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Remaining lifetime modeling using State-of-Health estimation

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ABSTRACT

Technical systems and system's components undergo gradual degradation over time. Continuous degradation occurred in system is reflected in decreased system's reliability and unavoidably lead to a system failure. Therefore, continuous evaluation of State-of-Health (SoH) is inevitable to provide at least predefined lifetime of the system defined by manufacturer, or even better, to extend the lifetime given by manufacturer. However, precondition for lifetime extension is accurate estimation of SoH as well as the estimation and prediction of Remaining Useful Lifetime (RUL). For this purpose, lifetime models describing the relation between system/component degradation and consumed lifetime have to be established. In this contribution modeling and selection of suitable lifetime models from database based on current SoH conditions are discussed.

Main contribution of this paper is the development of new modeling strategies capable to describe complex relations between measurable system variables, related system degradation, and RUL. Two approaches with accompanying advantages and disadvantages are introduced and compared. Both approaches are capable to model stochastic aging processes of a system by simultaneous adaption of RUL models to current SoH. The first approach requires a priori knowledge about aging processes in the system and accurate estimation of SoH. An estimation of SoH here is conditioned by tracking actual accumulated damage into the system, so that particular model parameters are defined according to a priori known assumptions about system's aging. Prediction accuracy in this case is highly dependent on accurate estimation of SoH but includes high number of degrees of freedom. The second approach in this contribution does not require a priori knowledge about system's aging as particular model parameters are defined in accordance to multi-objective optimization procedure. Prediction accuracy of this model does not highly depend on estimated SoH. This model has lower degrees of freedom.

Both approaches rely on previously developed lifetime models each of them corresponding to predefined SoH. Concerning first approach, model selection is aided by state-machine-based algorithm. In the second approach, model selection conditioned by tracking an exceedance of predefined thresholds is concerned. The approach is applied to data generated from tribological systems. By calculating Root Squared Error (*RSE*), Mean Squared Error (*MSE*), and Absolute Error (*ABE*) the accuracy of proposed models/approaches is discussed along with related advantages and disadvantages. Verification of the approach is done using cross-fold validation, exchanging training and test data. It can be stated that the newly introduced approach based on data (denoted as data-based or data-driven) parametric models can be easily established providing detailed information about remaining useful/consumed lifetime valid for systems with constant load but stochastically occurred damage.

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1. Introduction

Technical systems operating under different, usually intermittent and hardly predictable, loading profiles undergo gradual degradation over time. Examination of degradation mechanisms and modes often entails an examination of materials rather than the system components. Moreover, different systems/materials exhibit different types of degradation. For instance, either gradual degradation of machining tool or sudden tool fracture or breakage occurs due to high operational load (like high pressures, strong fatigue loads) on machine components during the machining processes [1,2]. However, gradual degradation of system ultimately leads to failure, whereas the failure is defined as a loss of functionality where the system is not capable to perform predefined tasks. Time point at which this happens is stated as end of service lifetime. From that point onwards the system becomes not anymore functional and has to be phased out of use. For diagnostic (and sometimes also for prognostics) purposes, the propagation of degradation over time is often continuously monitored [3,4]. Benefits achieved by continuous monitoring of current systems degradation level are primarily reflected in timely performed maintenance and operation action targeting to avoid catastrophic events (for instance: with life-threatening injuries of humans), or increased costs of repairment and operation actions if not done in right time. The benefit emphasized here is the possibility for service lifetime extension under the condition that the information about current level of system degradation is integrated in control strategy, so as the controller outputs are not generated solely on the basis of commonly based system parameters but also considers actual level of system degradation. For these purposes, the tasks to be solved are: (i) estimation of degradation indicator, (ii) tuning of controller, and (iii) adaption of the operating conditions. In this contribution, degradation level is discussed in terms of State-of-Health (SoH) and Remaining Useful Lifetime (RUL) estimation, both of them describing aging of systems/materials in similar way. The degradation level in case of RUL is expressed percentually and denotes the lifetime remained up to failure occurrence. If discussed in reliability framework, Probability of Failure (P_f) function is used to express RUL. Concerning T as the moment in time of failure occurrence and t as expected (predefined) survival time, P_f is expressed as

$$P_f = P(T - t > x | T < t). \tag{1}$$

Regardless of parameters used to describe degradation level, the determination of the degradation level is a precondition for lifetime extension. Consequently, deployment of lifetime model establishing relationship between operating conditions (model input) and degradation parameter (here: RUL) is of high importance. Thus, a number of lifetime model approaches are proposed in literature whereas all models can be grouped in data-based, model-based, and experience-based approaches [1–10]. Whilst model-based approaches attempt to find mathematical description of degradation processes, data-based approaches typically rely on statistical and artificial intelligence methods such as Hidden Markov Models (HMM), Neural Networks (NN), Unscented Kalman Filtering (UKF), and similar. To reveal information about degradation, experience-based approaches take into consideration previous knowledge of processes occurred in the system integrating the same into the model.

Inceptive steps towards systems lifetime determination using cumulative damage model are introduced in the work of Palmgren and Miner [5,6]. Cumulative damage model requires the knowledge about the relation between nominal stress and the number of cycles endurable by system under the assumption that the stress is held constant. The effects resulting from the stress applied to a system whose amplitude lies below predefined material specific level (so-called endurance limit) are neglected. Moreover, the sequence of stress appearance is not considered. It may be concluded, Palmgren-Miner rule has some shortcomings primarily reflected in aforementioned assumptions and model linearity. Due to this, some authors [7,8] proposed modifications of Palmgren-Miner rule. Modifications introduced by Henry [7] and Marco and Starkley [8] considers adding nonlinearities to Palmgren-Miner model to adapt the same to a specific systems. Contrary to those deterministic models, research on lifetime models conducted recently is focused on stochastic models capable to describe stochastic nature of degradation process.

Remaining useful lifetime estimation based on Rainflow Counting Algorithm (RCA) and Palmgren-Miner rule is introduced in [9]. This approach is used to model thermomechanical fatigue of semiconductors whose application is found in a variety of technical systems: wind turbines, speed drives, electric vehicles, airplanes, and similar. Equivalent temperature is considered as input. The effect of decreased stress endurability of metals with increased temperature is considered. To extract information about equivalent temperature, the authors use existing temperature-dependent model based on continuously monitored power factor. By using proposed time-temperature-dependent model, better accuracy in RUL calculation of semiconductors is obtained.

Singleton et al. [10] compare performance of Kalman Filter (KF) and Extended Kalman Filter (EKF) in RUL estimation of bearings. Different features are extracted from measurements originating from experimental tests done under different operating conditions. Further, time- and time-frequency-based features (variance and entropy) are calculated and compared with respect to their suitability for prognostics. Presented results proves that the entropy is more capable to describe gradual damage progression especially in inceptive degradation phase. Moreover, obtained prediction accuracy using EKF is better than the accuracy obtained using KF.

Concerning limitations of model- and data-driven-based approaches reflected primarily as necessary knowledge about underlying physical processes and the dependency on training data sets. Pecht et al. [11] propose a fusion of both approaches