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Fault Propagation Analysis by Implementing Nearest Neighbors Method Using Process Connectivity

Rinat Landman and Sirkka-Liisa Jämsä-Jounela

***Abstract*— Industrial systems often encounter abnormal conditions due to various faults or external disturbances which deteriorate the process performance. In such cases, it is essential to detect and eliminate the root cause of the faulty condition as early as possible in order to minimize its adverse effect on the entire process performance. Capturing the process causality plays a key role in identifying the propagation path of faults and their root cause. In recent times, several data-based methods have been developed in order to capture causality from the measured process data. However, each of the methods suffers from several limitations and deficiencies which might compromise their ability to provide an adequate causal model, especially in multivariate (MV) systems. This paper proposes a new methodology for retracing the propagation path of oscillation using a nearest neighbors method by utilizing the information on process connectivity. The two-phase methodology yields a directionality measure based on the type of connectivity in the process using a unique search algorithm. In phase I, the bivariate directionality measure is calculated to include only the interactions that are considered as direct based on the plant topology. In phase II, a new MV directionality measure based on the nearest neighbors method is introduced in order to exclude indirect interactions. The methodology is successfully demonstrated on industrial board machine exhibiting oscillations in its drying section.**

***Index Terms*— Causality, fault propagation, nearest neighbors, process connectivity, time series analysis.**

I. Introduction

INDUSTRIAL processes often encounter abnormal conditions, resulting from faults and errors due to various causes, inducing a deviation in one or more of the process variables from its desired values [1]. Different types of faults in industrial processes include process parameter changes and actuator and sensor problems [2]. Faults can easily propagate via the process components through material or information flows, thereby deteriorate the overall process performance [3]. Consequently, it is of major importance to isolate and eliminate the root cause of a fault as early as possible. For this purpose, it is essential to identify the variables affected by the fault and its effect on each variable [4].

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The authors are with the School of Chemical Technology, Process Control and Automation Research Group, Aalto University, FI-00076 Espoo, Finland (e-mail: rinat.landman@aalto.fi; sirkka-liisa.jamsa-jounela@aalto.fi).

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Capturing the causal dependencies between the process variables can assist in identifying the propagation path of a fault and its root cause. Essentially, process causality can be captured from process knowledge and/or process data. When a fault propagates through the process equipment, it changes the nature of the process, and thus, specific features can be used to track the propagation path. Examples of such features include time delays, oscillations, conditional probabilities, signal attenuation, and information transfer. Data-based methods exploit those features and aim to provide a quantitative measure of the directionality between two variables [3]. Such methods include the cross correlation [5], Granger causality (GC) [6]–[8], transfer entropy (TE) [9]–[11], and several frequency-domain methods [12]–[14]. There is a large number of published studies [3], [15]–[17] that review and compare between different causality estimators. Overall, these studies suggest that each of the methods has its own advantages and limitations, and their performance depends on the type of investigated system and fault.

Most of the methods are limited to pairwise analysis which cannot distinguish between the direct and indirect causalities. For instance, it cannot determine whether two variables are interacting or are driven by a third common source [3]. Furthermore, the data-based methods typically require estimation of several parameters and determination of a statistical threshold, which are not always straightforward while the computational complexity increases with the dimensionality of the analysis. For example, the TE method requires estimation of the probability density function that considerably contributes to the computational complexity of the method and requires a large amount of data. Therefore, the dimensionality of the analysis has to be limited when selecting the parameters [18], [19]. Moreover, in most industrial applications, a single method cannot produce satisfactory results unless few methods are fused or process knowledge is acquired to validate the results [3].

Process knowledge is the most reliable and, in most cases, a readily available source for obtaining a qualitative causal model of an industrial system. Such sources include piping and instrumentation diagrams (P&IDs) and other expert knowledge accumulated in the human brain [16]. Causal models that are based on the P&ID of the process are known as topology-based models [20]. More specifically, topology-based models capture the structure of the process and are represented as a digraph or as a binary matrix, namely, a connectivity matrix [20].

