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Published in:
Control Engineering Practice

DOI:
10.1016/j.conengprac.2016.04.010

Published: 01/08/2016

Please cite the original version:
Hybrid approach to casual analysis on a complex industrial system based on transfer entropy in conjunction with process connectivity information

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Abstract

Industrial processes often encounter disturbances that propagate through the process units and their control elements, leading to poor process performance and massive economic losses. Thus, one major concern in the chemical industry is the detection of disturbances and identification of their propagation path. Causal analysis based on process data is frequently applied to identify causal dependencies among process measurements and thereby obtain the propagation path of disturbances. One significant challenge in data-based causal analysis is investigating industrial systems with a high degree of connectivity due to multiple causal pathways. This paper proposes a new hybrid approach for detecting causality based on the transfer entropy (TE) method by incorporating process connectivity information using an explicit search algorithm. Based on the hybrid approach, initially, the TE is only calculated for pathways that are considered as direct pathways based on the process topology. Then, the direct transfer entropy (DTE) is employed to discriminate spurious and/or indirect pathways obtained by the initial TE results.
To facilitate the DTE calculation, the search algorithm is invoked once again to extract the intermediate pathways. This concept is demonstrated on an industrial board machine. In particular, the propagation path of an oscillation due to valve stiction within multiple control loops in the drying section of the machine is studied. Finally, the results are discussed and evaluated.

Keywords: Transfer entropy, causality, process connectivity, propagation path, control loops, board machine

1. Introduction

Industrial systems are often subjected to abnormal conditions, known as faults which lead to a deviation in one or more of the system properties (Isermann & Ball, 1996). Undesired process conditions deteriorate the product quality, increase operational costs, and potentially lead to hazardous situations. Furthermore, the complexity of modern industrial systems imposes additional challenges in the control and monitoring of those conditions. In recent years, there has been an increasing demand from the process industry for an efficient tool that can detect and diagnose disturbances (Thornhill et al., 2003; Yang et al., 2012). In particular, when an abnormal event occurs, one major challenge is to identify the root cause of the event and the fault propagation path. The identification is usually performed by investigating the causal dependencies among the process measured variables. Essentially, identifying the cause-and-effect relationships among the process variables is a crucial step in fault diagnosis, alarm management, and incident investigations (Yu & Yang, 2015; Shu & Zhao, 2013).

In recent years, data-driven methods have been widely used for investi-
gating the causal interactions among process variables in the form of a time series. Methods such as the cross-correlation (Bauer & Thornhill, 2008), Granger causality (Granger, 1969), and transfer entropy (Schreiber, 2000) have attracted attention of many scientists and engineers since they do not necessarily require deep process knowledge in order to obtain satisfactory results. In addition, the process measurements are usually readily available. However, recent studies (Landman et al., 2014; Thambirajah et al., 2007; Yang et al., 2012) suggest that process knowledge, in particular, the information on process connectivity, is essential for validating the results of data-based methods. Therefore, there have been several attempts to combine data-driven causal analysis with topology-based models (Di Geronimo Gil et al., 2011; Landman et al., 2014; Thambirajah et al., 2007, 2009; Yang et al., 2012). Topology-based models describe the physical connectivity among the process elements and are typically derived from a process flow diagram (PFD) or from the piping and instrumentation diagram (P&ID) (Di Geronimo Gil et al., 2011).

This study is focused on the transfer entropy (TE) method. The TE method is perhaps the most commonly used method for evaluating causal relationships in non-linear systems by quantifying the amount of information transfer among time series (Schreiber, 2000). TE can be seen as an approximation of the predictability improvement when estimating series $y$ based on the past values of series $x$ and $y$ compared with the past values of $y$ alone. TE has been successfully applied to various applications for estimating causal dependencies between time series (Bauer et al., 2007; Duan et al., 2014a; Lee et al., 2012; Yang et al., 2012; Yu & Yang, 2015). Recently,
literature has emerged that offers modifications to the method, and several new measures based on TE have been proposed. Feldmann & Bhattacharya (2004) introduced the concept of predictability improvement, which is analogous to the concept of TE, but it is also applicable to short time series by considering nearest neighbors. Shu & Zhao (2013) introduced a modification to the TE method, which enables effective estimation of the time delay based on the prediction horizon. Vakorin et al. (2009) introduced the partial TE, which considers the environmental variables in an interacting network. Duan et al. (2014b) proposed a new measure for causal analysis, the transfer 0-entropy method based on 0-entropy and 0-information without the assumption of probability space.

The main complexity of the TE implementation arises from the probability density function (PDF) computations, which is required for estimating the multi-dimensional conditional and joint probabilities. Typically, the kernel estimation method is used for the PDF estimation; however, the computational burden of this method significantly increases with the dimensionality of the analysis. Despite recent investigations, no alternative method has been presented that would offer more accurate and less burdensome estimation. Furthermore, determining the TE parameters such as the prediction horizon and the embedding dimensions is not a straightforward task and requires a significant computation time. Numerous studies have proposed methods for selecting the embedding dimensions (Kim et al., 1998; Small & Tse, 2004). Bauer et al. (2007) performed several simulations on a reference case study and provided guidelines for setting the initial TE parameters. Based on those recommendations, Duan et al. (2013) proposed a procedure for determining
the embedding dimensions.

