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# Particle filter based hybrid prognostics for health monitoring of uncertain systems in bond graph framework

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ABSTRACT

The paper's main objective is to address the problem of health monitoring of system parameters in Bond Graph (BG) modeling framework, by exploiting its structural and causal properties. The system in feedback control loop is considered uncertain globally. Parametric uncertainty is modeled in interval form. The system parameter is undergoing degradation (prognostic candidate) and its degradation model is assumed to be known *a priori*. The detection of degradation commencement is done in a passive manner which involves interval valued robust adaptive thresholds over the nominal part of the uncertain BG-derived interval valued analytical redundancy relations (I-ARRs). The latter forms an efficient diagnostic module. The prognostics problem is cast as joint state-parameter estimation problem, a hybrid prognostic approach, wherein the fault model is constructed by considering the statistical degradation model of the system parameter (prognostic candidate). The observation equation is constructed from nominal part of the I-ARR. Using particle filter (PF) algorithms; the estimation of state of health (state of prognostic candidate) and associated hidden time-varying degradation progression parameters is achieved in probabilistic terms. A simplified variance adaptation scheme is proposed. Associated uncertainties which arise out of noisy measurements, parametric degradation process, environmental conditions etc. are effectively managed by PF. This allows the production of effective predictions of the remaining useful life of the prognostic candidate with suitable confidence bounds. The effectiveness of the novel methodology is demonstrated through simulations and experiments on a mechatronic system.



## 1. Introduction

Health Monitoring aims at ensuring system safety, reliability and efficient functionality and deals with *fault detection* and prediction of the *Remaining Useful Life* (RUL) of the system in a holistic way. While the former two is mainly dealt by using a diagnostic module, the latter is performed by a prognostic module. The primary focus lies in scheduling the maintenance

*Abbreviations and Acronyms:* RUL, Remaining Useful Life; EOL, End of Life; DM, Degradation Model; BG, Bond Graph; BG-LFT, Bond Graph in Linear Fractional Transformation; PF, Particle Filters; I-ARR, Interval Valued Analytical Redundancy Relations; DPP, Degradation Progression Parameter; RMAD, Relative Median Absolute Deviation; RA, Relative Accuracy; RMSE, Root Mean Square Error; SIR, Sampling Importance Resampling; ARR, Analytical Redundancy Relations

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**Notations**

| | |
|---|---|
| $\theta$ | System parameter |
| $\theta^d$ | System parameter under degradation (prognostic candidate) |
| $\theta_n^d$ | Nominal value of $\theta^d$ |
| $\Delta\theta$ | Additive uncertainty on $\theta$ |
| $\delta_\theta$ | Multiplicative uncertainty on $\theta$ |
| $[\delta_\theta]$ | Multiplicative uncertainty in interval form, equivalent to $\left[\underline{\delta_\theta}, \overline{\delta_\theta}\right]$ |
| $[w_\theta]$ | Uncertain effort or flow brought by interval uncertainty on $\theta$, to the system. |
| $r_n(t)$ | Numerical evaluation of the nominal part of I-ARR |
| $\hat{X}$ | Estimated value of species $X$ |
| $[\underline{R}, \overline{R}]$ | Interval valued ARR (I-ARR) |
| $\boldsymbol{\Psi}_2$ | Interval function (uncertain part of I-ARR) |
| $\Psi_1$ | Point-valued nominal part of I-ARR |
| $\Psi_2$ | Interval function $\boldsymbol{\Psi}_2$ with point valued arguments |
| $b(t)$ | Numerical evaluation of $\Psi_2$ |
| $\left[\underline{B(t)}, \overline{B(t)}\right]$ | Range of interval function $\boldsymbol{\Psi}_2$ |
| $\gamma^d$ | Degradation progression parameter associated to $\theta^d$ |
| $\gamma^{d*}$ | True value of $\gamma^d$ |
| $p$ | probability |
| $\sigma_X$ | Standard deviation value of random specie $X$ |
| $\sigma_X^2$ | Variance of population values of $X$ |
| $N$ | Number of particles in PF |
| $w_k^i$ | Weight of $i^{th}$ particle at discrete time $k$ |
| $y^d$ | Measurement of prognostic candidate $\theta^d$ |
| $w^d(t)$ | Noise associated with measurement of $\theta^d$ |
| $\xi^d$ | Normally distributed random walk noise for $\gamma^d$ |
| $P^d$ | Proportional gain constant in variance adaptation of $\xi^d$ |
| $v^{\xi^d}$ | RMAD (spread) of $\xi^d$ |
| $v^{\xi^d*}$ | Reference RMAD (spread) involved in variance adaptation scheme |
| $\left[\gamma_l^{d*}, \gamma_u^{d*}\right]$ | Interval containing $\gamma^{d*}$ |
| $\bar{\hat{\gamma}}_k^d$ | Moving average of mean estimations of $\gamma^d$ |

