Landman, Rinat; Kortela, Jukka; Sun, Qiang; Jämsä-Jounela, Sirkka-Liisa

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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. Jämä-Jounela

Aalto University, School of Chemical Technology, Process Control and Automation Research Group, P.O Box 16100 FI-00076 Espoo Finland (e-mail: rinat.landman@aalto.fi).

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.

Keywords: Causal analysis, Fault propagation, Control loops, Paper machine, Connectivity information, Industrial application.
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 & 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 Geron-
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 & Thornhill, 2008), the Granger causality (Bressler & 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 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 propaga-
tion 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 & 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 & 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:

\[
X_1(t) = \sum_{j=1}^{p} A_{11,j}X_1(t - j) + \sum_{j=1}^{p} A_{12,j}X_2(t - j) + \epsilon_1(t) \\
X_2(t) = \sum_{j=1}^{p} A_{21,j}X_1(t - j) + \sum_{j=1}^{p} A_{22,j}X_2(t - j) + \epsilon_2(t)
\] (1)
where \( p \) is the model order and \( \epsilon_1, \epsilon_2 \) are the residuals for each series. (1) is typically referred to as the *unrestricted model* (Bressler & Seth, 2010). The GC from \( X_2 \) to \( X_1 \) is defined as:

\[
F_{x2\rightarrow x1} = \ln \left( \frac{\text{var}(\epsilon'_1)}{\text{var}(\epsilon_1)} \right)
\]

(2)

where \( \epsilon'_1 \) is obtained from (1) by omitting all \( A_{12} \) coefficients for all \( j \) (Seth, 2010). The model after omitting all \( A_{12} \) coefficients is typically referred to as the *restricted model* (Bressler & Seth, 2010). The statistical significance of the GC can be determined via the \( F \)-statistic test (Greene, 2002):

\[
F = \frac{\text{RSS}_r - \text{RSS}_{ur}}{\text{RSS}_{ur}} \times \frac{T - 2p - 1}{p}
\]

(3)

where \( \text{RSS}_r \) and \( \text{RSS}_{ur} \) are the residual sum of squares of the *restricted* and *unrestricted* models respectively and \( T \) is the total number of observations.

For MV processes, the MV (conditional) GC (Guo et al., 2008), which is based on the expansion of a univariate Auto Regressive (AR) model to a Multivariate Auto Regressive (MAR) model to include all measured variables can be used. The method requires that the time series are stochastic and wide sense stationary (WSS). Otherwise, the AR model can produce spurious results (Granger & Newbold, 1974). The main limitation of the method lies in its linearity, thus its application to non-linear systems may not be appropriate (Bressler & Seth, 2010).

2.2.2. Frequency domain methods

The frequency domain methods represent the energy transfer between each pair of time series at each frequency. The evaluation of directional interactions in the frequency domain is especially useful for a process with
oscillatory behavior (Faes et al., 2010). The methods are applied by estimating the MAR model of the time series followed by Fourier transform into frequency domain. A MAR model is defined as:

\[
\begin{bmatrix}
  x_1(t) \\
  \vdots \\
  x_N(t)
\end{bmatrix}
= \sum_{r=1}^{p} A_r 
\begin{bmatrix}
  x_1(t-r) \\
  \vdots \\
  x_N(t-r)
\end{bmatrix} + 
\begin{bmatrix}
  e_1(t) \\
  \vdots \\
  e_N(t)
\end{bmatrix}
\]

(4)

where \(X_t = [x_1(t), x_2(t), \ldots x_N(t)]\) is the vector of \(N\) process variables, \(E_t = [e_1(t), e_2(t), \ldots e_N(t)]\) is \(N\) dimensional vector of the MV noise terms, \(A_1, A_2, \ldots A_p\) are \(NxN\) matrices of the model coefficients and \(p\) is the model order. By applying the Z transform operation \((Z^{-i} = e^{-i2\pi f})\) on (4), it is transformed into frequency domain:

\[
X(f) = H(f)E(f)
\]

(5)

where \(H(f)\) is the transfer function of the MAR model with the following relation to the model coefficients:

\[
H(f) = (I - A(f))^{-1} = \overline{A}(f)^{-1}
\]

\[
= (I - \sum_{r=1}^{p} A_r Z^{-r})^{-1}
\]

(6)