Moreover, the traditional TE method is suitable for bivariate analysis, i.e., it does not distinguish between direct and indirect interactions. When investigating large-scale systems with a high degree of connectivity, it is essential to determine whether the interactions occur along direct or indirect pathways in order to obtain the propagation path. Vakorin et al. (2009) proposed the partial transfer entropy method, which considers the effect of indirect influences on the causal interactions in a multivariable environment. However, partial TE is defined such that all the environmental variables are considered to be intermediate, which is not necessarily true in chemical processes. On the other hand, Duan et al. (2013) introduced the direct transfer entropy (DTE) method, which discriminates between direct and indirect causal relationships in both linear and non-linear processes. More specifically, the DTE method is able to reveal whether the interaction is direct or indirect by considering the connectivity among intermediate variables. Furthermore, Duan et al. (2013) suggested quantification of the TE magnitude by defining the normalized differential TE \(NTE_{diff}\) and the normalized differential DTE \(NDTE_{diff}\), which provide an estimation of the strength of the interactions (Duan et al., 2013). Difficulties arise, however, when the DTE/NDTE method is implemented on a large complex system.

The main challenge in applying the TE on a complex system can be attributed to the following factors: PDF estimation, TE parameter estimation, determination of a statistical threshold for the results, and the treatment of highly connected networks. The primary aim of this investigation is to consider the latter issue by reducing the computational load. Large-scale systems
do not only increase the computational burden of the analysis but also extend
the difficulty of interpreting the results, especially if the network topology
is complex. For example, the topologies of processes with numerous recycle
streams and/or multiple pathways originating from a single unit are difficult
to capture precisely.

Thus, this study proposes a new hybrid approach for applying the TE
method by considering the process connectivity information in the form of
an adjacency (i.e., connectivity) matrix (Jiang et al., 2008), which can be
extracted from a P&ID of the process. The connectivity information is in-
corporated into the TE analysis by means of an explicit search algorithm
(Landman et al., 2014). The search algorithm is employed for two purposes:
first, to determine whether a path between two controllers is direct or indi-
rect, and then to extract the indirect pathways between two controllers using
the adjacency matrix. The analysis consists of two phases. In phase I, the bi-
variate TE is calculated only for the interactions that are considered as direct
according to the output of the search algorithm and an initial causal model
is obtained. In phase II, the interactions that are suspected to be spurious
or indirect are further examined by calculating the DTE. In this phase, the
search algorithm is utilized once again to retrieve the intermediate variables
of the indirect pathways. Consequently, this approach has several advantages
over the traditional TE analysis: First, the computational time is reduced
since not all the TE values are calculated, but only the ones that correspond
to interactions that are considered as direct based on the process topology.
Second, the results are easier to interpret and an initial causal model can
be obtained without determining a statistical threshold. Third, we tackle
the complexity of a highly connected system in phase II by extracting the
intermediate variables via the search algorithm. Consequently, the analysis
becomes more automated and efficient.

The investigation takes the form of a case study of an industrial board
machine with a persistent oscillation in its drying section due to valve stiction.
In particular, this study examines the propagation path of an oscillation
among controllers in the drying section. This paper is organized as follows.
In section 2, the overall approach for the TE implementation using process
connectivity information is described, including the extraction of connectivity
information from a P&ID and the implementation of TE and DTE. The case
study, the analysis and the results are introduced in Section 3. Finally, the
summary and conclusions are given in section 4.

2. The overall approach for TE analysis

The overall hybrid approach for implementing the TE using a dedicated
search algorithm shown in Figure 1. Initially, a topology-based model in the
form of a connectivity matrix is generated from a P&ID. The TE analysis
is performed in two phases: in phase I an initial causal model is generated
according to the TE while in phase II the model is further refined to exclude
indirect interactions according to the DTE. The search algorithm is utilized to
incorporate the connectivity information into both phases of the TE analysis
as depicted in Figure 1. In the following subsections a detailed description
of each step in the analysis is given. First, a procedure of generating a
topology-based model is described. Next, the logic of the hybrid approach
for TE analysis and the search algorithm are explained in detail. Finally, a
2.1. Generating a topology-based model

Generating a topology-based model based on a process schematic (P&ID) is a practical method for extracting the physical connectivity information among process components and is often used for causal analysis of disturbances and alarm logs (Schleburg et al., 2013). Moreover, P&IDs are readily available in XML-based formats, which enables the extraction of a text document describing the process equipment and instrumentation along with their properties and connectivity (Schleburg et al., 2013).

In the current study, the connectivity information was extracted from an electronic P&ID drawn by a specialized Autodesk AutoCAD P&ID drafting application, which was developed based on Autodesk AutoCAD (Landman et al., 2014). The topology data generation includes the following steps.
First, a drawing which indicates all information on the initial and terminal components of each pipe-line and control signal is generated. Then, this information is retrieved via the database object of the drawing that includes all the connectivity information, namely, the component names, their coordinates and their connectivity. Finally, this information is further processed in a MATLAB programming environment and converted into a topology-based model. (Sun, 2013)

There are two types of topology-based models, the causal digraph and connectivity (adjacency) matrix, which can be considered to be a graphical and numerical representation of the drawing, respectively. In this study, the connectivity matrix, which is a binary matrix whose elements are assigned as '1' if there is a direct connection from the row element to the column element and '0' otherwise is utilized (Sun, 2013; Thambirajah et al., 2009).

