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Component- and system-level degradation modeling of digital Instrumentation and Control systems based on a Multi-State Physics Modeling Approach

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ABSTRACT

A system-level degradation modeling is proposed for the reliability assessment of digital Instrumentation and Control (I&C) systems in Nuclear Power Plants (NPPs). At the component level, we focus on the reliability assessment of a Resistance Temperature Detector (RTD), which is an important digital I&C component used to guarantee the safe operation of NPPs. A Multi-State Physics Model (MSPM) is built to describe this component degradation progression towards failure and Monte Carlo (MC) simulation is used to estimate the probability of sojourn in any of the previously defined degradation states, by accounting for both stochastic and deterministic processes that affect the degradation progression. The MC simulation relies on an integrated modeling of stochastic processes with deterministic aging of components that results to be fundamental for estimating the joint cumulative probability distribution of finding the component in any of the possible degradation states.

The results of the application of the proposed degradation model to a digital I&C system of literature are compared with the results obtained by a Markov Chain Model (MCM). The integrated stochastic-deterministic process here proposed to drive the MC simulation is viable to integrate component-level models into a system-level model that would consider inter-system or/and inter-component dependencies and uncertainties.

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1. Introduction

In support to the implementation of risk-informed decision-making approaches, Probabilistic Safety Analysis (PSA) of modernizing Nuclear Power Plants (NPPs) demands for detailed dynamic models of digital Instrumentation and Control (I&C) systems that can adequately represent digital components failure modes and quantify their contribution to the overall risk of the NPPs (Aldemir et al., 2007, 2006).

To this aim, dynamic methods are being increasingly integrated into existing PSA frameworks for digital I&C systems reliability assessment, such as: Dynamic Flowgraph Methodology (DFM) (Guarro et al., 2012; Aldemir et al., 2006, 2009), Markov/cell-to-cell mapping technique (CCMT) (Aldemir et al., 2006, 2009; Zhou et al., 2014), Petri Net (Lee et al., 2006; Kim and Kim, 2014), Bayesian Networks (Boudali and Dugan, 2006; Broy et al., 2011), Dynamic Fault Tree (DFT) (Dehlinger and Dugan, 2008), Dynamic Event Tree (DET) (Bucci et al., 2006) and Fuzzy C-Means (FCM) clustering method (Di Maio et al., 2011; Zio and Di Maio, 2009). On a system level, these methods can be used to tackle the twofold purpose of PSA: on one side, the identification of the system failure domain and, on the other side, the quantification of the system failure probability.

With respect to the latter, given a failure threshold γ_Y not to be exceeded by a safety-relevant physical variable Y during the system operation, a limit-state function G can be defined as:

$$G = G(\bar{X}, \gamma_Y) = Y(\bar{X}) - \gamma_Y \quad (1)$$

where $\bar{X} = \{X_1, X_2, \ldots, X_n\}$ defines the system parameters and operational conditions. This leads to the definition of a system

Abbreviations: PSA, Probabilistic Safety Analysis; NPP, Nuclear Power Plant; I&C, Instrumentation and Control; MSPM, Multi-State Physics Model(ing); MCM, Markov Chain Model; MC, Monte Carlo; RTD, Resistance Temperature Detector; RPS, Reactor Protection System; BPL, Bistable Processor Logic; LCL, Local Coincidence Logic; PTS, Partial Tripping Signal; ESS, Emergency Shutdown Signal; RTB, Reactor Trip Breaker; CDF, Cumulative Distribution Function; PDF, Probability Density Function.

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Notations

γ_Y	failure threshold
Y	physical variable
G	limit-state function
$\bar{\mathbf{X}}$	vector of system parameters
S	safety domain
F	failure domain
∂F	failure boundary
t	time
$\bar{\boldsymbol{\delta}}$	vector of physical parameters
$\bar{\boldsymbol{\Phi}}_m$	vector of m-dimensional manufacturing features
$\bar{\boldsymbol{\Theta}}_k$	vector of k-dimensional stochastic parameters
$\bar{\mathbf{B}}_l$	vector of l-dimensional external parameters
$\varepsilon(t)$	error term
$\bar{\mathbf{P}}(t,\bar{\boldsymbol{\delta}})$	state probability vector obtained from MSPM
$p_j(t,\bar{\boldsymbol{\delta}})$	state probability of state j in MSPM
M^i+1	number of states in ith component/module-level MSPM
C_j^i	degradation state j of component (module) i
$\lambda^i_{(j,k)}(t,\bar{\boldsymbol{\delta}})$	failure rate of component (module) i from state C_j^i to C_k^i
$\mu^i_{(j,k)}(t,\bar{\boldsymbol{\delta}})$	repair rate of component (module) i from state C_k^i to C_j^i
σ	RTD measurement accuracy
τ	RTD response time
δ	RTD air gap size
α_t	scale factor
$P_S(t,\delta)$	CDF of the RTD new-to-drift failure mode
δ_0	initial air gap size
dt	time interval
$d\delta_t$	noise of air gap size
t_m	mission time
N_M	simulation times
$p_S(t\|\delta)$	conditional PDF given air gap size interval
$P_S(t\|\delta)$	conditional CDF given air gap size interval
$\lambda_S(t\|\delta)$	conditional failure rate given air gap size interval
$R_S(t\|\delta)$	conditional reliability of RTD given air gap size interval
λ_S	failure rate in RTD-MCM
μ_S	repair rate in RTD-MCM
$P_S(t)$	unreliability obtained from RTD-MCM
$N+1$	number of layers in system-level MSPM
L^l	layer l in system-level MSPM
M^l+1	number of degradation states of layer l
L^l_m	degradation state m of layer l
$\mu_{L^l_m\to L^0}(t,\bar{\boldsymbol{\delta}})$	repair rate from state L^l_m to state L^0
$\lambda_{L^l_m\to L^\omega_n}(t,\bar{\boldsymbol{\delta}})$	failure rate from state L^l_m to state L^ω_n
$\lambda_{L^l_m\to L^N}(t,\bar{\boldsymbol{\delta}})$	failure rate from state L^l_m to system failure state L^N
λ_{B}	BPL failure rate
λ_{L}	LCL failure rate
β	common cause factor
λ_{BC}	BPL common cause failure rate
λ_{LC}	LCL common cause failure rate
λ_{R}	RTB failure rate
$P(t\|\delta)$	RPS unreliability obtained from RPS-MSPM
$P(t)$	RPS unreliability obtained from RPS-MCM