\(\Sigma\) is the noise covariance matrix of the model and is defined as:

\[
\Sigma = 
\begin{bmatrix}
  \sigma_{11}^2 & \cdots & \sigma_{1N} \\
  \vdots & \ddots & \vdots \\
  \sigma_{N1} & \cdots & \sigma_{NN}^2
\end{bmatrix}
\]

(7)

where \(\sigma\) refers to covariance and \(\sigma^2\) to the variance of the noise terms. Notice that since it is assumed that the noise terms are uncorrelated, \(\Sigma\) is diagonal.
matrix and independent on frequency. If the model coefficients were estimated correctly, the diagonal elements of the \( \Sigma \) matrix should be relatively small.

The Directed Transfer Function (DTF) introduced by Kaminski \& Blinowska (1991) is defined as:

\[
\gamma_{ij}(f) = \frac{H_{ij}(f)}{\sqrt{\sum_{j=1}^{N} |H_{ij}(f)|^2}}
\]

(8)

The DTF represents the signal power that spreads from variable \( j \) to variable \( i \) over all possible pathways. The DTF is constructed solely from the transfer function and does not depend on the noise covariance matrix of the MAR model. In contrast, the Partial Directed Coherence (PDC) (Baccala \& Sameshima, 2001) reveals only the power of the direct interactions between each pair of variables. The PDC from variable \( j \) to \( i \) is defined as:

\[
\pi_{ij}(f) = \frac{A_{ij}(f)}{\sqrt{\sum_{i=1}^{N} |A_{ij}(f)|^2}}
\]

(9)

Notice that the PDC is a function of \( A_{ij}(f) \) alone and similarly to the DTF it does not depend on the noise covariance matrix. While the DTF can be seen as a spectral measure of the total causal influence of one variable on the other, the PDC can be seen as a measure of the direct influence of one variable on the other. Furthermore, the PDC can be seen as the frequency domain representation of the GC (Baccala \& Sameshima, 2001), thus, it can efficiently complement the time domain GC analysis.

According to Winterhalder et al. (2005), if the diagonal terms of the noise covariance matrix differ by orders of magnitude, a false detection of influences from a low variance variable to a high variance variable may occur. Therefore,
Baccala et al. (2007) and Yameshita et al. (2005) proposed a renormalized definition of the PDC and the DTF respectively using the variance of the noise terms.

Several techniques are available for determining the statistical significance of the PDC and the DTF (Faes et al., 2010; Schelter et al., 2005; Takahashi et al., 2007).

2.3. Refinement of the Causality Matrix

The refinement of the causality matrix is based on the process connectivity information. The aim of this operation is to eliminate all the values in the causality matrix which do not represent direct causal interactions. The realization of the refinement procedure of nxn causality matrix $X$ is obtained according to the following implementation:

1. In matrix $X$, select the next non-zero $(i,j)^{th}$ element that has not been tested.
2. Check if there is a direct physical path from controller $i$ to controller $j$ using the search algorithm.
3. If there is no direct path from controller $i$ to $j$, set $X(i,j)$ to zero.
4. Repeat steps 1-3 until all non-zero elements in matrix $X$ are tested.

Note that we define a direct path from controller $i$ to controller $j$ if it does not transverse any other controller other than $j$. Recall that the data-driven methods identify interactions according to their level of influence since when a fault propagates along a certain path it may stop at some point due to signal attenuation (Yang et al., 2010a). As a result, the data-driven methods capture only the interactions associated with the fault while the topology-based
models capture all physical interactions between the process components. Hence, in the refinement procedure, the connectivity information is used to validate the results of the data-driven causal analysis and not the other way around.

2.3.1. The Search Algorithm

The search algorithm consists of two steps: first, it finds whether a feasible propagation path between two control elements exists using the connectivity matrix. Then, if a physical path is found, it checks whether the path is direct or indirect. A detailed description of both steps is given below while an example of the algorithm implementation in the investigated case study is shown in Section 3.4.1.