2.2. The hybrid approach for calculating TE using connectivity information

The implementation consists of two consecutive phases. In phase I, all physical pathways from each controller \(i\) to controller \(j\) are examined. This study investigates causal dependencies among control loops; thus, the measurements of the process-controlled variables (PVs) are investigated. If there is no physical path, it can be concluded that there is no causal influence from controller \(i\) to controller \(j\). Next, the algorithm determines if there is a direct path between the two controllers. If a direct path exists, the TE from controller \(i\) to \(j\) is calculated.

Phase II focuses on all the interactions that are suspected to be indirect or spurious based on the initial causal model and our process knowledge. For each path from controller \(i\) to controller \(j\) that is suspected as indirect the
DTE is calculated by considering all the possible physical pathways between controller $i$ to $j$. When investigating small-scale systems, the indirect paths can be easily fetched manually. On the other hand, in complex systems, it would take a great deal of time and effort to determine manually all physical pathways between all variables involved. The search algorithm makes this procedure notably faster and efficient, thereby reducing the computational effort. Initially, the search algorithm returns all possible pathways from controller $i$ to $j$, then, it retrieves the intermediate controllers for each path. Note that the algorithm “ignores” paths traversing controllers that are not part of the investigation. Once the intermediate variables are obtained using the search algorithm, the DTE is calculated for each path. This procedure is repeated for all physical pathways from controller $i$ to $j$. The logic of the overall approach is illustrated in Figure 2. The flowchart on the left side of Figure 2 describes phase I, while the flowchart on the right side describes phase II.

2.3. TE implementation

The TE method can be seen as an improvement of the prediction of $y$ using the past values of both $x$ and $y$ compared to the past information of $y$ alone. Let $y(i+h1)$ denote the value of $y$ at instant $i+h1$, where $h1$ is referred to as the prediction horizon. Here, $y_i^{k_1} = [y_i, y_{i-\tau_1}, \ldots, y_{i-(k_1-1)\tau_1}]$ and $x_i^{l_1} = [x_i, x_{i-\tau_1}, \ldots, x_{i-(l_1-1)\tau_1}]$ denote embedding vectors with elements from the past values of $y$ and $x$, respectively, where $k_1$ and $l_1$ are the embedding dimensions of $y$ and $x$, respectively. Moreover, $\tau 1$ is the time interval that allows the time scaling of the embedding vector, which is usually set to be $\tau 1 = h1 \leq 4$. (Bauer et al., 2007; Duan et al., 2013)
Figure 2: The procedure for calculating TE based on the process connectivity: Phase I (left) and Phase II (right). TE=Transfer Entropy, NTE=Normalized Transfer Entropy, DTE=Direct Transfer Entropy, NDTE=Normalized Direct Transfer Entropy
This study focuses on the differential TE ($TE_{diff}$) for continuous variables since chemical processes are continuous. The $TE_{diff}$ is defined as:

$$T_{x\rightarrow y} = \int f(y_{i+h_1}, y_i^{k_1}, x_i^{l_1}) \cdot \log \frac{f(y_{i+h_1} | y_i^{k_1}, x_i^{l_1})}{f(y_{i+h_1} | y_i^{k_1})} dw$$ (1)

where $f(y_{i+h_1}, y_i^{k_1}, x_i^{l_1})$ is the joint PDF, and $f(\cdot | \cdot)$ denotes the conditional PDF. The base of the logarithm is 2, and $w$ denotes the random vector $[y_{i+h_1}, y_i^{k_1}, x_i^{l_1}]$. (Duan et al., 2013).

In general, TE does not distinguish between direct and indirect interactions. Duan et al. (2013) proposed the DTE in order to detect whether a direct information transfer exists between two signals. The differential DTE ($DTE_{diff}$) from $x$ to $y$ considering intermediate variable $z$ is defined as

$$D_{x\rightarrow y} = \int f(y_{i+h}, y_i^k, z_{i+h-h_3}^{m_2}, x_i^{l_1}) \cdot \log \frac{f(y_{i+h} | y_i^k, z_{i+h-h_3}^{m_2}, x_i^{l_1})}{f(y_{i+h} | y_i^k, z_{i+h-h_3}^{m_2})} dv$$ (2)

where $v$ denotes the random vector $[y_{i+h}, y_i^k, z_{i+h-h_3}^{m_2}, x_i^{l_1}]$. Here, $h_3$ and $k_2$ are the prediction horizon and the embedding dimension of $y$ when calculating $T_{z\rightarrow y}$, respectively, while $z^{m_2}$ is the embedding vector with time interval $\tau_3$. The prediction horizon is set to be $h = max(h_1, h_3)$. If $h = h_1$, then $y_i^k = y_i^{k_1}$, and if $h = h_3$, then $y_i^k = y_i^{k_2}$ (Duan et al., 2013).

Moreover, $DTE_{diff}$ represents the future information about $y$ obtained from past observations of $x$ and $z$ compared with the past information of $z$ alone. Eq. 2 can be extended to multiple intermediate variables if the causal effect of $x$ on $y$ is considered via the pathway of $z_1, z_2, z_3, \ldots, z_q$. 

