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Fault diagnosis of locomotive electro-pneumatic brake through uncertain bond graph modeling and robust online monitoring

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ABSTRACT

To improve reliability, safety and efficiency, advanced methods of fault detection and diagnosis become increasingly important for many technical fields, especially for safety related complex systems like aircraft, trains, automobiles, power plants and chemical plants. This paper presents a robust fault detection and diagnostic scheme for a multi-energy domain system that integrates a model-based strategy for system fault modeling and a data-driven approach for online anomaly monitoring. The developed scheme uses LFT (linear fractional transformations)-based bond graph for physical parameter uncertainty modeling and fault simulation, and employs AAKR (auto-associative kernel regression)-based empirical estimation followed by SPRT (sequential probability ratio test)-based threshold monitoring to improve the accuracy of fault detection. Moreover, pre- and post-denoising processes are applied to eliminate the cumulative influence of parameter uncertainty and measurement uncertainty. The scheme is demonstrated on the main unit of a locomotive electro-pneumatic brake in a simulated experiment. The results show robust fault detection and diagnostic performance.

1. Introduction

To improve reliability, safety and efficiency, advanced methods of supervision, fault-detection and fault diagnostics become increasingly important for many technical processes—including safety related processes like aircraft, trains, automobiles, power plants and chemical plants [1]. A fault is defined as an unpermitted deviation of at least one characteristic of a variable from an acceptable behavior. Therefore, a fault may lead to a malfunction or failure of the system. Accordingly, a fault diagnosis system can be defined as a system that is used to “detect faults and diagnose their location and significance” [2].

A fault diagnosis system consists of the tasks of fault detection (FD), fault isolation (FI) and fault identification. FD makes a determination that either everything is operating within the specified normal range or that something has gone wrong. FI determines the kind and location of the fault, e.g., which component has degraded. Fault identification estimates the size,

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nature, and onset of the fault. Therefore, fault diagnosis is the indication of a fault and the determination of the kind, location, and time of detection-follows fault detection and includes fault isolation (fault identification, depending on the researcher, may also be included in this definition). A well-designed diagnostic system must provide quick detection and diagnosis, be able to differentiate between various failures and classify different faults, be robust to various uncertainties (disturbance, noise, etc.), and assist the human operator in explaining the origin of the fault and actions to be taken [3].

There are two technical approaches to treat issues of fault diagnosis: model-based and data-driven methods. Model-based fault diagnosis comprises fault detection and isolation. Fault detection includes residual generation and residual evaluation [4]. For fault diagnosis of a multi-energy domain system, like a mechatronic system or a fluid power system, a model-based approach is generally considered, because its analysis results can be easily related to control and repair actions. Model-based (qualitative and quantitative) approaches use causal analysis as the basis of knowledge representation (i.e., they link individual component malfunctions to deviations in measured values). However, establishing diagnostic knowledge in practice is difficult.

In this situation, Bond graph (BG) modeling [5] is suggested that provides a systematic method for modeling dynamic systems with different energy domains, such as electrical, mechanical and hydraulic systems, in a unified framework. BG is based on the energy conservation law that automatically generates system equations. The BG model can also be used to obtain a mathematical and graphical representation that lays a foundation for monitoring ability analysis (ability to detect and to isolate faults) and supervision system design [6].

Similar to other model-based methodologies, BG-based methods can be classified as quantitative [7–10] or qualitative [11,12]. Quantitative BG-based approaches utilize BG models to derive quantitative analytical redundancy relationships (ARRs). These quantitative ARRs are evaluated to generate quantitative residuals to assess the system fault status in both transient and steady-state operations. Quantitative BG-based methods can be divided into symbolic and numerical methods. For symbolic methods, symbolic ARRs are derived from the BG to generate residuals for fault detection and isolation (FDI). In contrast, a numerical BG-based method formulates each quantitative ARR implicitly based on simpler constraint equations that allow residuals to be generated in graphical-programming environments, such as Matlab® Simulink®.

To confirm the presence of a fault and to identify it, it is necessary to generate residuals that are not only fault sensitive, but also fault selective. Therefore, uncertainties from modeling inaccuracy, parameter dynamics and measurement errors should be investigated and treated to decrease the missed alarms and false alarms. Parameter uncertainty [3] can be defined as a slight deviation of the parameter from its nominal value, without any effect on the functioning of the system. It may be constant or variable and may vary randomly in a positive or in a negative sense. While measurement uncertainty [13] includes systematic error (an estimate of which is known as a measurement bias) and random error; mainly refers environment noise, sensor inaccuracy etc.

For this aim, this paper develops a LFT [7–9] based bond graph for parameter uncertainties modeling, and an AAKR [14,15] based residual estimation for measurement uncertainties improvement. This paper develops a robust fault monitoring and diagnosis framework for multi-energy domain dynamic system that integrates data-driven online monitoring (OLM) with a model-based diagnostic scheme. The combined influence of parameter and measurement uncertainties is treated through a denoising methodology and followed by anomaly detection based on the SPRT [16,17] to generate indicators for anomaly alarm and fault diagnosis. The remaining parts of this paper are organized as follows. Section 2 introduces LFT-based uncertain bond graphs, empirical model estimation based on AAKR, and online monitoring based on SPRT methodology. In Section 3, the framework is developed. Section 4 describes a simulation case for a pneumatic equalizer control device (PEC) of a locomotive electronically controlled pneumatic brake (ECP) to demonstrate the developed system. Finally, the conclusions and future work are described in Section 5.

2. Techniques description

This section introduces the relevant knowledge used in the developed scheme, including the LFT-based BG modeling, AAKR, and SPRT techniques.

2.1. LFT-based uncertain bond graph modeling

The LFT-based bond graph tool provides a practical solution to the problem of parameter dependency, because it is possible to track the spread of the influence of uncertainties in terms of effort or flow across the model through causal paths.

2.1.1. Bond graph theory

The Bond graph was invented by Henry Paynter at the Massachusetts Institute of Technology (MIT) in April 1959, [5] and subsequently developed into a systematic methodology by Rosenberg, Margolis and Karnopp [6]. A bond graph is a labeled directed graph in which each link has an assigned orientation, of which the two types of edges are called bonds. As a unified multi-energy domain modeling method, it provides an approach to model a complex system, which allows both a structural and a behavioral system analysis [18]. It provides a systematic and formal way to model dynamic systems with different energy domains, such as electrical, mechanical, and hydraulic in a unified framework. BG is based on the energy conservation law that automatically generates system equations. The BG model can also be used to obtain a mathematical and graphical representation that lays a foundation for monitoring ability analysis (ability to detect and to isolate faults) and