Engineering Applications of Artificial Intelligence 71 (2018) 73–86

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

A generic framework for decision fusion in Fault Detection and Diagnosis

Khaoula Tidriri *, Teodor Tiplica, Nizar Chatti, Sylvain Verron

LARIS, Avenue Notre Dame du Lac, 49000 Angers, France

ARTICLE INFO

Keywords:
Generic framework
Fault detection
Fault diagnosis
Decision fusion
Hybrid methods

ABSTRACT

In this paper, we propose a unified framework that enables decisions fusion for applications dealing with multiple heterogeneous Fault Detection and Diagnosis (FDD) methods. This framework, which is a discrete Bayesian Network (BN), is generic and can encompass all FDD method, whether it requires an accurate model or historical data. The main issue concerns the integration of different decisions emanating from individual FDD methods in order to obtain more reliable results.

The methodology is based on a theoretical learning of the BN parameters, according to the FDD objectives to be reached. The development leads to a multi-objective problem under constraints, which is solved with a lexicographic approach.

The effectiveness of the proposed decision fusion approach is validated through the Tennessee Eastman Process (TEP), which represents a challenging industrial benchmark. The application demonstrates the viability of the approach and highlights its ability to ensure a significant improvement in FDD performances, by providing a high fault detection rate, a small false alarm rate and an effective strategy for the resolution of conflicts among different FDD methods.

1. Introduction

Nowadays, industrial systems are becoming more and more complex and require new effective methods for their supervision. This latter comprises a monitoring phase that aims to improve the system's performances and ensure a safety production for humans and materials.

The occurrence of a fault can lead to a critical failure which is defined by Isermann (2006) as "a permanent interruption of a system's ability to perform a required function under specified operating conditions". Detection and diagnosis of faults in a fast and correct manner is highly important since it includes economic and safe operation of processes. Indeed, undetected faults can have catastrophic impact on human life and high-cost missions.

Therefore, faults need to be detected and diagnosed as soon as they occur. In order to address such issue, there has been an increasing interest in developing Fault Detection and Diagnosis (FDD) approaches.

In the literature, two major categories of approaches can be identified to achieve FDD: data-driven and model-based one (Venkatasubramanian et al., 2003b, c, a).

In the last years, some interesting research focused on the use of combined model-based and data-driven approaches in order to improve the monitoring performances and to overcome the limitations of individual methods used separately (see the review in Tidriri et al. (2016) for more details). Furthermore, according to several research studies (Venkatasubramanian et al., 2003b; Ding et al., 2009, 2011; Tidriri et al., 2016), there is a need for integrating various complementary FDD methods.

Among the earliest examples of hybrid approaches that attempted to combine the features of several methods, one can cite (Mylaraswamy and Venkatasubramanian, 1997). The objective was to benefit from the quickness of a statistical classifier and qualitative trend analysis (QTA) in detecting faults as well as the knowledge of Signed Digraph (SDG) for the isolation of the causes.

SDG and QTA were also used in Maurya et al. (2007) to respectively reduce the set of candidate faults and then to determine the true fault case.

An original combination of Kalman Filter with Neural Network was also developed in Siswantoro et al. (2016) to improve the classification accuracy while the authors in Benkouider et al. (2009) focused on statistical methods as well as the Extended Kalman Filter for faults detection in semi-batch reactors.

Another research area related to hybrid approaches aimed at developing unified frameworks for the integration of different methods. For instance, a strategy was proposed in Zhao et al. (2013) for chiller experts. The framework consisted in a BN where useful information and

* Corresponding author.
E-mail addresses: khaoula.tidriri@univ-angers.fr (K. Tidriri), teodor.tiplica@univ-angers.fr (T. Tiplica), nizar.chatti@univ-angers.fr (N. Chatti), sylvain.verron@univ-angers.fr (S. Verron).

https://doi.org/10.1016/j.engappai.2018.02.014
Received 29 September 2017; Received in revised form 12 January 2018; Accepted 19 February 2018

List of abbreviations

FDD	Fault Detection and Diagnosis
BN	Bayesian Network
QTA	Qualitative Trend Analysis
SDG	Signed Digraph
NOC	Normal Operating Conditions
FAR	False Alarm Rate
FDR	Fault Detection Rate
CPT	Conditional Probability Table
HAC	Hierarchical Ascendant Classification
PCA	Principal Component Analysis
BNT	BayesNet Toolbox
ARR	Analytical Redundancy Relation
BG	Bond Graph
DA	Discriminant Analysis
TEP	Tennessee Eastman Process
SNN	Simple Neural Network
SVM	Support Vector Machine

expert knowledge were integrated. However, it appears that setting the BN parameters is a difficult task and represents the major drawback of this strategy.

The same difficulties have been faced by the authors in Atoui et al. (2015a). Basically, they combined the T^2 statistic and a residual obtained from a model-based method, under the conditional Gaussian BN. This framework was tested on a water heater process and proved a better performance compared to the methods used separately.