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The calculation proceeds according to Eq. 2, except the $q$-dimensional vector \$z_{s1,1}, z_{s2,1}, \ldots, z_{sq,i_q}\$ is considered as the intermediate variable. Here, $s_1, s_2, \ldots, s_q$ and $i_1, i_2, \ldots, i_q$ are determined by calculating TE from $z_1, z_2, \ldots, z_q$ to $y$ (Duan et al., 2013).

A normalization is required to quantify the strength of the causal relationships. The normalized differential TE ($NTE_{diff}$) is defined as (Duan et al., 2013):

$$NTE_{x \rightarrow y}^c = \frac{2^{H^c(y_{i+h1}|y_i^{k1})} - 2^{H^c(y_{i+h1}|y_i^{k1}, x_i^{l1})}}{2H_0 - 2^{H^c(y_{i+h1}|y_i^{k1}, x_i^{l1})}} \in [0, 1]$$  \hspace{1cm} (3)

where $H_0 = \log(y_{\text{max}} - y_{\text{min}})$ and $y_{\text{max}}$ and $y_{\text{min}}$ are the maximum and minimum values of $y$, respectively. $H^c(y_{i+h1}|y_i^{k1})$ and $H^c(y_{i+h1}|y_i^{k1}, x_i^{l1})$ are the differential conditional entropies. Similarly, the normalized DTE ($NDTE_{diff}$) is defined as

$$NDTE_{x \rightarrow y}^c = \frac{D_{x \rightarrow y}}{H^c(y_{i+h1}|y_i^{k1}) - H^c(y_{i+h1}|y_i^{k1}, z_{i+h-h3}, x_i^{l1})} \in [0, 1]$$  \hspace{1cm} (4)

where $H^c(y_{i+h1}|y_i^{k1})$ and $H^c(y_{i+h1}|y_i^{k1}, z_{i+h-h3}, x_i^{l1})$ are the differential conditional entropies. $NDTE_{diff}$ is the amount of information transferred from $x$ to $y$ via direct pathway compared to the total amount of information transferred to $y$ from both $x$ and $z$ (Duan et al., 2013).

2.3.1. Estimation of $TE_{diff}$ and $DTE_{diff}$

In this study, $TE_{diff}$ from $x$ to $y$ (Eq. 1) can be approximated by

$$T_{x \rightarrow y} = \frac{1}{N - h1 - r + 1} \sum_{i=r}^{N-h1} \log \frac{f(y_{i+h1}|y_i^{k1}, x_i^{l1})}{f(y_{i+h1}|y_i^{k1})}$$  \hspace{1cm} (5)
where $N$ is the number of samples and $r = \max\{(k_1 - 1)\tau_1 + 1, (l_1 - 1)\tau_1 + 1\}$ (Duan et al., 2013).

Similarly, based on Eq. 2, $DTE_{diff}$ can be approximated by

$$DTE_{x\rightarrow y} = \frac{1}{N - h - j + 1} \sum_{i=j}^{N-h} \log \frac{f(y_i+h|y_i^k, z_{i+h-h_3}^{m_2}, x_{i+h-h_3}^{l_1})}{f(y_i+h|y_i^k, z_{i+h-h_3}^{m_2})}$$

(6)

where $j = \max\{(k_1 - 1)\tau_1 + 1, (k_2 - 1)\tau_3 + 1, -h + h_3 + (m_2 - 1)\tau_3 + 1, -h + h_1 + (l_1 - 1)\tau_1 + 1\}$ (Duan et al., 2013).

2.3.2. Estimation of the PDF

The PDF estimation has a pivotal role in the TE calculation. In fact, this step is crucial both in terms of accuracy and computational burden. The most widely used method for estimating the PDF is kernel estimation. The kernel estimation of the joint PDF can be performed using the Fukunaga method (Silverman, 1986).

Considering $q$-dimensional vectors $[X_1, \ldots, X_N](X_i \in \mathbb{R}^q)$, the kernel estimation for the $q$-dimensional vector $[x_1, \ldots, x_q]^{T}$ is

$$\hat{f}(x) = \frac{(\text{det}S)^{-1/2}}{N\Gamma_{q}^{2}} \sum_{i=1}^{N} K\{\Gamma^{-2}(x - X_i)^{T}S^{-1}(x - X_i)\}$$

(7)

where $\Gamma$ is the bandwidth, which is calculated by $\Gamma = 1.06N^{-1/(4+q)}$, $S$ is the covariance matrix of the data, and $K$ is the Gaussian kernel function:

$$K(u) = (2\pi)^{-q/2}e^{-\frac{1}{2}u}$$

(8)

From Eq. 7, it is evident that the number of samples and the embedding dimensions of the vectors determine the computational complexity of the PDF estimation. Hence, these values should be selected carefully. Moreover,
the number of the intermediate variables in the calculation of $DTE_{diff}$ has a substantial impact on the computational burden of the PDF estimation.

2.3.3. Estimation of the TE parameters

Estimating the TE parameters (i.e., the prediction horizon ($h$), the time interval ($\tau$), and the embedding dimensions of all variables involved) is another crucial step that not only affects the credibility of the results but also contributes to the computational burden. Bauer et al. (2007) performed several simulations on a reference case study in order to determine the optimal parameters for the embedding dimensions, minimum number of samples, time interval and prediction horizon.