actions according to progression of the system to a time where it may be considered beyond the limits of certified functionalities [1]. Such a time-horizon of interest is termed as the *End of Life* (EOL) and the time remaining until that point is called RUL of the system [2,3]. Prognostics are focused on the study of fault (or damage) evolution and prediction of the RUL of the system/component. Accurate prediction of EOL/RUL enables efficient and optimal planning of the future maintenance actions, and renders the capability of assessing reliability of the system [4]. This leads to system/component's life extension by modification of the system demand, operating conditions, workload etc. [5].

The failures of most systems can be attributed to the degradation of a given component, subsystem or material with time, environmental and operational conditions etc. Such system components/sub-systems can be identified as the potential prognostic candidates through Failure Modes, Mechanisms and Effect Analysis or through other ways [6]. The underlying physical degradation is usually captured by *Degradation Model*(*s*) (DM) that can be obtained based upon physics of degradation or statistical (experimental) modeling approach as described in Gebraeel et al. [7] and Guo et al. [8]. In cases where physics of degradation is not available or reliable, the respective DM can be obtained statistically by finding a mathematical model that best fits a given set of degradation data. In this context, commonly employed DMs to fit the data are of linear, logarithmic, power or exponential form [8]. For example, approximation of degradation model by a linear part and logarithmic/exponential part [9], employment of exponential fit growth models [10], log-linear model for current drain degradation process [11] and stochastic degradation model [12].

Prognostic approaches are broadly divided into three categories [3,13]: model-based prognostics [14], data-driven prognostics [15,16] and hybrid prognostics [9,17]. In model based approach, the degradation model is physics based and requires a detailed understanding of the underlying phenomenon [1]. Inadequate modeling information, variation in behavioral physics or environmental conditions, un-modeled/unclassifiable sources of noise etc., result in limiting its adequacy. Data-driven methods tend to learn the damage progression. However, they generalize damage progression over large sets of component population and remain unreliable in assessing the variability of damage progression trend from component to component in a population [1]. As such, they provide inferior results especially in absence of complete data and large unit to unit variations. Hybrid approaches on the other hand, benefit from the fusion of the advantages of the former two [9]. They employ physics or statistical based degradation models and use measured information to adapt the damage progression, accounting for un-modeled variations, environmental changes, external noise etc.

Prognostic approaches set as a joint state-parameter estimation problem [18], have been widely useful and may fall under hybrid approach wherein, the prediction of RUL is based on current estimate of damage state and state of damage propelling hidden parameters. Prediction of the RUL is obtained as probability distribution and accounts for the various uncertainties involved [18–21].

Choice of the filter for estimation and prediction process depends on the assumptions that can be made about the system, and desired performance [22]. Well-known Kalman filter, an optimal estimator for linear systems, has been used for prognostics in [23,24]. *Extended Kalman Filter* (EKF) [25] or Unscented Kalman filter [26], may also be used for parameter estimation posing the problem as joint state-parameter estimation or as Expectation-Maximization problem [27] etc.

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