Search for a Physical Path

The algorithm for finding a physical path between two process components is a generic algorithm which is based on a graph traversal which searches a series of nodes, ensuring that each node is only traversed once (Thambirajah et al., 2009). Particularly, the method uses the depth-first search algorithm whereby the search begins at a specific node and continues along a set of nodes until it reaches termination or the target node (Thambirajah et al., 2009). This recursive algorithm starts by moving from the row in the connectivity matrix representing the 'cause' variable in the causality matrix and then searches for '1' which indicates that the row element is connected to the column element. The search then proceeds to the row now representing the column element and so on until one of the following conditions occurs: its reaches the 'effect' variable and hereby the path is identified, it reaches a
component which had been visited before (i.e., there is a circulation path), or it reaches a component that is not connected to any other element. If one of the two latter scenarios occurs, the algorithm backtracks to other nodes until it checks every possible path originating from the ‘cause’ variable (Thambirajah et al., 2009).

In this study, the ‘cause’ and ‘effect’ variables represent control elements, thus, the elements used in the search are the components which are directly connected to the control elements via signal lines or pipe lines (Thambirajah et al., 2009). The search first begins by checking which equipment elements are attached to the ‘cause’ controller and then proceeds from those elements to find if there is a path leading to the ‘effect’ controller. The prolog code equivalent to this algorithm was described in detail by Yim et al. (2006) while few generic examples for the algorithm implementation were depicted by Thambirajah et al. (2007, 2009).

**Search for a Direct Path**

Once a physical path between the ‘cause’ variable and the ‘effect’ variable is found, an additional unique algorithm is employed to find if it is direct or not. According to (Jiang et al., 2008) a direct interaction between controller $i$ and controller $j$ exists if the output of controller $i$ can directly affect controller $j$ without going through the controller output of any other controller. Based on this concept, the algorithm checks every possible physical path originating from the component connected to controller $i$ to see if it intersects with an element which belongs to a controller that is neither $i$ or $j$. Namely, if the path between controllers $i$ and $j$ traverses a controller that is neither $i$ or $j$, then the path cannot be considered as direct.
In the initial phase of implementation, all the components in the connectivity matrix are classified into four categories: equipment, controllers, sensors and valves. The algorithm checks the type of each element in each physical path that had been found in the previous step. If it finds a control element (i.e., valve, controller or sensor) which belongs to a control loop that is neither the ‘cause’ nor the ‘effect’, the corresponding path is indirect. Otherwise, if the component belongs to the ‘effect’ control loop, the path is direct. The logic behind this algorithm is illustrated in Fig. 1.

3. Process Case Study

In this section, we first describe the process case study. Next, spectral analysis is applied to identify the variables associated with the fault. Finally, the fault propagation analysis is applied along with a demonstration of the search algorithm. The data-driven causal analysis involves the implementation of the time domain Granger causality (GC) while the frequency domain methods are applied as an auxiliary step in order to provide further insights on the level of interactions among the controllers.

3.1. Process Description

The process case study is a large-scale board machine (BM) which produces a three-layer liquid packaging boards and board cups. The analysis is focused on the drying section of the BM since the web conditions in this section such as temperature and moisture content have a significant effect on the board quality, thus, they require proper control and monitoring (Karlsson, 2000). Moreover, due to the high connectivity among the process units
Figure 1: The logic of finding a direct path between two controllers

and the control elements in this section, faults can easily propagate through its subsystems.

In the drying section, the remains of excess water in the web are evaporated to achieve the desirable moisture content in the board using steam-filled drying cylinders. The condensing steam in the cylinders releases latent heat which is used to evaporate the bound water in the web. The condensate from the cylinders is collected by siphons to condensate tanks where steam
and condensate are separated. Steam is then delivered back to the process and condensate is returned to a power plant. A scheme of the drying section and its control loops can be seen in Fig. 2. The drying section contains 74 drying cylinders in total which are divided into six steam groups (SG). Each SG and its corresponding condensate tank (CT) form a single drying group (DG). Each DG has its own controllers to control the steam pressure, the steam pressure difference between steam and condensate headers and the level of the condensate. The pressure controllers (PCs) are used to control steam pressure in each SG using 5 and/or 10 bar pressurized steam headers (denoted as the red lines at the top of Fig. 2). The pressure difference control between the steam headers and the condensate tanks is important for proper operation of the drying section since condensate removal with a siphon requires a proper pressure difference. This is achieved by manipulating the control valves in the steam outlet of the condensate tanks (CTs) using pressure difference controllers. The level of the condensate tanks is controlled by regulating their outlet flow valves using level controllers (LCs).