In this study, the optimal parameters were determined based on the suggestion of Duan et al. (2013). First, the initial prediction horizon and time interval values were set based on the suggestion of Bauer et al. (2007). Then, for each variable, the embedding dimension was determined by calculating the differential conditional TE of each variable for different embedding dimensions. Finally, the embedding dimension for each pair of variables was determined by calculating $TE_{x_i \rightarrow y_i}$ for different embedding dimensions of $x_i$. The selected embedding dimensions are the minimum of the above values in which the change rate of the differential conditional entropies and TE do not vary significantly (Duan et al., 2013).

It is evident that, even for a single pair of variables, the task of determining all TE parameters is very time consuming and becomes extremely tedious, especially as the number of variables increases. However, according to Duan et al. (2013), the DTE parameters can be determined based on the TE parameters. Therefore, the inclusion of intermediate variables in the
DTE calculation does not increase the computational effort with regard to the parameters estimation.

3. Process case study

In this section, an industrial board machine case study is investigated using the approach described in Section 2. The results are then discussed and evaluated.

3.1. Process description

The process case study involves a large-scale board machine (BM) that produces three-layer liquid packaging and board cups. In particular, the analysis is focused on the drying section of the machine, where the remains of the excess water in the web are removed to achieve the desired moisture content. The drying section consists of six drying groups (DGs), each of which includes a steam group (SG) containing steam filled cylinders and a condensate tank (CT), where the condensate is collected by syphons and separated into water and steam. Each DG has three types of controllers: pressure controllers, which provide steam for each SG using 5 and/or 10 bar pressurized steam headers; pressure difference controllers, which are used to manipulate the steam outlet of the CTs in order to maintain the proper pressure difference between each SG and its CT for allowing efficient condensate removal; and level controllers, which are used to maintain the appropriate condensate level in the CTs by regulating their outlet flow. The entire drying section is illustrated in Figure 3.

The current study investigates the propagation of oscillation among control loops. Oscillations in control loops are very common in industrial systems
Figure 3: The drying section of the BM. Red pipelines denote steam, purple pipelines denote a mixture of condensate and steam, and blue pipelines denote condensate. SG=Steam Group, PC=Pressure Controller, C=Condensate tank, LC=Level Controller, PI=Pressure Indicator

and are typically caused by valve stiction (static friction), poor control tuning or controller interactions (Hägglund, 1995). The current case study focuses on oscillation caused by valve stiction in the pressure controller PC1652 of DG3. The cyclic nature of a stiction typically manifests as oscillatory behavior of the control loops because the stiction delays the valves movement without changing the process inputs. Oscillations generated by valve stiction can easily propagate among control loops and eventually deteriorate the overall control performance (Pozo Garcia et al., 2013).

Determining the propagation path of an oscillation is helpful for identifying its root cause and for understanding how it affects the neighboring control loops. The stiction was initially diagnosed by applying the stiction detection system proposed by Zakharov et al. (2013) and was later confirmed
Figure 4: The time series of the PVs in the drying section. The PV originating in the sticky valve, PC1652, is colored in red.

based on long-term maintenance records of the plant. The time series corresponding to the process measurement (PVs) are shown in Figure 4. In this study, 3000 samples with a sampling interval of 10 s were collected for the analysis. Prior to the investigation, the series were normalized by removing the mean and scaling to a unit standard deviation. A persistent oscillation is present in control loops PC1653, PCC651, PC652, PC653, PC670, PC1652, PC671, PC672, PC673, LC653, and LC654.

3.2. Variable subset selection

It is essential to select the variables that are pertinent to the fault prior to the investigation. This step has several benefits. It reduces the dimensionality of the analysis, which is highly important in the case of TE, and the results are more reliable and easier to interpret (Yuan & Qin, 2013). Some
common clustering methods include principle component analysis, spectral analysis, and oscillation analysis (Bauer et al., 2005; Yuan & Qin, 2013).

Due to the oscillatory behavior of the time series, the power spectra of the series were examined in order to detect measurements with a similar spectral behavior. The power spectra of the series are shown in Figure 5. The spectra reveal that the most pertinent oscillation occurs at a frequency of 0.007Hz (14 samples per cycle). The control loops which share this common oscillation frequency are: PC1653, PC651, PC652, PC653, PC670, LC652, PC1652, PC671, LC653 and PC673.

![Figure 5: The spectra of the time series (PVs) (The spectra of the signal originating in the sticky valve PC1652 is shown in red)](image)

3.3. Implementation of the TE

The TE implementation follows the approach described in Section 2. The analysis was performed on the measurements corresponding to the control
loops, which were found to be oscillating at the same frequency based on the spectral analysis. The TE parameters were estimated based on the steps and recommendations provided in (Duan et al., 2013), while the PDFs were estimated using the kernel estimation method (Eq. 7). The collected data should be stationary in order to obtain a satisfactory PDF estimation (Bauer et al., 2007). In this case, the stationarity of the time series was verified by testing for unit roots using the augmented Dicky–Fuller (ADF) test (Seth, 2010). Two series were found to be non-stationary due to a slight change in their set-points and were differentiated.

First, the TE was applied without the search algorithm, i.e., the TE was calculated between each of the controlled variables. The results are summarized in Table 1.

