



## Fault isolation based on residual evaluation and contribution analysis<sup>☆</sup>

Jing Wang<sup>\*</sup>, Wenshuang Ge, Jinglin Zhou, Haiyan Wu, Qibing Jin

*College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China*

Received 9 November 2015; received in revised form 12 July 2016; accepted 2 September 2016

---

### Abstract

A new fault isolation strategy for industrial processes is presented based on residual evaluation and contribution plot analysis. Based on the space projection, the residual evaluation and contribution plot are unified into a framework. First, parity space and subspace identification methods are used to generate residuals for fault detection. Then, the optimal residuals are utilized to obtain a process fault isolation scheme. A new contribution index is calculated according to the average value of the current and previous residuals. The smearing effect can be eliminated, and the fault evolution can be acquired based on this index. This would be helpful for engineers to find the fault roots and then eliminate them. A numerical model and the Tennessee Eastman process are considered to assess the isolation performance of the proposed approach. The results demonstrate that the smearing effect is improved and the primary faulty variable can be located accurately when several different faults occur simultaneously. A superior isolation performance is obtained compared with the PCA-based isolation method. The reasonability of the isolation results is analyzed using fault propagation.

© 2016 The Franklin Institute. Published by Elsevier Ltd. All rights reserved.

*Keywords:* Fault isolation; Residual evaluation; Contribution plots; Fault evolution; Smearing effect

---

---

<sup>☆</sup>The work is supported by the National Natural Science Foundation of China, China (61473025, 61403017, 61573050), State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, (20160107).

<sup>\*</sup>Corresponding author.

*E-mail address:* [jwang@mail.buct.edu.cn](mailto:jwang@mail.buct.edu.cn) (J. Wang).

<http://dx.doi.org/10.1016/j.jfranklin.2016.09.002>

0016-0032/© 2016 The Franklin Institute. Published by Elsevier Ltd. All rights reserved.

## 1. Introduction

Fault detection and isolation (FDI) have attracted much attention for complex industrial processes during the last decades. FDI monitoring systems are very useful and effective to detect faults in a timely fashion and accurately isolate the faulty equipment. This can avoid shutting the plant down or accidents. Some researchers have reviewed and surveyed the development of different FDI methods and schemes [1–3]. These approaches can be categorized into two classes: model-based and data-driven methods. The analytical redundancy approach [2] is a typical model-based method. Statistical process monitoring (SPM) or latent space approaches, such as principal component analysis (PCA), partial least squares (PLS) and independent component analysis (ICA) [4,5], are classified as data-driven methods. A unified and composite scheme of model-based and data-driven methods in FDI systems is given in [6].

Recently, [7,8] proposed a new data-driven design based on observer or parity space monitoring. A fault estimation strategy based on parity space is designed for linear time-varying systems [9]. A two-step incipient fault detection strategy is proposed based on fault extraction and residual evaluation [10]. This scheme combines the subspace identification methods (SIM) with the residual evaluation, which is different from the typical data-driven techniques. Its advantage is to address process dynamics and obtain the process model identified from process data. Similarly, this paper focuses on the method of fault detection and isolation based on residual evaluation in parity space.

Fault isolation is performed to determine the fault roots when a fault alarm is triggered by the fault detection system. The structured residual approach based on residual evaluation is a popular tool for fault isolation. A residual that is insensitive to one subset of faults is generally sensitive to other fault subsets. Li and Shah [11] presented a structured residual vector (SRV) approach to identify sensor faults. Some expansible works have been presented in [12]. Partial principal component models are introduced to optimize the structured residuals [13], which produce some results in the integration of residual evaluation and data-driven methods. These methods, however, need many prior knowledge of the process fault to identify the potential fault direction.

According to the classification of fault isolation methods [14], another fault isolation strategy is based on contribution plots, in which only process data are used to find faulty variables without any prior fault knowledge. A contribution plot is an unsupervised method that is commonly used to isolate faults in multivariate statistical process monitoring. [15,16] summarized and reviewed the contribution plot methods, such as complete decomposition contributions (CDC), partial decomposition contributions (PDC) and reconstruction-based contributions (RBC), and they also analyzed their diagnosable characteristics. A successful contribution plot should follow these properties: The contribution of each variable has the same mean in normal conditions, and the fault variable has an extremely large contribution value compared to other normal variables when a fault is presented. For example, it can be proven that the RBC of a normal variable is less than or equal to that of a faulty variable according to the Cauchy–Schwarz inequality analysis.

Sometimes the contribution plot suffers from the smearing effect, *i.e.*, a non-faulty variable exhibits a larger contribution value while the contribution of the faulty one is smaller. This variable will be smeared out to the other variables in performing the PCA process [17]. Kerkhof mathematically analyzed the smearing effect of three contributions: CDC, RBC and PDC [18]. The smearing effect is caused by the compression and expansion operation when process data are mutually transformed between the measurement space and the latent space. A numerical case is used to explain the smearing effect, in which contribution analysis cannot guarantee the correct fault isolation in multiple sensor fault conditions. A data-driven fault isolation method is

Download English Version:

<https://daneshyari.com/en/article/4974388>

Download Persian Version:

<https://daneshyari.com/article/4974388>

[Daneshyari.com](https://daneshyari.com)