Valve stiction, one of the main faults in the drying section, has a detrimental effect on the control loops performance and the board quality (Pozo Garcia et al., 2013). The present case study entails a valve stiction in the pressure controller PC1652 and its effect on the interacting loops of the drying section of the board machine. The stiction diagnosis is based on the long-term maintenance records of the plant. The normalized time series of the controlled variables (PVs) are shown in Fig. 3 where the measurement of PC1652 is colored in red. The series were normalized by removing the mean values and scaling to a unit standard deviation. The sampling interval is 10 seconds and
3000 samples were included in the analysis. There were slight changes in the set points during the episode, particularly in control loop PC654 (after 2000 samples). Oscillating signals can be clearly seen in loops PC1653, PC651, PC652, PC653, LC652, PC670, PC1652, PC671, PC672, PC673, LC653 and LC654.
3.2. Variable Subset Selection

The aim of this step is to select the subset of variables which are the most pertinent to the fault. This operation can reduce the dimensionality of the analysis, improve the results and facilitate their interpretation (Yuan & Qin, 2013). Commonly used methods for this purpose are different clustering algorithms, spectral and oscillation analysis or principal component analysis (PCA) (Bauer et al., 2005; Yuan & Qin, 2013). In this study, the power spectra of the time series were examined in order to detect measurements with similar dynamic behavior. The power spectra of the process controlled variables (PVs) can be seen in Fig. 4 where the spectra of PC1652 is shown...
in red.

Figure 4: Spectra of the process measurements (PVs)

The results show that the most prominent oscillation occurs at a frequency of nearly 0.007 Hz (0.07 on the frequency axis) corresponding to $1/0.07 \approx 14$ samples per cycle. The loops oscillating at a common frequency are: PC668, PC1653, PC651, PC652, PC670, LC652, PC1652, PC671, LC653, PC672 and PC673. Thus, the disturbance is mainly affecting SG1, SG2 and SG3.

3.3. Results of the GC Analysis

Seeing that this study is concerned with control loops, the concept of the control loop digraph (Jiang et al., 2008) was adopted for the causal analysis. According to this concept, the GC method was applied by evaluating the influences of the controllers outputs (OPs) on the process controlled variables.
and included only the control loops which were found to be oscillating at the same frequency based on the spectral analysis. The time domain MV (conditional) GC analysis was applied according to Guo et al. (2008). The MAR model estimation was performed using the least squares method and model order was chosen based on the AIC criteria \((p = 10)\). In addition to mean removal and division by standard deviation, further pre-processing of the data was required to ensure that the series are WSS. The stationarity of the series was examined by testing for ‘unit roots’ using the Augmented Dickey-Fuller (ADF) test (Seth, 2010). Time series which were found to be non-stationary were differentiated (i.e., \(x'_t = x_t - x_{t-1}\)). The statistical significance was determined via the \(F\)-statistic test (Granger, 1969) and the results were corrected using the Bonferroni correction for multiple comparisons with a \(p\)-value of 0.01 (Seth, 2010). The initial causality matrix based on the GC analysis is shown in Fig. 5. Each \((i,j)\) entry in the causality matrix is the GC from \(OP_i\) to \(PV_j\). Zeros correspond to GC values which failed the \(p\)-value significance testing.

3.4. Construction of The Causal Model

This step involves the utilization of the search algorithm in order to refine the causality matrix. First, the search algorithm is demonstrated and then the results of the causality matrix refinement are given.

3.4.1. Demonstration of The Search Algorithm

The first example of the output of the search algorithm is given for the entry \((PC_{652} \rightarrow PC_{651})\) in the causality matrix (marked in green in Fig 5) and is presented in Fig. 6. The corresponding connectivity matrix is
7.2   Construction of the causal model

This step involves the utilization of the search algorithm in order to refine the causality matrix. The procedure was implemented on the GC causality matrix according to the scheme presented in Fig. 1. First, the search algorithm is demonstrated and then the results of the GC causality matrix refinement are given.

