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Isolation of plant-wide faults using causality detection methods

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Abstract: Isolation of plant-wide faults in large-scale complex systems is particularly challenging. A methodology to detect and isolate faults is proposed, detecting the faulty variables using univariate control charts and the causality information between them to indicate the source. The clustering of faulty variables uses univariate analysis to avoid the smearing effect brought by multivariate analysis. The variable where the fault took place is indicated, handling fault novelties in a very natural manner. The proposed method is discussed and illustrated through its application to the Tennessee Eastman Process and to routine operating data from a thermoelectric power plant.

Keywords: Causality Detection, Fault isolation, Transfer Entropy, PCA, Process Control.

1. INTRODUCTION

Detection and isolation of plant-wide faults are major problems in the process industry. To isolate a fault in large-scale complex systems is particularly challenging because of the high degree of interconnections among different parts. A simple failure may propagate along information and affect other parts of the system.

Fault detection techniques range from fault trees, digraphs and analytical frameworks to knowledge-based systems and neural networks. From the perspective of modeling Venkatasubramanian et al. (2003) divides into 3 categories: quantitative models, qualitative models, and process history based models or simply data-driven. In contrast to methods based on prior knowledge (both quantitative and qualitative) data-driven methods only require access to a large amount of historical process data. There are different ways to transform and present this data as a priori knowledge to a diagnostic system. This process, known as feature extraction, can be qualitative, such as specialist systems and trend modeling, or quantitative, such as statistical models and neural networks. Statistical process monitoring (SPM) is successful in feature extraction, Qin (2003) reviewed the use of fault detection indices such as T^2 and Q, which were calculated directly from statistical projection methods using normal operating data.

Unlike the fault detection problem, fault isolation has received less attention in the SPM research community. The detection of cause-effect relationships in signals from industrial processes is useful to discover signal flow paths. The estimation of time delays has been used to find the source of disturbances caused by faults (Bauer and Thornhill, 2008; Stockmann et al., 2012). However, the estimation of time delay is very prone to errors. Additionally, this method fails in estimating the propagation in non-linear systems. One of the methods to find the causal relationships is the transfer entropy (Schreiber, 2000), which relies on conditional probabilities. This measure can be used to identify the propagation path of disturbances (Bauer et al., 2007), to overcome the problem of time delay estimation.

Any method used to find the causal relationships to indicate the source of the fault may fail if variables that are only correlated with faulty variables are included. This paper presents a methodology that can circumvent this issue, highlighting the results that one can obtain for the usual situations.

The paper is organized as follows. In Section 2, the concepts of fault detection and isolation and causality are reviewed. Section 3 describes the proposed methodology. In Section 4 Tennessee Eastman Process and a Thermoelectric Power Plant are used to demonstrate the effectiveness of the proposed approach, followed by concluding remarks in Section 5.

2. FAULT DETECTION AND ISOLATION

Due to the wide scope of the fault detection area and the difficulty of real-time solutions, various techniques have been developed over the years. The most well-known statistical methods for feature extraction in data-driven fault detection are the Principal Component Analysis (PCA), the Partial Least Square (PLS), and the Independent Component Analysis (ICA).

PCA is the most widely used method in industrial systems (Chiang et al., 2001). Given a set of n variables and m observations stacked into a matrix $X \in \mathbb{R}^{mxn}$, the loading vectors are calculated by solving an eigenvalue decomposition of the sample covariance matrix,

$$S = \frac{1}{(m-1)} X^T X = V \Lambda V^T \quad (1)$$

where the diagonal matrix Λ contains the non-negative real eigenvalues in decreasing magnitude ($\lambda_1 \geq \lambda_2 \geq$

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... $\geq \lambda_n \geq 0$). The loading vectors are the orthonormal column vectors in V. The variance of the training set projected on the i^{th} column of V is λ_i. The columns of the loading matrix $P \in \mathbb{R}^{nxa}$ are the columns of matrix V associated to the a largest eigenvalues, while $\tilde{P} \in \mathbb{R}^{nxn-a}$ holds the remaining loading vectors. The projections of an observation $x \in \mathbb{R}^n$ into the lower-dimensional principal and residual subspaces are $\hat{x} = PP^T x$ and $\tilde{x} = \tilde{P}\tilde{P}^T x$.

With the normal condition modeled (feature extraction), the next step in statistical data-driven methods is to calculate multivariate statistics to detect abnormal situations. Hotelling's T^2 statistic (eq. 2) and the squared prediction error known as Q statistic (eq. 3) can be used to detect faults for multivariate process data.

$$T^2 = x^T P \Lambda^{-1} P^T x \tag{2}$$

$$Q = x^T \tilde{P}\tilde{P}^T x \tag{3}$$

Thresholds for these statistics for a given significance level α (T^2_α and Q_α) can be calculated (Chiang et al., 2001) to detect faults.

