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A fuzzy expectation maximization based method for estimating the parameters of a multi-state degradation model from imprecise maintenance outcomes

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ABSTRACT

Multi-State (MS) reliability models are used in practice to describe the evolution of degradation in industrial components and systems. To estimate the MS model parameters, we propose a method based on the Fuzzy Expectation-Maximization (FEM) algorithm, which integrates the evidence of the field inspection outcomes with information taken from the maintenance operators about the transition times from one state to another. Possibility distributions are used to describe the imprecision in the expert statements. A procedure for estimating the Remaining Useful Life (RUL) based on the MS model and conditional on such imprecise evidence is, then, developed. The proposed method is applied to a case study concerning the degradation of pipe welds in the coolant system of a Nuclear Power Plant (NPP). The obtained results show that the combination of field data with expert knowledge can allow reducing the uncertainty in degradation estimation and RUL prediction.

1. Introduction

Multi-State (MS) degradation modelling is receiving considerable attention in the domain of reliability and maintenance engineering (Zio, 2016), due the fact that MS models offer a description of the degradation evolution which is more realistic than that given by binary models: the evolution of many degradation processes proceeds in successive phases, which reflect the relative degree of deterioration (Moghaddass and Zuo, 2014). A further reason which justifies the growing interest in MS degradation models is their fit with the field maintenance data acquired from the operating systems. For example, operators typically assign a qualitative tag to the equipment health during periodic inspections such as 'not degraded', 'slightly degraded', 'badly degraded', etc.

Given these characteristics, MS models have been adopted to describe the evolution of degradation of components of diverse application fields: membranes of pumps operating in Nuclear Power Plants (NPPs) (Baraldi et al., 2011), turbine nozzles for the Oil&Gas industry (Compare et al., 2016), turbofan engines (Moghaddass and Zuo, 2014), Diesel engines (Giorgio et al., 2011), to cite a few.

A Multi-State (MS) degradation model has also been developed in (Fleming and Smit, 2008) for the Piping System (PS) of NPPs, where PSs are highly risk-sensitive structural elements (Gopika et al., 2003; Di Maio et al., 2015). In details, in the model by (Fleming and Smit, 2008), which is general enough to represent all known NPP pipe failure mechanisms (Fleming, 2004), the degradation process affecting a PS is discretized into four states, each one associated to a physically different phenomenon, with state transition rates that are taken constant over time and, consequently, sojourn times in each state that obey exponential distributions (e.g., Fleming and Smit, 2008). However, it has been shown in (Veeramany and Pandey, 2011; Chatterjee and Modarres, 2008), that the constant rate assumption is not coherent with the evidence coming from many real industrial applications. Thus, to overcome the limitation of constant transition rates, the theoretical framework of the Homogeneous Continuous-Time Semi-Markov Processes (HCTSMPs, Howard, 1964) has been embraced to develop MS degradation models, which allow considering arbitrary sojourn time distributions, thus, taking into account the influ-