7.2.1    Demonstration of the search algorithm

An example for the search algorithm output results for the entry \((\text{PC652} \rightarrow \text{PC651})\) in the causality matrix (bolded in green) is presented below:

<table>
<thead>
<tr>
<th></th>
<th>PC1653</th>
<th>PC651</th>
<th>PC652</th>
<th>PC653</th>
<th>PC670</th>
<th>PC1652</th>
<th>PC671</th>
<th>PC673</th>
<th>LC652</th>
<th>PC1652</th>
<th>PC671</th>
<th>LC652</th>
<th>PC673</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1653</td>
<td>-</td>
<td>0</td>
<td>0.072</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.028</td>
<td>0</td>
<td>0.024</td>
<td>0.016</td>
<td>0.016</td>
<td>0</td>
</tr>
<tr>
<td>PC651</td>
<td>0.039</td>
<td>-</td>
<td>0.056</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC652</td>
<td>0.065</td>
<td>0.016</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC653</td>
<td>0.014</td>
<td>0.019</td>
<td>0.017</td>
<td>-</td>
<td>0.017</td>
<td>0</td>
<td>0.024</td>
<td>0.018</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>PC670</td>
<td>0.018</td>
<td>0.029</td>
<td>0.031</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>0.018</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>LC652</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC1652</td>
<td>0.024</td>
<td>0.013</td>
<td>0</td>
<td>0.016</td>
<td>0.018</td>
<td>0</td>
<td>-</td>
<td>0.113</td>
<td>0</td>
<td>0.044</td>
<td>0.032</td>
<td>0</td>
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</tr>
<tr>
<td>PC671</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.016</td>
<td>0.029</td>
<td>0.144</td>
<td>-</td>
<td>0.074</td>
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<td>-</td>
<td>0.012</td>
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<td>LC653</td>
<td>0.105</td>
<td>0.013</td>
<td>0.014</td>
<td>0.015</td>
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<td>0.068</td>
<td>0.019</td>
<td>0.021</td>
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<td>-</td>
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</tr>
<tr>
<td>PC673</td>
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<td>0</td>
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<td>0</td>
<td>0</td>
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<td>0</td>
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<td>0</td>
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<td>0</td>
<td>-</td>
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</tr>
</tbody>
</table>

Checking cause and effect relationship between PI-651 and PI-652...

PI-651 is connected to SG1_Steam_Line
There are 2 feasible propagation paths from SG1_Steam_Line to PI-652...
Path 1 is

SG1_Steam_Line
PI-651
PC-651
PV-651
SG-1
PI-652

There is a direct link between SG1_Steam_Line and PI-652...
The direct path is:

SG1_Steam_Line
SG-1
PI-652

Figure 5: The initial causality matrix based on the GC analysis

shown in Table 1. Note that according to the search algorithm, PV denotes control valve, PI denotes pressure indicator, PC denotes controller, C denotes condensate tank, SG denotes steam group and Steam_Lines denote the pipes providing high pressure steam to the SGs (see Fig. 2).

The algorithm starts by specifying the start and end points of the paths. In this case, the starting and end points are the pressure indicators (PI) of controllers PC651 and PC652. Next, the algorithm finds that PI-651 is connected to the steam line of SG1 and it finds two propagation paths from

<table>
<thead>
<tr>
<th>Element</th>
<th>PI-651</th>
<th>SG1_Steam_Line</th>
<th>PC-651</th>
<th>PV-651</th>
<th>SG-1</th>
<th>PI-652</th>
</tr>
</thead>
<tbody>
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<td>PI-651</td>
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<td>SG1_Steam_Line</td>
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</tr>
<tr>
<td>PC-651</td>
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<td>-</td>
<td>1</td>
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<td>0</td>
</tr>
<tr>
<td>PV-651</td>
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<td>0</td>
<td>-</td>
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<td>0</td>
</tr>
<tr>
<td>SG-1</td>
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<td>0</td>
<td>0</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>PI-652</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
</tbody>
</table>
7.2 Construction of the causal model

This step involves the utilization of the search algorithm in order to refine the causality matrix. The procedure was implemented on the GC causality matrix according to the scheme presented in Fig. 1. First, the search algorithm is demonstrated and then the results of the GC causality matrix refinement are given.