<table>
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<tr>
<th></th>
<th>PC1653</th>
<th>PC651</th>
<th>PC652</th>
<th>PC653</th>
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<td>0.754</td>
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<tr>
<td>PC671</td>
<td>0.967</td>
<td>0.903</td>
<td>0.822</td>
<td>1.132</td>
<td>0.895</td>
<td>0.760</td>
<td>0.513</td>
<td>-</td>
<td>0.996</td>
<td>0.911</td>
</tr>
<tr>
<td>LC653</td>
<td>1.095</td>
<td>0.877</td>
<td>0.823</td>
<td>0.932</td>
<td>1.197</td>
<td>0.859</td>
<td>0.554</td>
<td>0.654</td>
<td>-</td>
<td>0.945</td>
</tr>
<tr>
<td>PC673</td>
<td>0.926</td>
<td>0.843</td>
<td>0.820</td>
<td>0.768</td>
<td>0.840</td>
<td>0.739</td>
<td>0.374</td>
<td>0.788</td>
<td>0.762</td>
<td>-</td>
</tr>
</tbody>
</table>

A brief inspection of Table 1 reveals that the results interpretation is highly laborious since most of the TE values are relatively high (> 0.8). Hence, without calculating a statistical threshold, obtaining a reliable causal model is nearly impossible. Therefore, the TE was applied once again in
conjunction with the search algorithm, according to the logic presented in Figure 2 (phase I). Namely, TE/NTE was calculated provided that there is a direct path between two controllers based on the search algorithm. Consequently, the empty cells indicate one of the following: there is no physical connectivity between the controllers, or the path is indirect. Tables 2 & 3 show the calculated TE and NTE values from the row elements to the column elements, respectively. As expected, high TE values correspond to high NTE values and vice versa.

Table 2: The calculated TE values between each of the controllers. The highlighted values denote a causality that is suspected to be spurious or indirect.

<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>
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<tbody>
<tr>
<td>PC1653</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>PC651</td>
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<td>0.961</td>
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</tr>
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<td>PC652</td>
<td>0.837</td>
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<tr>
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</tr>
<tr>
<td>PC670</td>
<td>0.830</td>
<td>0.761</td>
<td>0.879</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>LC652</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>0</td>
</tr>
<tr>
<td>PC1652</td>
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</tr>
<tr>
<td>PC671</td>
<td>0.132</td>
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<td>0.513</td>
<td>-</td>
<td>0</td>
<td>0.996</td>
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<tr>
<td>LC653</td>
<td>0</td>
<td>0.877</td>
<td>0.823</td>
<td>0.768</td>
<td>0.840</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PC673</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Next, the initial causal model based on the TE values was constructed. The causal model based on the TE/NTE values is shown in Figure 6. Arcs that correspond to TE values that are higher than 0.9 are bold while arcs that correspond to TE values lower than 0.8 are dashed. The remaining arcs correspond to TE values between 0.8-0.9.

The next step is to exclude indirect or spurious interactions from the initial causal model. Therefore, we selected those interactions we suspected
Table 3: The calculated NTE values between each of the controllers. The highlighted values denote a causality that is suspected to be spurious or indirect.

<table>
<thead>
<tr>
<th></th>
<th>PC1653</th>
<th>PC651</th>
<th>PC652</th>
<th>PC653</th>
<th>PC670</th>
<th>PC652</th>
<th>PC653</th>
<th>PC670</th>
<th>PC671</th>
<th>PC653</th>
<th>PC673</th>
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<tr>
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<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>PC651</td>
<td>0</td>
<td>-</td>
<td>0.089</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>PC652</td>
<td>0.102</td>
<td>0.108</td>
<td>-</td>
<td>0</td>
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<td>0</td>
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</tr>
<tr>
<td>PC653</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>0.180</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td>PC670</td>
<td>0</td>
<td>0.107</td>
<td>0.068</td>
<td>0.108</td>
<td>-</td>
<td>0.079</td>
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</tr>
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<td>LC652</td>
<td>0.077</td>
<td>0.100</td>
<td>0.076</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>0</td>
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</tr>
<tr>
<td>PC1652</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>-</td>
<td>0.107</td>
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<tr>
<td>PC671</td>
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<td>0.135</td>
<td>0.174</td>
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<td>0.021</td>
<td>-</td>
<td>0.078</td>
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<td>LC653</td>
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<td>-</td>
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<tr>
<td>PC673</td>
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<td>0.091</td>
<td>0.163</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
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</table>

as indirect or spurious to be investigated in phase II of the analysis. The initial topology suggested that several interactions could be indirect. For instance, PC1652 could affect LC653 via PC671 but not directly as suggested by the TE results. Furthermore, the arcs originating in PC673 were suspected to be unrelated to the fault propagation based on our previous studies. All the pathways that were suspected as indirect or spurious are marked as red arcs in Figure 6 while the corresponding TE/NTE values are highlighted in Tables 2-3).