safety domain $S=\{\bar{X}: G(\bar{X},\gamma_Y)<0\}$ and of a system failure domain $F=\{\bar{X}: G(\bar{X},\gamma_Y)>0\}$, that are partitioned by a system failure boundary $\partial F=G(\bar{X},\gamma_Y)=0$, for a given γ_Y.

The identification of the failure domain F is crucial especially when the system dynamics is complex and its component reliability assessment cannot be described by a Boolean, discrete and abrupt physics of failure, but rather by a multi-valued, and continuous degradation model as it is for digital I&C systems (Li et al., 2012; Lin et al., 2015; Lisnianski and Levitin, 2003). The biggest challenge to be overcome for devising realistic and effective degradation models consists in the collection of component reliability data that are, often, affected by multiple and competing failure modes that are difficult to be untangled and reduced to a single-lumped failure criterion analysis that would leverage the degradation modeling task. To avoid simplification and overlooking of failure interdependencies, we propose to resort to a Multi-State Physics Modeling (MSPM) approach at the component level, which can be easily upscaled for system-level degradation modeling. The MSPM approach is based on the structure of Markov (or semi-Markov) modeling for the quantification of components reliability measures (Unwin et al., 2011, 2012; Rocco and Zio, 2013; Fleming et al., 2010). Recently, the MSPM approach has been proposed for modeling nuclear component degradation by accounting for both the effects of stochastic parameters affecting the degradation and the environmental parameters with their uncertainties (Lin et al., 2015; Di Maio et al., 2015).

In this study, a component-level MSPM model for a digital I&C system is developed by integrating in the model both the stochastic and the deterministic processes that affect component degradation. The physical variable Y to be considered for the failure domain F identification is given in Eq. (2) (Kaiser and Gebraeel, 2009):

$$Y=Y(\bar{X})=f(t,\bar{\boldsymbol{\delta}})+\varepsilon(t)=f(t,\bar{\boldsymbol{\Phi}}_m,\bar{\boldsymbol{\Theta}}_k,\bar{\mathbf{B}}_l)+\varepsilon(t) \quad (2)$$

where t is the deterministic aging time, $\bar{\boldsymbol{\delta}}$ is a collection of physical parameters affecting the degradation process that can be seen as composed by $\bar{\boldsymbol{\Phi}}_m=\{\varphi_1,\ldots,\varphi_m\}$ which is a vector of m-dimensional manufacturing features that affect the degradation (e.g., burn-in, contamination, etc.), $\bar{\boldsymbol{\Theta}}_k=\{\theta_1,\ldots,\theta_k\}$ which is a vector of k-dimensional stochastic parameters that account for the components variability (e.g., nominal frequency stability, calibration error after maintenance, etc.), $\bar{\mathbf{B}}_l=\{\beta_1,\ldots,\beta_l\}$ which is a vector of l-dimensional external parameters that capture the variability of time-varying operating and environmental conditions (e.g., temperature, flux, etc.), and $\varepsilon(t)$ that is an error term that captures noise and disturbances. In principle, a component response surface to any possible different setting of degradation features (stochastic and external parameters, and error terms) can be built (with infinite computational resources) such that the safety domain S can be partitioned from the failure domain F by setting a failure threshold γ_Y.

In this work, a Monte Carlo (MC) simulation is used to estimate the transition probabilities among the degradation states of MSPM and drive, by random walks, the stochastic process of the evolution of the air gap size in time and the deterministic evolution of the component aging on the response surface for the identification of the limit surface of the drift event of a Resistance Temperature Detector (RTD) that is embedded into a digital I&C system of a NPP.

Finally, as for traditional PSA (where system-level models are developed by combining or replacing subsystem or component models in the overall structure of a Fault Tree (FT) or an Event Tree (ET) (Aldemir et al., 2007, 2009; Gulati and Dugan, 1997)), the system failure probability of the digital I&C system is quantified by upscaling the component-level MSPM into a system-level model that considers the inter-system or/and inter-component

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