7.2.1 Demonstration of the search algorithm

An example for the search algorithm output results for the entry \((PC652 \rightarrow PC651)\) in the causality matrix (bolded in green) is presented below:

<table>
<thead>
<tr>
<th></th>
<th>PC1653</th>
<th>PC651</th>
<th>PC652</th>
<th>PC653</th>
<th>PC670</th>
<th>LC652</th>
<th>PC1652</th>
<th>PC671</th>
<th>LC653</th>
<th>PC673</th>
</tr>
</thead>
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<tr>
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<td>0.072</td>
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<td>0</td>
<td>0</td>
<td>0.028</td>
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</tr>
<tr>
<td>PC651</td>
<td>0.039</td>
<td>-</td>
<td>0.056</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC652</td>
<td>0.065</td>
<td>0.016</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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</tr>
<tr>
<td>PC653</td>
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<td>0.019</td>
<td>0.017</td>
<td>-0.017</td>
<td>0</td>
<td>0.024</td>
<td>0.018</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC670</td>
<td>0.018</td>
<td>0.029</td>
<td>0.031</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>0.018</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>LC652</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC1652</td>
<td>0.024</td>
<td>0.013</td>
<td>0</td>
<td>0.016</td>
<td>0.018</td>
<td>0</td>
<td>-</td>
<td>0.113</td>
<td>0.044</td>
<td>0.032</td>
</tr>
<tr>
<td>PC671</td>
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<td>0</td>
<td>0</td>
<td>0.016</td>
<td>0.029</td>
<td>0</td>
<td>0.144</td>
<td>-</td>
<td>0.074</td>
<td>0.031</td>
</tr>
<tr>
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<td>0.013</td>
<td>0.014</td>
<td>0.015</td>
<td>0</td>
<td>0.068</td>
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<td>0.021</td>
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</tr>
<tr>
<td>PC673</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
</tbody>
</table>

Checking cause and effect relationship between PI-651 and PI-652...

PI-651 is connected to SG1_Steam_Line
There are 2 feasible propagation paths from SG1_Steam_Line to PI-652...

Path 1 is: SG1_Steam_Line
Path 2 is: SG1_Steam_Line

PI-651
PC-651
PV-651
SG-1
PI-652

There is a direct link between SG1_Steam_Line and PI-652...

The direct path is:
SG1_Steam_Line
SG-1
PI-652

Figure 6: Example 1: The output of the search algorithm for the link \(PC652 \rightarrow PC651\)

the steam line to PI-652. In fact, both paths are the same, but since the SG1 steam line is connected to both PC-651 and to SG1 (see Fig. 2), both paths are identified. However, since path 1 passes through the 'cause' controller, it is not considered as direct and only path 2 is considered therefore as direct. This ensures that the shortest path is identified as direct. In this case, since at least one direct path had been found between the controllers, the corresponding GC value in the causality matrix (0.016) remains. On the other hand, calling the search algorithm for the entry \((PC1652 \rightarrow PC653)\) in the causality matrix (marked in red in Fig. 5) leads to the results shown in Fig. 7.

In this case, the algorithm found five feasible propagation paths from PC1652 to PC653, however none of them is direct since all of them pass
Figure 7: Example 2: the output of the search algorithm for the link PC1652 → PC653 through control loop PC671. Therefore, the corresponding entry in the causality matrix (0.016) is eliminated.

3.4.2. The Refined Causality Matrix and The Causal Model

The refined GC causality matrix (i.e., after all the non-zero entries have been checked by the search algorithm) is shown in Fig. 8. All the GC values which correspond to non-direct interactions based on the process connectivity have been set to zero. The causal model based on the refined causality matrix
In this case, the algorithm found five feasible propagation paths from PC1652 to PC653; however, none of them is direct since all of them pass through control loop PC671. Therefore, the corresponding entry in the causality matrix (0.016) is eliminated.

### 7.2.2 The refined causality matrix and the causal model

The refined GC causal matrix (i.e., after all the non-zero entries have been checked by the search algorithm) is shown in Figure 9. All the GC values which correspond to non-direct interactions based on the process connectivity have been set to zero. The causal model based on the refined causality matrix is shown in Figure 10.

