Journal of Process Control 38 (2016) 31–41

Contents lists available at ScienceDirect

Journal of Process Control

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

Efficient faulty variable selection and parsimonious reconstruction modelling for fault isolation

Chunhui Zhao*, Wei Wang

State Key Laboratory of Industrial Control Technology, Department of Control Science and Engineering, Zhejiang University, Hangzhou 310027, China

ARTICLE INFO

Article history:
Received 4 September 2014
Received in revised form
18 November 2015
Accepted 2 December 2015
Available online 11 January 2016

Keywords:
Faulty variable selection
Reconstruction modelling
Fault isolation
Principal component analysis

ABSTRACT

Reconstruction-based fault isolation, which explores the underlying fault characteristics and uses them to isolate the cause of the fault, has attracted special attention. However, it does not explore how the specific process variables change and which ones are most significantly disturbed under the influences of abnormality; thus, it may not be helpful to understanding the specifics of the fault process. In the present work, an efficient faulty variable selection algorithm is proposed that can detect the significant faulty variables that cover the most common fault effects and thus significantly contribute to fault monitoring. They are distinguished from the general variables that are deemed to follow normal rules and thus are uninformative to reveal fault effects. To further reveal the fault characteristics, the selected significant faulty variables are then chosen to obtain a parsimonious reconstruction model for fault isolation in which relative analysis is performed on these selected faulty variables to explore the relative changes from normal to fault condition. The faulty variable selection can not only focus more on the responsible variables but also exclude the influences of uninformative variables and thus probe more effectively into fault effects. It can also help in finding a more interesting and reliable model representation and better identify the underlying fault information. Its feasibility is illustrated with simulated faults using data from the Tennessee Eastman (TE) benchmark process.

1. Introduction

Online fault detection and isolation in modern industrial processes has been an extremely important practice driven by plant safety, product quality improvement, plant economics, etc., over the last few decades. Various methods [1–13] have been developed and reported in practical applications. Multivariate statistical process control (MSPC) charts based on multivariate statistical projection methods such as principal component analysis (PCA) [14] and partial least squares (PLS) [15,16] have been shown to be successful for online monitoring of new processes. They are able to reduce the dimensions of the monitoring space by projecting the measurement data into a low-dimensional space defined by a few latent variables. The processes are then monitored by calculating fault detection statistics in the reduced space, where visual inspection and interpretation are much easier. The purpose behind MSPC is the timely detection of any deviation from normal or “in-control” behaviour so that operators and engineers can then examine the relevant processing unit in time and quickly identify why the process has moved outside the desired operating region.

There has been tremendous interest [17–33] in diagnosing the possible root causes of a fault situation. Previously, the task of fault isolation has been simply left up to the troubleshooting skills of the process operators and engineers. With the development of data-driven methods, automatic fault isolation strategies are more desirable for industrial process operations and have drawn increasing attention. In industrial processes with many variables, the work involved in fault isolation may be more difficult. The isolation of faulty variables can provide additional information for investigating the root causes of the faults. The contribution plot [24,25,29,30] is a popular tool to isolate faulty variables without a priori knowledge by determining the contribution of each variable to the fault detection statistics. The assumption behind the contribution plot method is that faulty variables have high contributions to the fault detection index. To determine how many variables are related to a fault, a progressive PCA algorithm [31] was developed in which the highly fault-responsible variables are identified by calculating variable contribution to one monitoring statistic, and a new PCA model is developed with the remaining variables to determine whether there are any other variables exhibiting abnormal behaviour. Although the contribution plot approach does not

* Corresponding author. Tel.: +86 571 87951879; fax: +86 571 87951879.
E-mail address: chhzhao@zju.edu.cn (C. Zhao).

http://dx.doi.org/10.1016/j.jprocont.2015.12.002
0959-1524/

require prior fault knowledge except for a normal statistical monitoring model, it may not well explain the correlations of the process variables. For some faults, the same set of faulty variables may be disturbed, which may have different variable correlations. Therefore, the contribution plot approach may not be able to distinguish among these faults.