One possible explanation for the mis-detection of direct causality is the control mechanism of the pressure difference controllers (PDCs). The proper pressure difference between the steam cylinders and the condensate tanks is maintained by manipulating two control valves in the steam outlet of each condensate tank. However, if the required pressure difference is low, only one valve is opened, while the second valve is opened only if a higher pressure difference is needed. Thus, when one of the valves is closed, there is
no information transfer through that valve. In this case, direct physical connectivity does not imply direct causality. Consequently, the DTE/NDTE were calculated in order to evaluate the causality of those connections that were suspected to be indirect or spurious (denoted by red arcs in Figure 6). The task of determining the intermediate variables when investigating a highly inter-connected system is not straightforward. Therefore, the search algorithm was invoked in order to find all feasible pathways between two controllers. First, the indirect pathways were obtained by virtue of the search algorithm, and then the DTE/NDTE values were calculated for each indirect path. In the author’s opinion, this would be the most appropriate approach for handling multiple pathways between two controllers. Figure 7 presents an example of the output of the search algorithm when searching for all physical
pathways from LC652 to PC1653.

Checking cause and effect relationship between LI-652 and PI-1653...
LI-652 is connected to C-3. There are 5 feasible propagation paths from C-3 to PI-1653...

<table>
<thead>
<tr>
<th>Path 1 is</th>
<th>Path 2 is</th>
<th>Path 3 is</th>
<th>Path 4 is</th>
<th>Path 5 is</th>
</tr>
</thead>
<tbody>
<tr>
<td>C-3</td>
<td>C-3</td>
<td>C-3</td>
<td>C-3</td>
<td>C-3</td>
</tr>
<tr>
<td>LI-652</td>
<td>LV-652</td>
<td>SG1_Steam_Line</td>
<td>SG1_Steam_Line</td>
<td>SG1_Steam_Line</td>
</tr>
<tr>
<td>LC-652</td>
<td>C-2</td>
<td>PI-651</td>
<td>PI-651</td>
<td>SG-1</td>
</tr>
<tr>
<td>LV-652</td>
<td>PI-1653</td>
<td>PC-651</td>
<td>PC-652</td>
<td>PI-652</td>
</tr>
<tr>
<td>C-2</td>
<td>PV-651</td>
<td>C-2</td>
<td>PV-652</td>
<td>PC-652</td>
</tr>
<tr>
<td>PI-1653</td>
<td>PC-652</td>
<td>PI-1653</td>
<td>PI-1653</td>
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<td>PV-652</td>
<td>C-2</td>
<td>PI-1653</td>
<td></td>
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</table>

Figure 7: Finding physical pathways between \( LC652 \rightarrow PC1653 \) using the search algorithm.

According to Figure 7, five paths were found. Two different indirect paths: \( LC652 \rightarrow PC652 \rightarrow PC1653 \) (path 5) and \( LC652 \rightarrow PC651 \rightarrow PC652 \rightarrow PC1653 \) (paths 3 & 4), while paths 1 & 2 are direct. Therefore, the algorithm ensures that DTE is calculated twice: once with PC652 as a single intermediate variable and once with PC651 and PC652 as intermediate variables. The DTE/NDTE results for all indirect interactions based on the initial model are shown in Table 4.
Table 4: The calculated DTE/NDTE values for the indirect paths in the initial model.

<table>
<thead>
<tr>
<th>Indirect pathways</th>
<th>DTE</th>
<th>NDTE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC673 → PC653</td>
<td>0.571</td>
<td>0.764</td>
</tr>
<tr>
<td>PC673 → PC670</td>
<td>0.706</td>
<td>0.707</td>
</tr>
<tr>
<td>PC1652 → LC653</td>
<td>0.137</td>
<td>0.291</td>
</tr>
<tr>
<td>LC653 → PC651</td>
<td>0.236</td>
<td>0.595</td>
</tr>
<tr>
<td>LC653 → PC652</td>
<td>0.187</td>
<td>0.408</td>
</tr>
<tr>
<td>LC652 → PC651</td>
<td>0.266</td>
<td>0.726</td>
</tr>
<tr>
<td>LC652 → PC1653</td>
<td>0.291</td>
<td>0.423</td>
</tr>
</tbody>
</table>

Based on the DTE/NDTE calculations, it can be deduced that there is a direct causality from PC673 to PC653 and PC670. One of the discharge valves of C8 is connected to the pipeline that provides steam to SG2, thereby affecting both the pressure controller (PC653) and the pressure difference controller (PC670) of SG2. Even though the results indicate a certain level of direct causality from PC673 to PC653 and from PC673 to PC670, it is unlikely that they reflect the propagation of the valve stiction in PC1652. Based on the initial model (Figure 6), controller PC1652 affects all controllers except PC673 via direct and indirect pathways. Thus, although the TE results suggest that there is a direct causality from PC670 to PC653 and PC670, it is inexplicable how the stiction could propagate to PC673 since no oscillation was observed in controller PC659. Therefore, it is assumed that those causal interactions detected by the TE results are most likely not associated with the fault and are spurious. This assumption supports the
The affect of PC1652 on LC653 can be considered as indirect since both DTE and NDTE values are relatively low. The DTE/NDTE results also imply a certain level of direct causality between $LC_{653} \rightarrow PC_{651}$ and $LC_{653} \rightarrow PC_{652}$, although the DTE values are relatively low. However, level controller LC653 primarily affects the level of the consecutive condensate tank (C3) rather than the pressure in SG1. Thus, although LC653 has a certain affect on the pressure controllers of SG1 the affect is secondary to its affect on the level of C3.