Within this context, BN was also combined to the BG method in Zaidi et al. (2010) and tested on a controlled two-tank system. Additional information about the reliability have been used to improve the performances, especially with regards to unknown and identical signatures of failures.

However, combining different FDD methods is bound to generate conflicts in results. In order to address this issue, several decision fusion strategies has been used such as utility-based and evidence-based strategies. Utility-based methods are very simple to implement but they do not exploit any prior knowledge about the method's performances, unlike evidence-based methods.

Detailed reviews and comparative studies of utility-based and evidence-based strategies can be found in Rahman et al. (2002), Ghosh et al. (2011) and Zhang and Ge (2015).

Despite the significant number of publications related to implementations of hybrid approaches and decision fusion strategies (Mylaraswamy and Venkatasubramanian, 1997; Maurya et al., 2007; Siswantoro et al., 2016; Benkouider et al., 2012; Atoui et al., 2015a; Schubert et al., 2011; Ghosh et al., 2011; Kacprzyk, 2008; Guy et al., 2013), the theoretical basis is still missing and achieved improvements are inconsistent or dedicated to particular applications.

In this work, we seek to overcome this theoretical and generic lack by developing a novel unified and theoretical framework for hybrid approaches, as encouraged by the state of the art (Tidriri et al., 2016; Ding et al., 2005). The proposed framework is a BN that enables fusing the results of multiple heterogeneous FDD methods in order to strengthen correct decisions while invalidating incorrect ones. A generic methodology is hence developed in order to match the detection and diagnosis objectives, to provide a complete fault coverage and to ensure notable improvements to the overall monitoring performances.

Accordingly, the rest of the paper is organized as follows. In Section 2, a general formulation of the FDD problem and objectives are introduced. In Section 3, the proposed unified framework and the FDD methodology are detailed. Section 4 shows the effectiveness of our approach through the TEP, which is extensively used as a realistic benchmark to test and compare different FDD strategies. Finally, the last section highlights the interest of the proposed approach and concludes the paper.

2. Problem formulation and FDD objectives

In this section, the general context of our methodology is presented and the problem formulation is provided. Then, the FDD objectives to meet in order to improve the overall performances of the system are discussed.

2.1. Context for the proposed methodology

The main interest in combining FDD methods lies in the fact that various methods can usually complement each other, leading to an improvement of the monitoring performances. Indeed, detection and diagnosis errors can be greatly reduced especially when the individual methods present varying performances for different faults.

Hence, this work focuses particularly on situations where individual methods provide different FDD performances and/or comparable ones. Basically, it appears that for few industrial applications, every single FDD method that can be used provides a framework that enables to detect the occurrence of a specific set of faults. From one FDD method to another, these faults can be identical or totally different. Therefore, there is a need for developing a decision-making tool that enables the fusion of different decisions in order to obtain a complete faults coverage and a reliable decision to be displayed to the operator.

2.2. Problem formulation

In this article, the problem of decision fusion of individual FDD methods is addressed.

First, a set of faults $S = \{s_1, \dots, s_n\}$ that may occur in the system is defined. These faults can affect the actuators, the sensors or the plant and may have different time-varying profiles. Second, a set of classes $C = \{NOC, s_1, \dots, s_n\}$ that represent all the states of the system is introduced. Indeed, a system can be either in Normal Operating Conditions NOC (i.e. fault free state), or in a faulty state $S = \{s_1, \dots, s_n\}$.

Hence, the following definition is given for a *decision* of a FDD method.

Definition 1 (*Decision*)**.** A *decision* $d \subseteq C$ is defined as the class or the set of classes chosen by the FDD method as the state of the system.

For generalization, let us assume that the developed approach considers two FDD methods to be integrated. Hence, two types of decisions have to be defined: (i) d_1 given by the first FDD method and (ii) d_2 given by the second one. The set of all decisions are respectively denoted as D_1 and D_2.

In the case of hybrid approaches, d_1 and d_2 can represent respectively the decisions of a model-based and a data-driven method.

In order to evaluate the performance of FDD methods, two generally used indices, i.e. false alarm rate (FAR) and fault detection rate (FDR), also known as overall recognition rate, are considered in this work and defined in the following.

Definition 2 (*False Alarm Rate (FAR)*)**.** The FAR is the percentage of normal samples identified as fault during the NOC of the system. It is computed as:

$$FAR = \frac{\text{No. of normal samples identified as fault}}{\text{Total No. of normal samples}} * 100. \quad (1)$$

Definition 3 (*Fault Detection Rate (FDR)*)**.** The FDR is the percentage of samples correctly diagnosed. This includes diagnosing the correct faults in faulty scenarios, and not diagnosing any faults in NOC. It is computed as:

$$FDR = \frac{\text{No. of samples correctly diagnosed}}{\text{Total No. of samples}} * 100. \quad (2)$$