Control Engineering Practice 71 (2018) 61–78

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

Robust fault detection with Interval Valued Uncertainties in Bond Graph Framework

Mayank-Shekhar Jha [a,*], Genevieve Dauphin-Tanguy [a], Belkacem Ould-Bouamama [b]

[a] CRIStAL UMR CNRS 9189, Ecole Centrale de Lille, Cité Scientifique 59650 Villeneuve d'Ascq, France
[b] CRIStAL UMR CNRS 9189, Polytech Lille, Université de Lille 1, Cité Scientifique 59650 Villeneuve d'Ascq, France

ARTICLE INFO

Keywords:
Bond graph
Analytical redundancy relations
Interval analysis
Uncertain system
Fault detection
Interval-valued uncertainties

ABSTRACT

This paper describes a novel formalism for modelling uncertain system parameters and measurements, as interval models in a Bond Graph (BG) modelling framework. The main scientific interest remains in integrating the benefits of BG modelling technique and properties of Interval Analysis (IA), for efficient diagnosis of uncertain systems. Structural properties of Bond graphs in Linear Fractional transformation (BG-LFT) are exploited to model interval-valued uncertainties over a BG model in order to form an uncertain BG. The inherent causal properties are exploited to generate interval-valued fault indicators. Then, various properties of IA are used to generate point valued residual and interval-valued thresholds. The latter must contain the point valued residuals under nominal system functioning. A systematic procedure is proposed for passive-type fault detection method which is robust to uncertain system parameters and measurements. The viability of the method is shown through experimental study of a steam generator system. The limitations associated with existing fault detection method based on BG-LFT are alleviated by the proposed approach. Moreover, it is shown that proposed approach generalizes the BG-LFT method. This work forms the initial step towards integrating interval analysis based capabilities in BG framework for fault detection and health monitoring of uncertain systems.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Advanced methods of supervision, fault detection and fault diagnostics become increasingly significant for improving the reliability, safety and efficiency of technical processes in various domains of engineering (Chen & Patton, 2012; Gertler, 1997; Isermann, 2005; Samantaray & Bouamama, 2008). The past decade has seen tremendous usage of *Analytical Redundancy Relations* (ARRs) for the purpose of fault detection (FD) and isolation (FDI) (Ould Bouamama, Medjaher, Bayart, Samantaray, & Conrad, 2005; Staroswiecki & Comtet-Varga, 2001). ARRs represent the physical constraints laws derived from the mathematical model of the system. They have the form: $\boldsymbol{h}(\boldsymbol{k}) = 0$ for any function $\boldsymbol{h}$ and set of known variables $\boldsymbol{k}$. ARRs are usually sensitive to known system parameters (like resistor in an electrical circuit) and measurements (sensor data, control inputs etc.). Residuals are the numerical evaluation of ARRs. Ideally, residuals remain within a certain bound of error when evaluated using measured data from the real system (Chen & Patton, 2012).

Recently, the Bond Graph (BG) modelling technique has been used extensively for ARR based supervision (Karnopp, Margolis, & Rosenberg, 2012; Rosenberg & Karnopp, 1972). BG has been established as an efficient modelling tool due to its well-developed graphical, structural and causal properties. A concise discussion on BG technique is provided in Appendix A. For a detailed introduction from *ab-initio* (causal and structural properties), readers are referred to Borutzky (2011), Karnopp et al. (2012), Mukherjee and Samantaray (2006) and Thoma and Bouamama (2000). Traditionally, BG models in *preferred integral causality* have been used for simulations/analysis and *preferred derivative causality* has been exploited for development of FD theory and supervision. *Derivative causality* leads to alleviation of initial condition problems. BG enabled FD for deterministic systems and notion of monitorability, isolability, fault signature matrix, ARR generation algorithms etc. are well detailed in Medjaher, Samantaray, Ould Bouamama, and Staroswiecki (2006) and Ould Bouamama, Medjaher, Samantaray, and Staroswiecki (2006). Some of the major FD related works include supervision of thermo-chemical systems (Bouamama, Samantaray, Medjaher, Staroswiecki, & Dauphin-Tanguy, 2005; Bouamama, Staroswiecki, Riera, & Cherifi, 2000; Medjaher et al., 2006), industrial chemical reactors (El Harabi,