<table>
<thead>
<tr>
<th></th>
<th>PC1653</th>
<th>PC651</th>
<th>PC652</th>
<th>PC653</th>
<th>PC670</th>
<th>LC652</th>
<th>PC1652</th>
<th>PC671</th>
<th>LC653</th>
<th>PC673</th>
</tr>
</thead>
<tbody>
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<tr>
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<tr>
<td>PC653</td>
<td>0</td>
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<td>0</td>
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<td>0.113</td>
<td>0.044</td>
<td>0</td>
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<td>PC671</td>
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<td>0</td>
<td>0</td>
<td>0.016</td>
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<td>0</td>
<td>0.144</td>
<td>-</td>
<td>0.074</td>
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</tr>
<tr>
<td>LC653</td>
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<td>0.013</td>
<td>0.014</td>
<td>0</td>
<td>0</td>
<td>0.068</td>
<td>0</td>
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</tr>
<tr>
<td>PC673</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>-</td>
</tr>
</tbody>
</table>

Figure 8: The refined causality matrix based on the GC analysis

The search algorithm was able to eliminate most of the redundant results from the GC analysis, however the model was still assumed to have few redundant arcs (denoted by the dashed arcs in Fig. 9 and highlighted entries in Fig. 8) based on process knowledge. The links $LC653 \rightarrow PC651$ and $LC653 \rightarrow PC652$ were identified as direct since the level controller LC653 discharges the condensate from CT4 into CT3 and the steam outlet of CT3 is discharged to SG1 (see Fig. 2), thus affecting the pressure in SG1. However, LC653 primarily affects the level of CT3 while the steam pressure of SG1 is mainly affected by PC670. Similarly, the pressure controller PC1652 directly affects the pressure difference in SG3 rather than the level of CT4. Those types of ambiguous results are sometimes inevitable and in-depth process knowledge is needed to detect them. Nonetheless, the search algorithm was able to eliminate approximately 88% of the spurious results obtained from the GC analysis, herewith affirming the efficacy of the refinement procedure.
3.5. Frequency Domain Analysis

As discussed above, the search algorithm was able to eliminate most of the spurious results from the GC analysis, however, due to the high level of connectivity among the controllers in the drying section, the causal model indicates on multiple propagation paths. Furthermore, the causal model in Fig. 9 implies on two possible root causes: PC1652 and PC671 since only those controllers can affect all the other ones. Thus, it is essential to identify the most powerful interactions in order to determine the most probable propagation path. Consequently, the frequency domain analysis was applied as an auxiliary step. The frequency domain analysis is especially useful if the oscillation period in known. In particular, we utilized the PDC to validate the refined causal model due to its ability capture the direct causal interactions. On the other hand, the DTF was used to isolate the root cause.
3.5.1. Results of the Frequency Analysis

The frequency domain analysis was applied by evaluating the values of the PDC and the DTF between each pair of PVs. The MAR model \((p = 10)\) was estimated similarly as in the GC analysis. Some of the diagonal variance terms of the noise covariance matrix differed by order of magnitude. Therefore, the PDC and the DTF were calculated according the renormalization offered by Baccala et al. (2007) and Yameshita et al. (2005) respectively. The thresholds for the statistical significance of the PDC and DTF were determined using the Direct Causal Fourier Transform (CFTd) and the Full Causal Fourier Transform (CFTf) surrogates respectively (Faes et al., 2010). The threshold for significance for each computed value at each frequency was set at the 95\(^{th}\) percentile of the empirical distribution of the PDC/DTF values computed over 100 sets of multivariate surrogate series. Due to the ability of the PDC to reveal only the direct interactions among variables, the plots of the PDC values of each pair of variables in the model were utilized in order to identify the most prominent propagation path. This approach is especially useful in this case study due to the high number of mutual interactions among the controllers. The PDC grid of plots are shown in Fig. 10. The PDC plots clearly show that the links \(LC653 \rightarrow PC052, LC653 \rightarrow PC651, PC1652 \rightarrow LC653\) which were previously assumed to be specious are indeed most likely indirect. Therefore, the assumptions made earlier are reasonable. The maximum PDC and DTF values corresponding to the plots are shown in Table 2 with the most powerful interactions highlighted in gray.

In order to isolate the root cause, the DTF was utilized since it can be
seen as the ‘amount’ of variation originated from each ‘cause’ variable to the ‘effect’ variable through direct and indirect paths (Gigi & Tangirala, 2010). Under this logic, the variable which ‘contributed’ the most to the variation in the process can be seen as the root cause of a disturbance. Furthermore, since the spectral analysis revealed a common oscillation at the frequency of 0.007 Hz, the sum of the DTF originating for each source \( j \) at that frequency was calculated (i.e., \( \sum_{i=1}^{N} |h_{ij}(0.007)|^2 \)). The results are shown in Figure 11.