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Nomenclature

CDF	Cumulative Distribution Function
EM	expectation-Maximization
FEM	fuzzy Expectation-Maximization
HCTSMM	homogeneous Continuous-Time Semi-Markov Model
MC	Monte Carlo
MS	Multi-State
MLE	Maximum Likelihood Estimation
NPP	Nuclear Power Plant
PDF	Probability Density Function
PFM	Probabilistic Fracture Mechanics
PS	Piping System
PWR	Pressurized Water Reactor
RCS	Reactor Cooling System
RUL	Remaining Useful Life
C_0	case 0
C_1	case 1: moderately risk-averse expert
C_2	case 2: risk averse expert
C_3	case 3: risk prone expert
D	dataset of inspection outcomes
E	state space
$f_{T_{i\to i+1}}$	PDF of $T_{i\to i+1}$
$f_{T_{i\to i+1}}(\cdot \mid t^0_{n,i})$	conditional PDF of $T_{i\to i+1}$ provided that $T_{i\to i+1} \geqslant t^0_{n,i}$
$f_{RUL(k\tau)}$	PDF of $RUL(k\tau)$
$F_{T_{i\to i+1}}$	CDF of $T_{i\to i+1}$
$F^{failure}$	CDF of $T^{failure}$
$\tilde{f}_{T_{i\to i+1}}$	PDF of fuzzy observations
$k_{n,i}$	inspection at which the nth component is found in state i for the first time
L	likelihood function
$L^{\sim}$	likelihood function of fuzzy observations
$\mathcal{L}_{i\to i+1}$	ith contribution to the log-likelihood function
$\mathcal{L}^{\sim}_{i\to i+1}$	ith contribution to log-likelihood function of fuzzy observations
$\mathcal{L}_{log}$	log-likelihood function
$\mathcal{L}^{\sim}_{log}$	log-likelihood function of fuzzy observations
M_n	number of inspections on component n
N	number of components
Q	log-likelihood function conditional on fuzzy evidence
$R_{T_{i\to i+1}}$	reliability function of $T_{i\to i+1}$
$R^{failure}$	reliability function of $T^{failure}$
t	time
$\boldsymbol{t}$	transition time dataset
t_n	vector of transition times of the nth component
$T_{i\to i+1}$	transition time from state i to state $i+1$, random variable
T_m	mission time
$T^{failure}$	failure time
$t_{n,i\to i+1}$	transition time of the nth component from state i to state $i+1$, observed value
$\tilde{t}_{n,i\to i+1}$	fuzzy transition time, observed value
$\underline{t}_{n,i\to i+1}$	lower bound of the support of $\mu_{\tilde{t}_{n,i\to i+1}}(t_{i\to i+1})$
$\overbrace{t}_{n,i\to i+1}$	core of $\mu_{\tilde{t}_{n,i\to i+1}}(t_{i\to i+1})$
$\bar{t}_{n,i\to i+1}$	upper bound of the support of $\mu_{\tilde{t}_{n,i\to i+1}}(t_{i\to i+1})$
$t^0_{n,i}$	Sojourn time in state i of the nth component
$\dot{t}^0_{n,i}$	elapsed time from the first inspection time in which the component has been found in state i, and the last one
α_i	scale parameter of the Weibull distribution describing the uncertainty on the transition time from state i to state $i+1$
β_i	Shape parameter of the Weibull distribution describing the uncertainty on the transition time from state i to state $i+1$
δ	vector of δ^n, $n = 1\ldots N$
δ_n	vector of binary variables associated to the nth component
$\delta_{n,i\to i+1}$	binary variable associated to the nth component indicating the censoring of the transition time from state i to state $i+1$
$\lambda_{i\to i+1}$	transition rate from state i to state $i+1$
λ_{C0}	transition rate for Case $C0$
λ_{C2}	transition rate for Case $C2$
λ_{C3}	transition rate for Case $C3$
$\mu_{\tilde{t}_{n,i\to i+1}}$	Possibility distribution on $\tilde{t}_{n,i\to i+1}$
τ	Interval between two successive inspections
ϑ	Vector of the transition time parameters vector
$\hat{\vartheta}_{mle}$	MLE estimates of ϑ
ϑ^q	Estimates of ϑ at iteration q
i	state index, $i = 1, 2, 3$
k	inspection index, $k = 1\ldots M_n$
n	component index, $n = 1..N$
q	FEM iteration index

ence of the history of the degradation process on its future evolution. In particular, (Veeramany and Pandey, 2011) developed a HCTSMP model to describe the degradation of PSs in NPPs.

For practical application, the estimation of the parameters of the MS semi-Markov degradation model, with associated uncertainty, is fundamental and different approaches have been proposed in the literature to adjust the model to the knowledge, information and data available.

When sufficient field data is available, statistical techniques such as Maximum Likelihood Estimation (MLE) can be adopted (Zio, 2007; Gosselin and Fleming, 1997). However, the availability of rich datasets of NPP PS degradation and maintenance data is not typical and the problem of parameter estimation is further complicated by at least two other aspects:

- The inherent complexity of the PSs in NPPs and diversity in the degradation influenced by operating and ambient conditions (Tipping, 2010); then, it becomes difficult to identify mechanisms and homogeneous populations of PS for statistical inference.
- The possible noninformativeness of the data, i.e., of the outcomes of inspections performed every 2–5 years, in which the PS is typically found in the first degradation states, due to its very high reliability (Nánási, 2014; Fleming, 2004; Veeramany and Pandey, 2011; Simonen and Goselin, 2001).

With this scarcity of data, it is necessary to exploit any additional knowledge or information available to build more accurate reliability models (Zio, 2016). In this respect, Probabilistic Fracture Mechanics (PFM) models have been developed to predict PS crack initiation and growth from existing flaws (Verma and Srividya, 2011), which combine the knowledge about the physics of the crack propagation, modelled as a stochastic process, with PS service data that are used to tune the PFM model parameters. However, (Fleming, 2004) pointed out that one main limitation of the PFM approach is that the data used for model setting reflect the influence of previous PS inspection programs; thus, changes in these programs may introduce biases in the transition rates estimates.