* Corresponding author.
E-mail addresses: mayank-shekhar.jha@univ-lorraine.fr (M.-S. Jha), genevieve.dauphin-tanguy@ec-lille.fr (G. Dauphin-Tanguy), Belkacem.Ouldbouamama@polytech-lille.fr (B. Ould-Bouamama).

https://doi.org/10.1016/j.conengprac.2017.10.009
Received 23 January 2017; Received in revised form 12 October 2017; Accepted 13 October 2017
0967-0661/© 2017 Elsevier Ltd. All rights reserved.

Nomenclature

Abbreviations

ARR	Analytical Redundancy Relations
BG	Bond Graph
BG-LFT	Bond Graph in Linear Fractional Transformation
FDI	Fault Detection and Isolation
FD	Fault Detection
IA	Interval Analysis
I-ARR	Interval-valued Analytical Redundancy Relations
IEF	Interval Extension Functions
N-IEF	Natural Interval Extension Function
RIF	Rational Interval Function
URIF	uncertain residual interval function

Notations

θ	System parameter
θ^d	System parameter under degradation (prognostic candidate)
θ_n	Nominal value of θ^d
$\Delta\theta$	Additive uncertainty on θ
δ_θ	Multiplicative uncertainty on θ
$[\delta_\theta]$	Multiplicative uncertainty in interval form, equivalent to $[\underline{\delta_\theta}, \overline{\delta_\theta}]$
$[w_\theta]$	Uncertain effort or flow brought by interval uncertainty on θ, to the system.
SSe (SSf)	Dualized source of effort (flow)
$[-\Delta SSe_l, \Delta SSe_u]$	Interval valued Uncertainty on SSe
$[\underline{R}, \overline{R}]$	Interval valued ARR (I-ARR)
$R_n(t)$	Nominal part of the I-ARR $[\underline{R}, \overline{R}]$
$r_n(t)$	Numerical evaluation of the nominal part $R_n(t)$ of I-ARR
Ψ	Function with point-valued nominal parameters as arguments
$\boldsymbol{\Psi}$	URIF or Interval function of Ψ with interval valued arguments
$[\underline{B(t)}, \overline{B(t)}]$	Range or interval evaluation of URIF $\boldsymbol{\Psi}$
$\overline{MSe^*}$	Virtual source of effort
$[\zeta_{SSe}]$	Notation denoting $[-\Delta SSe_l, \Delta SSe_u]$

Ould-Bouamama, Gayed, & Abdelkrim, 2010) etc. A comprehensive review of BG based supervision is provided in Bouamama, Biswas, Loureiro, and Merzouki (2014) and Ould-Bouamama, El Harabi, Abdelkrim, and Ben Gayed (2012).

The last decade has witnessed a successful transition of BG based FD from deterministic domain to uncertain systems. This has been possible mainly due to emergence of BG in Linear Fractional Transformation (BG-LFT), for uncertain systems (Dauphin-Tanguy and Kam, 1999). BG-LFT methodology is well detailed in Sié Kam and Dauphin-Tanguy (2005). BG-LFT models represent parametric uncertainties in such a way that causal, structural and behavioural properties of BG theory remain applicable for successful FD. Robust FDI is achieved through generation of adaptive thresholds (*passive* type of diagnosis) which are robust to parametric uncertainties (Djeziri, Merzouki, Bouamama, and Dauphin-Tanguy, 2007). In Djeziri, Ould Bouamama, and Merzouki (2009b), BG-LFT model of an uncertain steam generator is used for robust FDI, (Djeziri, Merzouki, & Bouamama, 2009a) describes the robust monitoring of electric vehicle, (Niu, Zhao, Defoort, & Pecht, 2014) employs BG-LFT and auto-regressive kernel regression based threshold monitoring, (Benmoussa, Bouamama, & Merzouki, 2014; Loureiro, Benmoussa, Touati, Merzouki, & Ould Bouamama, 2014) deal with BG-LFT enabled robust FDI of intelligent vehicles and autonomous systems, (Touati, Merzouki, & Ould Bouamama, 2012) extends the methodology by including measurement uncertainties on BG-LFT. In this context, it is noteworthy to highlight that uncertain parameters may be broadly classified into two categories: (i) uncertain physical components (electrical resistances, capacitors, etc.) where uncertainty manifests in terms of manufacturing errors or tolerance-of-manufacturing (percentage errors) on either side of the fabricated value (nominal value), (ii) uncertain physical phenomena that deviate or exhibit natural variations based upon different operational conditions (friction coefficient, temperature dependent electrical resistivity etc.) and usually vary unidirectionally. Presence of uncertainties lead to the requirement of robustness. In the context of supervision, robust FD methods imply preferable sensitivity to faults/fault indicators and robustness against uncertainties, environmental noises etc.