The causality from LC652 to PC651 and to PC1653 can be considered to be direct (both DTE/NDTE values is relatively high for $LC_{652} \rightarrow PC_{652} \rightarrow PC_{651}$ and $LC_{652} \rightarrow PC_{652} \rightarrow PC_{1653}$). Although LC652 primarily affects LC651, the steam outlet of C3 is also affected by the condensate level. Therefore, the outlet steam of C3, which is discharged to the steam pipeline of SG1, simultaneously affects the pressure and the pressure difference controllers of the drying cylinders while the condensate discharged to C2 affects the pressure in the cylinder (PC1653). The final propagation path of the valve stiction in PC1652 is illustrated in Figure 8.

According to the model, the oscillation first propagated within DG3, propagating first to pressure difference controller PC671 and then to level controller LC653. From DG3, the oscillation continued to spread through the successive DGs. The TE method is invariant to time delay; thus, it is difficult to determine how fast the oscillation propagated within each DG. However, since there is a very strong mutual interaction between the pres-
sure controllers and the PDCs, it is reasonable to assume that the oscillation had propagated more rapidly toward the pressure controllers than toward the level controllers. Moreover, the investigation reveals that the stiction originating in PC1652 had propagated to all successive pressure controllers; however, only two level controllers (LC653 & LC652) had been affected by the fault. This emphasizes the strong dependency among the pressure controllers compared with the level controllers in the drying section.

4. Summary and conclusions

Industrial systems often encounter abnormal conditions such as plant-wide oscillations, which have a detrimental effect on the plant operations and ultimately deteriorate the product quality. Therefore, early detection of the source of a disturbance and its propagation path is of major importance in any industrial system.
This study set out to determine the propagation path of a disturbance by means of TE and plant topology. The TE method is widely used to identify non-linear causal dependencies among time series. However, the method implementation involves a high computational effort compared to that of linear methods. Furthermore, when the investigated system is highly interconnected, distinguishing between direct and indirect pathways is a rather strenuous task. Consequently, the main goal of this study was to obtain an adequate causal model depicting the propagation path with minimum computational effort. In particular, this study was designed to identify the propagation path of valve stiction among control loops in the drying section of an industrial board machine. According to the approach presented in this paper, the TE/NTE values were first calculated based on the information on plant connectivity among all pathways that were considered to be direct based on their physical connectivity using a unique search algorithm. Next, the DTE/NDTE values were calculated in order to exclude spurious or indirect interactions. For this purpose, the search algorithm was employed to extract the intermediate variables for every indirect pathway between two controllers. Ergo, the search algorithm is the cornerstone of the hybrid approach due to its ability to handle efficiently processes with a complex network topology.

The results suggest that the DTE has an important role in excluding indirect pathways from the initial model. In general, therefore, the TE method alone can be used for small-scale systems with a simple process topology. However, when the system is highly inter-connected, it is essential to use the process connectivity information for facilitating the analysis and for providing
adequate results. Another important practical implication is that breaking a highly complex system into smaller sub-systems and selecting the subset of variables pertinent to the disturbance significantly reduces the dimensionality of the analysis.

In spite of our efforts to limit the specious results using the search algorithm, the initial causal model yielded several indirect/spurious pathways. Moreover, the selection of the indirect pathways from the initial model to be investigated in phase II of the analysis requires careful attention and basic process knowledge was found to be useful. Hence, it remains a challenge to develop a fully automated data-based causal analysis without the need in human intervention.

An issue that was not addressed in this study is the statistical significance of the TE/DTE results. Typically, the causality from $x$ to $y$ should be tested according to, for instance, the Monte Carlo method (Bauer et al., 2007) using surrogate data. However, due to the difficulty and complexity of constructing the surrogate data (Duan et al., 2013), in this study, the TE/DTE values were evaluated according to their magnitude. Furthermore, by virtue of the search algorithm, both the TE and DTE results showed a relatively high level of accuracy. However, further studies need to be carried out to establish a threshold with a high confidence level.

To conclude, the findings of this study suggest that for complex systems, the application of TE alone is an extremely demanding task, which may result in many spurious results. Therefore, this paper proposes an alternative hybrid approach for applying the TE. Utilizing the process connectivity information using a self-programmed search algorithm is highly beneficial for
reducing the computation time and increasing the efficiency of the analysis. Furthermore, the DTE results can assist in discriminating between direct and indirect interactions. However, the complexity of the analysis significantly increases with the number of variables and the level of connectivity among them. It is important to bear in mind that although data-based analysis is very useful and likely to produce a model that enables identification of the propagation path, process knowledge acquired from the P&ID or site expertise might be vital in validating the results.

**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. The authors would like to thank Stora Enso Oyj for providing the data and the expert knowledge for the analysis.

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The time series of the PVs in the drying section. The PV originating in the sticky valve, PC1652, is colored in red.

The spectra of the time series (PVs) (The spectra of the signal originating in the sticky valve PC1652 is shown in red)

The initial causal model based on the TE/NTE results. Bold arcs correspond to TE values higher than 0.9 while dashed arcs correspond to TE values lower than 0.8. The red arcs indicate that causality can be detected but is suspected to be either indirect or spurious.

Finding physical pathways between LC652 → PC1653 using the search algorithm.

The final causal model illustrating the propagation path of valve stiction in PC1652


Schleburg, M., Christiansen, L., Thornhill, N., & Fay, A. (2013). A combined
analysis of plant connectivity and alarm logs to reduce the number of alerts in an automation system. *Journal of process control*, 23, 839–851.