The results confirm that control loop PC1652 is the root cause of the disturbance. Since PC1652 is highly interacting with the pressure difference controller PC671, the latter also significantly contributes to the variation in
Table 2: The maximum of the PDC and DTF of each link in the causal model

<table>
<thead>
<tr>
<th>Link</th>
<th>Max PDC</th>
<th>Max DTF</th>
</tr>
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<tbody>
<tr>
<td>$PC_{651} \rightarrow PC_{652}$</td>
<td>0.486</td>
<td>0.482</td>
</tr>
<tr>
<td>$PC_{652} \rightarrow PC_{1653}$</td>
<td>0.441</td>
<td>0.407</td>
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<td>0.221</td>
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<td>0.808</td>
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<td>0.417</td>
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</tr>
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<td>0.812</td>
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<td>0.749</td>
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the process. Finally, considering the results from the frequency analysis, the propagation path of the valve stiction in loop PC1652 is depicted in Fig. 12.

The oscillation caused by the stiction will initially propagate to the closely interacting loop PC671 which will primarily affect the pressure in the successive SG but also the level of condensate in CT4. From SG3 the oscillation will continue to propagate to SG2 (simultaneously affecting the pressure and pressure difference controllers) until it finally reaches SG1.
Figure 11: Sum of the magnitude of the DTF originating from each 'cause' variable at the frequency of 0.007 Hz

Figure 12: The propagation path of valve stiction originating in loop PC1652
4. Conclusions and Future Directions

This paper introduced a fault propagation analysis by the virtue of the automatic consolidation of data-driven causal analysis with topology-based model using a dedicated search algorithm. This combination results in an enhanced causal model due to the ability of the search algorithm to eliminate indirect interactions from the causality matrix.

The fault propagation analysis was successfully applied to a case study of a drying section of an industrial board machine where the search algorithm was able to eliminate most of the spurious results of the causal analysis. However, several redundant links remained in the causal model in spite of the refinement procedure, thus, process expert knowledge was essential in eliminating those. Alternatively, numerous data-driven methods can be employed in order to construct the causality matrix prior to the refinement procedure, particularly, in cases where the system is with a high degree of connectivity among variables.

A number of caveats need to be noted regarding the present study. First, the study was focused only on one case study with a specific fault (valve stiction). Thus, other case studies with different sources of oscillation should be examined in order to attain a more precise evaluation of the proposed analysis. Secondly, so far, only an oscillatory disturbance has been investigated. In the future, the proposed fault propagation analysis can be used to study how different types of faults propagate in a system and accordingly select the critical variables for monitoring. Moreover, studying how different faults propagate can facilitate their diagnosis; thereby, the source of the fault can be eliminated before it severely deteriorates the quality of the final product.
Acknowledgements

The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under Grant Agreement No. 257580. Especially, the authors would like to thank Stora Enso Oyj for providing the data and the expert knowledge for the analysis.

List of Figures

1  The logic of finding a direct path between two controllers . . .  15
2  Flow sheet of the drying section. Red lines indicate steam pipes, blue lines indicate condensate pipes and purple lines indicate mixed flow of steam and condensate (PI=pressure indicator, PC=pressure controller, LC=level controller, SG=steam group, C= condensate tank) . . . . . . . . . . . . . . . . . . . . . .  17
3  Process measurements . . . . . . . . . . . . . . . . . . . . 18
4  Spectra of the process measurements (PVs) . . . . . . . . . . . 19
5  The initial causality matrix based on the GC analysis . . . . . 21
6  Example 1: The output of the search algorithm for the link $PC652 \rightarrow PC651$ . . . . . . . . . . . . . . . . . . . . . . . . . 22
7  Example 2: The output of the search algorithm for the link $PC1652 \rightarrow PC653$ . . . . . . . . . . . . . . . . . . . . . . . . . 23
8  The refined causality matrix based on the GC analysis . . . . . 24
9  The causal model obtained from the refined causal matrix . . 25
The PDC values (blue lines) at each frequency between each pair of variables in the causal model and their corresponding threshold for significance estimated by the CFTd surrogates (red lines). $x$-axis: frequency (Hz), $y$-axis: magnitude of the PDC.

Sum of the magnitude of the DTF originating from each ‘cause’ variable at the frequency of 0.007 Hz.

The propagation path of valve stiction originating in loop PC1652.

References