In this context, although BG-LFT has been exploited for mitigation of uncertainty related issues, little efforts have been made to ameliorate the methodology itself. For instance, therein, parametric uncertainties are quantified in a statistical manner and uncertain parameters are modelled with equal magnitudes of additive (or multiplicative) uncertainties on either sides of its respective nominal value. As BG-LFT method is envisaged as a unified modelling language for various energetic systems, the existing method limits its scope in incorporating all types of uncertain components, viz., physical components and physical phenomena. Furthermore, it is noteworthy that efficiency of any *passive* type of FD significantly depends upon the sensitivity of the thresholds generated for detection of faults.

On the other hand, bounding approaches employ interval models to model the uncertain system variables and parameters etc., enabling variation of the interval variable within pre-defined numeric intervals (Moore, 1979). Interval Analysis (IA) deals with computations involving intervals defined as set of real numbers $\{x|\underline{x} \le x \le \bar{x}\}$ denoted as $X = [\underline{x}, \bar{x}]$, where $\underline{x}$ is the infimum and $\bar{x}$ is the supremum. The set of closed intervals is $I(\mathfrak{R}) = \{[a,b]\,|a,b \in \mathfrak{R}, a \le b\}$. Being extension to real numbers; a real number x can be treated as a *degenerate interval* $[x, x]$. Interval arithmetic generalizes real arithmetic. Appendix B lists important properties and definitions related to IA. Readers are referred to Moore (1979) and Moore, Kearfott, and Cloud (2009) for details of IA. Moreover, classical interval-arithmetic based FDI can be referred in Karim, Jauberthie, and Combacau (2008), Rinner and Weiss (2004).

Recently, Jha, Dauphin-Tanguy, and Ould Bouamama (2014b) proposed a strategy involving BG-LFT and IA, wherein the thresholds were generated by treating the uncertain part of BG-LFT derived ARR, as an *interval extension function* (IEF). In Jha, Dauphin-Tanguy, and Ould Bouamama (2014a), the latter was integrated in a health monitoring framework as a diagnostic module. However, these previous attempts did not discuss the interval propagation strategy and sought the description of a formalism that models various types of uncertainties (parametric and measurement) using BGs. Furthermore, in these works the method was neither applied in real time nor compared with existing methods.

This paper describes a novel formalism of modelling the uncertain system parameters and measurements, in interval form under BG framework. The main scientific interest remains in integrating the benefits of BG technique with IA properties leading to efficient diagnosis of uncertain systems. A systematic procedure is proposed for *passive* type fault detection, robust to uncertain system parameters and measurements. The proposed method alleviates several limitation associated with BG-LFT based FDI. Moreover, I-ARR generalizes the BG-LFT method technique through usage of interval models.

The paper is divided into 6 sections. After the introduction section, Section 2 introduces interval modelling technique in BG framework. Section 3 establishes the procedure to generate interval-valued fault indicators termed as Interval-Valued analytical redundancy relations (I-ARR). Further, properties of IA are used to generate point valued residual and interval-valued thresholds over the latter.

I-ARRs and discusses various aspects related to interval calculations and implementation. Section 4 presents the implementation of method on steam generator system. Section 5 presents a comparative study between the I-ARR method and the BG-LFT method. Section 6 draws conclusions.

Download English Version:

https://daneshyari.com/en/article/7110503

Download Persian Version:

https://daneshyari.com/article/7110503

Daneshyari.com