$\lfloor x \rfloor$	Integer part of x; that is, $n \le x < n+1$, $x \in \mathbb{R}$, $n \in \mathbb{N}$
N	Number of maximum RUL predictions before failure
k^*	Index of the first time channel at which the decision to remove the system from operation can be taken
h^*	Index of the first time channel at which a missing alarm is risky
R_λ	Uncertain predicted RUL at time indicated by λ
Υ_λ	Point summarizing the uncertainty in R_λ (e.g., mean, median, 10th percentile, etc.)
RUL^*_λ	Actual RUL at the time indicated by λ
T_{pr}	Time of the first RUL prediction
FP	False positives
FN	False negatives
m	Empirical estimate of metric M
f_{R_λ}	pdf of the predicted RUL at the time window indicated by λ
$\mathcal{N}(\mu, \sigma^2)$	Normal distribution with mean μ and variance σ^2
$\mathcal{U}(a, b)$	Uniform distribution between a and b

below such threshold), and the failure threshold, above which the component does not function any more or, more practically, must be maintained or replaced for avoiding a catastrophic failure.

The uncertainty in the time instant T_d at which the component reaches the first threshold is described by the probability density function (pdf) f_{T_d}. If no action is taken, the component continues its degrading up to failure occurring at time T_f; its uncertainty is described by pdf f_{T_f}. Finally, we also consider the random variable $T_\phi = T_f - T_d$, whose pdf is f_{T_ϕ}.

Realistically, it is assumed that detection is not perfect. Thus, metrics of literature are exploited to characterize the detection performance. In this respect, the following two are widely used in practice: false positive probability (i.e., the probability of triggering undue alarms) and false negative probability (i.e., the probability of missing alarm when required) [8]). In addition, Detection Time Delay (*DTD*, [12]) is a detection metric which measures the interval from the time when the detectable degradation state is reached by the component up to its detection. We use this performance metric, due to two main reasons: on one hand, *DTD* is viewed as a false negative indicator which depends on time (i.e., alarms are missing up to *DTD*); on the other hand, the *DTD* values are dependent on the detection algorithm settings, which can be adjusted so that the false positive probability is negligible in the inital part of the component life [12]. This way, the model development is simplified. To be realistic, we assume that *DTD* is affected by uncertainty, whose pdf is $f_{DTD}(\delta)$.

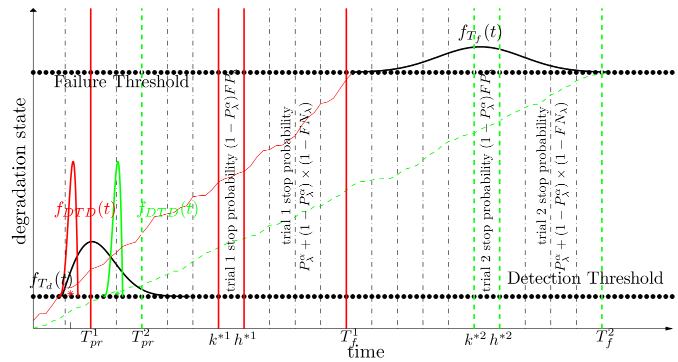

Fig. 1. Model setting description; $h = 4$, $\alpha = 0.1$, $N^1 = 11$ and $N^2 = 19$.

In this setting, the PHM system starts to predict the RUL at time $T_{pr} = (\lfloor \frac{T_d + DTD}{\Delta t} \rfloor + 1)\Delta t$, where $\lfloor \bigcirc \rfloor$ indicates the integer part of its argument. The number of predictions that the PHM can perform before failure is $N = \lfloor \frac{T_f - T_{pr}}{\Delta t} \rfloor$. From now on, it is assumed that the system actually fails at time $T_{pr} + N\Delta t$, instead of T_f; the smaller Δt, the smaller the approximation.

Notice that we have assumed, for simplicity, that the considered component is affected by a single failure mode, so that we do not have the need of tackling the issue of embedding diagnostic metrics into the reliability model, and of considering all scenarios originating from decisions based on erroneous diagnoses of the failure mode. Such diagnostic issue is left for the future research work.

Finally, notice also that, in practice, both detection and failure thresholds may not be easily determined. For example, in helicopter applications, PHM systems (also called Health and Usage Monitoring System, HUMS) are mainly based on vibration monitoring to infer the equipment health [17–19]; thus, there is no simple way to define a threshold directly related to failure. Similar challenges are encountered in the packaging industry, where the failure conditions of components may not be precisely known [20]. Nonetheless, the approach proposed in the present work applies to any system, provided that some criterion to define the thresholds exists. The definition of such criterion is out of the scope of this work, where we assume that the Decision Maker (DM) has already defined a threshold coherent with his/her objective.

3. Reliability model

In this Section, we illustrate the mathematical model developed to evaluate the increase in system reliability brought by a PHM system.

We assume that the PHM-equipped component is stopped when the $(100 - \beta)$th percentile (e.g., $100 - 90 = 10$th) of the currently predicted RUL pdf is smaller than $h \cdot \Delta t$: the larger the value of β, the smaller the value of the predicted RUL percentile, the more risk-averse the decision. Similarly, the larger the value of h, the more cautious the decision maker.

To set h and β in real industrial applications, it should be kept in mind that the value of h strongly depends on the time required to safely remove the component from operation (e.g., time required for system shutdown), whereas β relates to the risk associated to the failure (e.g., $\beta = 5$ is a very conservative value, suitable for safety critical application). To help the DM to set h and β we can use the proposed reliability model in a ‘reverse’ way, to find the combinations of values of h and β that allow meeting the system reliability requirements, also taking into account the considered PHM performance values. Furthermore, we can evaluate the sensitivity of the component reliability value to the selected applicable values of h and β, to find the settings which are less sensitive to the possible variability of the metrics due to the uncertainty in their estimations.

To evaluate the probability of removing the system from operation before failure, we need to consider a time-variant prognostic perfor-