A topology-based model represents the physical connectivity among the process components, i.e., it provides only qualitative information that is not sufficient in many cases. Consequently, in recent years, there have been an increasing number of studies combining the topology-based models with data-based analysis [8], [10], [21]–[23]. The automated capture of plant topology and the possibility to use a search algorithm to incorporate the connectivity information with the results of data-based analysis is a major step in the implementation of those methods for industrial systems in the future [10], [16].

In this paper, a nearest neighbors method is proposed as a *directionality measure* for identifying the propagation path of a fault in a complex industrial system [18], [24]. The nearest neighbors methods utilize embedded vectors of the process historical data in order to identify interdependency and directionality among time series corresponding to the process variables [18], [24]. The contribution of this paper is as follows. We propose a methodology that automatically incorporates the information on the process topology with the nearest neighbors method using a unique search algorithm. The cornerstone of the algorithm is the ability to determine whether a physical path between the two control elements is direct or indirect based on the process topology. Ergo, the directionality measure is calculated according to the process connectivity. This feature enables to efficiently tackle complex industrial systems with a high level of connectivity while minimizing the computational effort. Furthermore, we propose a new multivariate (MV) directionality measure that makes a distinction between the direct and indirect connectivities. The new measure can be seen as an extension of the bivariate nearest neighbors method to include intermediate variables between the "cause" and "effect" variables. The possibility to discriminate between the direct and indirect causal dependencies extends the application of the nearest neighbors method to both linear and nonlinear processes.

Several MV extensions to GC [25]–[27] have been proposed; however, both GC and its extensions are based on linear autoregressive (AR) modeling, thus the disadvantage is obvious. Nonlinear approaches to GC suggest replacing AR modeling with a Gaussian model [28], [29]. However, MV/conditional estimates are not addressed in those studies. On the other hand, the direct TE (DTE) [19] was proposed as an extension to the TE in order to detect direct causality in nonlinear MV systems. Yet, the computational burden of the DTE is extremely high when considering a large-scale system. Furthermore, the partial TE [30] was proposed to quantify the total amount of indirect coupling in an interacting network; however, it considers all the system variables as intermediate which are not necessarily true in chemical processes. Therefore, the nearest neighbors method is more practical in industrial applications where often nonlinear and computationally efficient methods are desired.

The two-phase methodology ensures that the directionality measure is calculated only if a physical pathway between the two control elements is detected while the causality is measured based on the type of connectivity. In phase I, the bivariate directionality measure is calculated only for the pathways that are considered as direct based on the process topology. In phase II, indirect interactions are excluded using the new MV directionality measure combined with the search algorithm. Both phases of the methodology are fully automated which makes it efficient and suitable for industrial applications. The methodology is demonstrated on a case study of an industrial board machine. In particular, it aims to retrace the propagation of oscillation in the drying section of the machine due to valve stiction.

This paper is structured as follows. Section II presents the overall methodology including a detailed description of each phase. Then, general background on extracting process topology from a P&ID and description of the search algorithm and the nearest neighbors method are provided in detail. Section III presents several applications. The first three examples are given to demonstrate the efficacy of the proposed MV measure, while the last example is an industrial case study of a board machine that serves to demonstrate the overall methodology and evaluate it with respect to other data-based methods. This paper ends with summary and conclusions in Section IV.

II. Overall Methodology for Fault Propagation Analysis Based on the Nearest Neighbors Method

The analysis aims to identify the propagation path of oscillations via control loops. The two-phase methodology utilizes the information on the process connectivity when calculating the directionality measure that yields an efficient and powerful causal analysis. The analysis consists of the following steps. First, the process connectivity information is extracted in the form of a connectivity matrix that is captured from an XML scheme using AutoCAD P&ID. Next, the data-based analysis is implemented in two phases. The aim of phase I is to obtain an initial causality matrix by applying the bivariate nearest neighbors method to the process data according to the connectivity information. The aim of phase II is to exclude indirect causal interactions based on the initial causality matrix. First, a new connectivity matrix is generated according to the initial causality matrix. Namely, each directionality measure obtained in phase I is replaced with "1" in the new connectivity matrix. Then, a new MV directionality measure is used to evaluate each indirect path based on the new connectivity matrix. In both the phases, the process topology is integrated into the analysis using a unique search algorithm which has the following functionalities: it determines whether there is a physical path between two control elements (in this case, the measurement points) and whether the path is direct or indirect. A scheme of the overall methodology is shown in Fig. 1.

