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Fault propagation analysis of oscillations in control loops using data-driven causality and plant connectivity

R. Landman*, J. Kortela, Q. Sun, S.-L. Jämsä-Jounela

Aalto University, School of Chemical Technology, Process Control and Automation Research Group, P.O Box 16100, FI-00076 Espoo, Finland

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ABSTRACT

Oscillations in control loops are one of the most prevalent problems in industrial processes. Due to their adverse effect on the overall process performance, finding how oscillations propagate through the process units is of major importance. This paper presents a method for integrating process causality and topology which ultimately enables to determine the propagation path of oscillations in control loops. The integration is performed using a dedicated search algorithm which validates the quantitative results of the data-driven causality using the qualitative information on plant connectivity. The outcome is an enhanced causal model which reveals the propagation path. The analysis is demonstrated on a case study of an industrial paperboard machine with multiple oscillations in its drying section due to valve stiction.

1. Introduction

Large-scale industrial systems are often subject to abnormal events such as faulty operations, external disturbances and control system failures leading to low productivity, increased operational costs and sometimes even hazardous operations (Yang et al., 2010a). In particular, oscillations in control loops are very common in industrial processes and lead to poor control performance, low product quality and excessive energy consumption (Yuan and Qin, 2013). Oscillations in control loops are typically caused by valve problems such as excessive friction (stiction), poor tuning of controllers or controller interactions (Hägglund, 1995). In large-scale systems with many interacting control loops, oscillations can easily propagate through the process units in multiple paths, making it difficult to determine the most probable propagation path.

In recent years, capturing causality between different process variables has become a vital tool in the diagnosis of faulty systems due to its ability to identify the propagation path of disturbances (Heim et al., 2002; Yang et al., 2012). Typically, the outcome of causal analysis is a causal model in the form of a signed directed graph (SDG) representing process variables as nodes and causal relationships as arcs (Heim et al., 2002).

SDGs can be constructed from process knowledge and/or process data. Models based on process knowledge can be developed using mathematical equations describing the system (Maurya et al., 2003, 2004, 2006) or they can be established directly from piping and instrumentation diagrams (P&IDs). Models which are based on the physical layout of the process are typically referred to as topology-based models or process connectivity models (Di Geronimo Gil et al., 2011). Several techniques for extracting plant connectivity information from P&IDs have been developed in recent years (Yim et al., 2006; Thambirajah et al., 2007, 2009). Topology-based models are qualitative, i.e., they do not provide any information on the level of interactions among variables.

On the other hand, data-driven causal analysis utilizes historical process data in the form of time series and measures to what extent the time series corresponding to specific variables influence each other. Usually, the analysis yields a causality matrix which contains the structural information of the causal model. Among the most commonly used methods are the cross-correlation (Bauer and Thornhill, 2008), the Granger causality (Bressler and Seth, 2010; Granger, 1969) and the transfer entropy (Bauer et al., 2007; Schreiber, 2000) methods. Unlike process knowledge-based modeling, data-driven modeling does not require prior information on the intrinsic system. Moreover, it produces a quantitative model due to its ability to estimate the level of interactions among variables. However, the data-driven methods suffer from several limitations and drawbacks. The main difficulty in data-driven causal analysis is in establishing the statistical significance

* Corresponding author. Tel.: +358 504382296.
E-mail address: rinat.landman@aalto.fi (R. Landman).

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of the results, hereby eliminating redundant links from the causal model. Furthermore, occasionally the causal model suggests several hypotheses for the root cause or in the case of using several methods each method points to a different potential source. In such occasions, it is essential to utilize process knowledge for isolating the most probable root cause. Indeed, both Bauer et al. (2005) and Yang et al. (2012) concluded that process insights derived from process schematic or site expertise are still essential for validating the results of the data-driven methods.

Consequently, several attempts have been made in recent years to combine data-driven causal analysis with topology-based models. For instance, Yang et al. (2010b, 2012) applied the cross-correlation and transfer entropy methods on an industrial case study in order to validate an SDG based on process knowledge and vice versa. Thambirajah et al. (2009) introduced the cause and effect analyzer which combines a causality matrix derived from process data and qualitative information about the process in the form of a connectivity matrix which is captured from an XML (extensive markup language) description of the process schematic. Then, if more than one probable root causes are detected, a search of the process connectivity matrix determines whether a propagation path is feasible and which one is most likely to be the root cause and propagation path. However, in cases where the system has a high degree of connectivity among the process units, finding feasible propagation paths among the process components might not be sufficient to capture precisely the causal topology.