Recently, historical faulty data have been widely explored for fault isolation. For the fault reconstruction technique, the fault correlations can be extracted, which are then used for fault identification by correcting the fault effects. For successful fault reconstruction, it is critical to obtain an accurate characterization of fault directions, along which the fault-free data can be restored and the monitoring statistics can be returned to normal. In previous work, the concerned fault directions were generally obtained by directly performing multivariate statistical analysis, such as PCA, on the fault measurement data. Through PCA, the directions with the largest distribution variances are extracted first, which may not be necessarily responsible for monitoring and thus may not well explore the fault effects. Zhao et al. [32] proposed the idea of relative changes to extract the fault reconstruction models in PCS and RS and thus remove out-of-control monitoring statistics more efficiently. Instead of directly modelling the faulty data, the relative changes from normal to fault condition are analyzed so that the responsible fault deviations that can cause out-of-control monitoring statistics are separated from the others in each monitoring subspace. The above modelling method can improve the reconstruction model, but it does not analyze the specific faulty variables in the concerned faults. In fact, not all measurement variables are relevant to the fault effects and useful for faulty data correction. Therefore, one important issue is to decide which variables to include in a reconstruction model to more effectively explore the fault effects and thus correct the alarm signals for fault isolation. Moreover, distinguishing the significant faulty variables that cover the most fault effects from those general variables can help identify the underlying fault information and obtain an enhanced understanding of the fault process.

The main purpose of this study is to investigate an effective way to reveal faulty variables and model fault effects for fault isolation. First, measurement variables are evaluated by checking their relationships with fault effects, which are separated into two parts, significant faulty variables and uninformative variables, by developing a faulty variable selection algorithm. During the selection procedure, quantitative evaluation indices are defined to check the roles of different variables in the correction of faulty data. The significant faulty variables that can cause monitoring alarm are deemed to be fault-relevant and thus distinguished from the others. To further reveal the fault effects, the selected variables are then used for reconstruction modelling to uncover their relationships. On the one hand, the uninformative variables that may be irrelevant to the concerned fault are excluded from model development. Therefore, fault reconstruction is realized more effectively by focusing on the informative alarm-responsible fault deviations. On the other hand, each fault type is dually marked by some specific faulty variables and their correlations for fault isolation, which is a better process for distinguishing different fault types. Related statistical analyses and discussions are conducted to further comprehend the proposed solution. The feasibility of the proposed algorithm is illustrated by simulated faults from the well-known Tennessee Eastman (TE) benchmark chemical process.

The remainder of the paper is organized as follows. First, the proposed algorithm is presented, in which an efficient faulty variable selection algorithm is first described and a parsimonious reconstruction model is then developed for fault correction. Its suitability and rationality are also highlighted. Based on simulated faults with data from the TE benchmark chemical process, the abovementioned recognition and argument are verified. Discussions are conducted to analyze the illustration results. Finally, conclusions are drawn in the last section.

2. Methodology

2.1. Motivation

In the context of PCA models, the concept of fault reconstruction has been defined [27] such that the fault subspace is designed to recover the fault-free part of the measurement data and estimate the fault magnitude. Reconstruction-based fault isolation is directly related to the fault detection results and is taken with the basic idea of removing those alarm monitoring signals. Therefore, for reconstruction-based fault isolation, the key step is to obtain a good reconstruction model that can well describe the significant fault deviations responsible for out-of-control monitoring statistics. The precision is affected by several factors, one of the most important of which is what variables to include in the reconstruction model. In general, the reconstruction model is calculated by performing statistical analyses on faulty data, such as singular-value decomposition (SVD) [34,35], in which all process variables are included. The fault variations with the largest distribution variances are regarded to be the most significant. However, it is clear that not all variables and variations are related to process disturbances and responsible for alarms. Therefore, the quality of a reconstruction model greatly depends on the quality of its modelling variables. Because the raw fault process observations often contain major sources of normal variations that have little or no fault-relevance, it is often observed that the first several distribution directions extracted capture most of general process variations but explain very little fault information. The inclusion of excessive variables in reconstruction modelling may introduce extra variations to the reconstruction model which may thus reduce the resolution of each specific fault and make it difficult to distinguish among different fault causes. Therefore, it is a common practice to apply a proper pretreatment before embarking on reconstruction modelling. Moreover, variable selection can help probe into a number of specific variables in a particular section of the plant, thereby making it much easier to isolate possible causes.

2.2. Faulty variable selection

Here, a faulty variable selection strategy is developed based on the fault reconstruction idea to distinguish the responsible variables from the measured process variables so that significant fault effects can be collected. The faulty variables that are related to the current abnormality are termed informative variables, each of which can correct the faulty data to a certain extent. The others are termed uninformative variables here. By this faulty variable selection procedure, uninformative variations are excluded, and only informative variables are kept for the extraction of the reconstruction model.

There are three important questions that should be answered during the selection procedure:

(1) How to evaluate the significance of different variables related to fault effects;
(2) How to distinguish the informative faulty variables;
(3) How to explore the underlying correlations of the responsible faulty variables owing to the reconstruction model.

A PCA-based monitoring system uses two subspaces and different monitoring statistics to supervise the status of a process. One is the principal component subspace (PCS), which is monitored by T^2 monitoring statistic, reflecting the major systematic