In Sections II-A–II-C, we first describe how to generate a topology-based model. Then, the logic of the search algorithm throughout the analysis is explained in detail. Finally, the description of the nearest neighbors method for calculating the directionality measures is given.

A. Generating a Topology-Based Model

A topology-based model describes the physical connectivity between the process units. The main resources for extracting the connectivity information are process flow diagrams

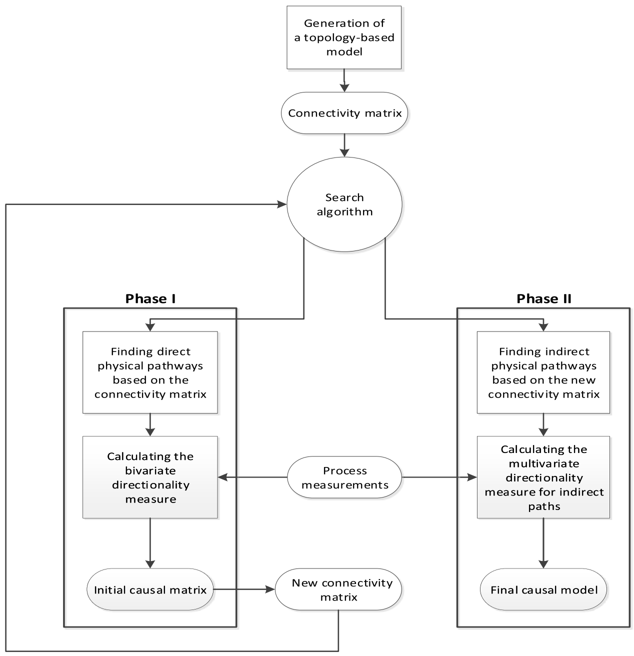

Fig. 1. Proposed methodology for causal analysis based on the nearest neighbors method.

and P&IDs which are converted into standard XML data formats [16], [31]. XML uses plain text to describe equipment, their properties, and the connections among them [32]. In this paper, the topology data were exported in the format of ISO-15926-compliant XML scheme XMpLant [33].

There are two types of topology-based models: a connectivity (adjacency) matrix and a causal digraph which can be seen as a numerical and graphical representation of the process topology, respectively. In a system with n elements, a connectivity matrix contains binary elements that are set to "1" in the case of a direct connectivity between elements and otherwise "0." In a causal digraph, each (i, j)th element in the connectivity matrix that is set to "1" is expressed as an arc between the (i)th and (j)th nodes. In this paper, the connectivity information was extracted from an electronic P&ID drawn by a specialized Autodesk AutoCAD drafting application [8]. The topology-based model, in this case, the connectivity matrix was generated in three consecutive steps. First, AutoCAD P&ID software was used to generate an electronic drawing that includes all process components and the connections among them such as process units, control elements, piping, and so on. Next, the topology information, i.e., the names and coordinates of the process units and the connectivity among them were retrieved via the database object of the drawing. Finally, this information was further processed via object-oriented programming tool of MATLAB and converted into a topology-based model, namely, a connectivity matrix [8], [34].

B. Logic of the Search Algorithm

The search algorithm is based on a graph traversal which searches a series of nodes originating from a cause node to an effect node using a depth-first search which ensures that each node is traversed only once [22]. In this paper, the algorithm "searches" through the connectivity matrix for propagation paths between the two control elements, particularly, the indicators. The basic idea of the algorithm is to move from the elements that are connected to the "cause" variable and look for columns with "1" which indicate on a direct connection to the column element. This procedure is repeated until the same element is visited twice or the row element is disconnected from any other elements. The algorithm then backtracks to follow all the remaining pathways [22]. A detailed example of the procedure to find propagation paths between two control elements is given in [22].