The present study was designed to identify the propagation path of oscillations in control loops by utilizing a dedicated search algorithm which validates each entry in the causality matrix obtained from the data-driven analysis using the connectivity matrix extracted from the P&ID. The search algorithm has two main functionalities: finding feasible propagation paths between two control elements and determining whether a path is direct or indirect. Consequently, the entries in the causality matrix which do not represent genuine direct interactions are excluded and the outcome is a refined causality matrix which contains the structural information of the propagation path. The efficiency of the analysis is successfully demonstrated on a case study of an industrial board machine utilizing the Granger causality (GC) to obtain the initial causality matrix while the connectivity matrix was captured from an AutoCAD P&ID as an XML schema.

This type of analysis can be applied in conjunction with different fault detection methods (Venkatasubramanian et al., 2003) in order to facilitate the fault diagnosis procedure and expedite process recovery. Consequently, it can assist in identifying the process units of concern once a certain fault is detected whilst gaining valuable insights on the process dynamics.

This paper is organized as follows. Section 2 describes the data-driven and topology based modeling techniques applied in the current study and how they are combined using the search algorithm. Section 3 describes the process case study and the fault propagation analysis. The paper ends with concluding remarks in Section 4.

2. Fault propagation analysis

This section first provides an overview on topology based models and data-driven causal analysis. Due to practical reasons, the section mainly concentrates on the methods which were implemented in the current study. Then, the refinement procedure using the search algorithm is described in detail including each of its functionalities.

2.1. Generation of a topology-based model

There are two types of topology-based models: causal digraph and connectivity matrix which can be considered as a graphical and a numerical representation of the process schematics, respectively. The digraph reflects physical or signal flows between the equipment and instruments based on the physical layout of the components it represents. Similarly to the digraph, the connectivity matrix indicates the relationships between process components in the form of a binary matrix whose elements are assigned according to the existence of a directional connection from the row header component to the column header component (Sun, 2013; Thambirajah et al., 2009).

In this study, topology data was extracted from an electronic P&ID which is drawn by the specialized Autodesk AutoCAD P&ID drafting application that has been developed based on Autodesk AutoCAD. In the developed application, the topology data is exported in the format of ISO 15926-compliant XML scheme XMpLant (Noumenon, 2008).

The automated generation of topology information includes the following tasks. First, the schematic information on the initial component and the terminal component of every line segment, such as pipes and control signals is included in the drawing. Secondly, this information is attained through the database object of the drawing which includes all the topology information, namely, the names of the process components, the coordinates of the components and the connections among them. Finally, this data is further processed by MATLAB program and converted into connectivity information which includes the tags, coordinates, and the connectivity between process components (Sun, 2013).

2.2. Data-driven causal analysis

Yang and Xiao (2012) have recently reviewed and evaluated different data-driven methods for capturing causality. In practice, the appropriate data-based method should be selected carefully based on process dynamics, the available data and type of fault. The outcome of the analysis is a causality matrix where each element (i, j) in the matrix represents the causal relationship from variable i to variable j. In this study, the analysis is aimed to identify causal relationships among controllers, thus, the nodes in the causal model represent the controllers. We used the Granger causality method to obtain the initial causality matrix. However, due to the high level of connectivity among the controllers, we employed the frequency domain methods as well to verify the final results of the analysis and to gain further insights on the level of interactions among the controllers. A description of the methods which were employed in the current study is given below.

2.2.1. Time domain Granger causality (GC)

Granger causality has received great attention in many areas due to its ease of implementation and efficiency when investigating causal relationships (Seth, 2005; Yuan and Qin, 2013). Moreover, the method has been extended to multivariate (MV) time series analysis (Geweke, 1982) which makes it highly beneficial when investigating large-scale systems.

The basic notion of the GC is that if one time series affects another series, then the knowledge of the former series should help to predict the future values of the latter one (Granger, 1969). To illustrate the concept of the method, consider two time series $X_1(t)$ and $X_2(t)$ and their corresponding autoregressive (AR) model:

$$\begin{aligned} X_1(t) &= \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + \epsilon_1(t) \\ X_2(t) &= \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + \epsilon_2(t) \end{aligned} \tag{1}$$