2.1 Fault Isolation

When an out-of-control situation is detected, a search for its cause is accomplished. This task has been traditionally performed with pattern classification methods, and requires data collected during out-of-control operations that are categorized into separate classes according to the faults. Assuming that the detected fault is present in the database, the fault can be properly diagnosed (Chiang et al., 2001).

In the context of SPM several methods were introduced in the literature for fault isolation. Contribution plots are based on the idea that variables with the largest contributions to the statistic indices are most likely to be associated with the fault. Alcala and Qin (2011) classified these methods as complete decomposition contributions (CDC), partial decomposition contributions (PDC), diagonal contribution (DC) and reconstruction-based contributions (RBC). The merit of the contribution plots is to narrow down the search for the variables where the fault took place. A drawback of these methods is the possibility of including in the group of candidate variables those that are correlated to variables affected by the fault, but are not affected by the fault. This problem, called smearing effect, was tackled by many authors. Recently Van den Kerkhof et al. (2013) showed that, after a multivariate fault detection, univariate fault isolation is superior to contribution plots in most of the situations to isolate the variables that were affected by the fault. These results are fundamental to the fault isolation method proposed here.

With the assumption that the faulty variables were clustered, information about the causality between these variables may allow improving fault isolation. Bauer and Thornhill (2008) proposes the use of causality to find the propagation paths of oscillatory disturbances in industrial plants based on time delay estimation. More recently, Stockmann et al. (2012) proposed the use of k nearest neighbor to have a better estimate of time delays in fault isolation. Although these methods require less computational effort, estimation of time delays is prone to errors when slow dynamics are present. This fact motivated the use of tests to check the consistency of the time delay estimates. These methods rely on properly clustering only the faulty variables. An incorrect source may be indicated if a variable is included due only to its correlation to faulty variables. Therefore, the combination of statistical methods to detect faults and methods to detect causality to isolate the faults is carefully examined in this paper.

Several methods are available to detect causality as discussed in Marques et al. (2015). The method used here is the transfer entropy, a nonparametric method that can be used even in the presence of nonlinearities. Schreiber (2000) proposes the transfer entropy as the measure that shares some of the desired properties of mutual information but takes the dynamics of information transport into account. With minimal assumptions about the dynamics of the system and the nature of their couplings, one is able to quantify the exchange of information between two systems, separately for both directions, and, if desired, conditional to common input signals.

2.2 Transfer Entropy

Let us consider two time series $\boldsymbol{x} = \{x_1, x_2, ..., x_n\}$ and $\boldsymbol{y} = \{y_1, y_2, ..., y_n\}$. The transfer entropy from $\boldsymbol{x}$ to $\boldsymbol{y}$ ($T_{\boldsymbol{x}\to\boldsymbol{y}}$) is different to the transfer entropy from $\boldsymbol{y}$ to $\boldsymbol{x}$ ($T_{\boldsymbol{y}\to\boldsymbol{x}}$), because of its inherent asymmetry:

$$T_{\boldsymbol{y}\to\boldsymbol{x}} = \sum_{x_{n+h}, x_n, y_n} p(x_{n+h}, x_n, y_n). \log\left(\frac{p(x_{n+h}, x_n, y_n).p(x_n)}{p(x_n, y_n).p(x_{n+h}, x_n)}\right) \tag{4}$$

$$T_{\boldsymbol{x}\to\boldsymbol{y}} = \sum_{y_{n+h}, y_n, x_n} p(y_{n+h}, y_n, x_n). \log\left(\frac{p(y_{n+h}, y_n, x_n).p(y_n)}{p(y_n, x_n).p(y_{n+h}, y_n)}\right) \tag{5}$$

Joint PDFs (Probability Density Function) for two stationary signals sequential in time are denoted by $p(x_{n+1}, x_n)$ with the same PDF for x_n, x_{n+1}, because of stationarity, that is, $p(x_n) = p(x_{n+1})$, where 1 is the prediction horizon of x_n and will be substituted by parameter h. The generalization of this joint PDF is the joint PDF for $k+l$ variables giving $p(\boldsymbol{x_n}, \boldsymbol{y_n})$, where $\boldsymbol{x_n} = \{x_n, x_{n-1}, , x_{n-(k-1)}\}$ and $\boldsymbol{y_n} = \{y_n, y_{n-1}, , y_{n-(l-1)}\}$ are embedded vectors. The parameters k and l are referred to as the embedding dimension of $\boldsymbol{x_n}$ and $\boldsymbol{y_n}$, respectively (Bauer et al., 2007). The conditions for the successful application of this method are discussed in Naghoosi et al. (2013).

3. PROPOSED METHODOLOGY

The direct application of causal maps in faulty variables clustered by faulty isolation methods can be misleading. This problem arises mainly because of the possible inclusion of variables that are only correlated to faulty variables, and also due to limitations of methods to detect causality. These situations are discussed in this Section yielding the proposed methodology.