Algorithm 1 presents the logic of calculating the directionality between each pair of controllers (i, j) in each phase. In phase I, the search algorithm finds all feasible propagation paths between each pair of controllers. Then, it determines whether each path is direct or not. If at least one direct path is detected, the directionality from controller i to j is calculated according to the nearest neighbors method. A path from controller i to controller j is considered as direct if it does not traverse any other control element which does not belong to control loop i or j [35]. The logic of the search algorithm is further explained and demonstrated in [8] and [10]. Next, a new connectivity matrix is generated according to the causality matrix which was obtained in phase I. In phase II, the search algorithm uses the new connectivity matrix to find all possible propagation paths between each (i, j) pair of controllers whose directionality had been calculated in phase I. If an indirect path is detected between the two controllers, a new proposed measure that includes the intermediate controllers is invoked to evaluate whether the directionality is direct or indirect. The MV directionality measure is calculated for each indirect path, and finally, the mean value of all indirect paths is taken as a measure of directionality. If the mean value is considerably higher than zero (in this paper, we consider values higher than 0.1 as high), then a direct causality can be inferred.

C. Nearest Neighbors Method

The nearest neighbors method is based on the concept of embedded vectors which can be seen as a high-dimensional representation of a dynamic system [36]. The method incorporates both the time delay and the attenuation of the signal to measure causality [18]. The implementation of the method is adapted from [24] as follows.

Consider process variable X with N samples. For time instance i, the embedded vector x_i is defined as $x_i = [x_i, x_{i-k}, \ldots, x_{i-(m-1)k}]$, where m is the embedded dimension and k is the embedding time delay. All the embedded vectors of X can be arranged in the following matrix [24]:

$$X = \begin{pmatrix} x_{(m-1)k+1} & \cdots & x_1 \\ x_{(m-1)k+2} & \cdots & x_2 \\ \vdots & & \vdots \\ x_N & \cdots & x_{\tilde{N}} \end{pmatrix} \quad (1)$$

where $\tilde{N} = N - (m-1)k$ is the number of embedded vectors. The nearest neighbors of x_i are defined as the embedded vectors that have the smallest Euclidian distance

Algorithm 1 Calculating the Directionality Measure in Phases I & II, * m Is the Embedded Dimension for $H_{i\to j}$

- Phase I
  foreach *pair (i,j)* $\ni \{i \neq j, m^* > 0\}$ **do**
  - **if** *there is a path from* i *to* j **then**
    - **if** *the path is **direct*** **then**
      - Calculate $H_{i\to j}$ and set the value in the causality matrix ▷$Equation5$
    - **else**
      - Move to the next *(i,j)*th pair;
    - **end**
  - **else**
    - Move to the next *(i,j)*th pair;
  - **end**

  end
- Generating a new connectivity matrix
  foreach (i, j) *cell in the new connecitivty matrix* **do**
  - **if** $H_{i\to j} > 0$ **then**
    - set the $(i, j)^{th}$ cell to '1';
  - **else**
    - set the $(i, j)^{th}$ cell to '0';
  - **end**

  end
- Phase II
  foreach (i, j) *cell in the new connecitivty matrix set to '1'* **do**
  - Obtain all paths from controller i to j using the new connecitivty matrix obtained from phase I ;
  - **if** *There are indirect paths from controller* i *to* j **then**
    - **foreach** *indirect path* z **do**
      - calculate $H_{i\to j,z}$ ▷$Equation7$
    - **end**
    - Set $\overline{H_{i\to j,z}}$ as the directionality measure in the new causality matrix ;
  - **else**
    - Set the value of directionality in the new causality matrix to '1';
  - **end**

  end

$d_{i,j} = \|x_i - x_j\|$. The K nearest neighbor indices are denoted as $r_{i,j}$, where $j = 1 \ldots K$, and $r_{i,j}$ denotes the jth nearest neighbor of the ith embedded vector x_i. Similarly, for each embedded vector y_i, the indices of the K nearest neighbors are denoted as $s_{i,j}$ [24].

The mutual predictability from y to x determines the similarity between the prediction of each x_i and the prediction value of each of the nearest neighbors $s_{i,j}$ of y_i [24], [37]

$$D_i(X|Y) = \frac{1}{K}\sum_{j=1}^{K}|x_{i+h} - x_{s_{i,j}+h}| \tag{2}$$

where x_{i+h} is the prediction value of x_i, while $x_{s_{i,j}+h}$ is the prediction value assigned according to the index of the jth nearest neighbor of y_i. For example, consider two time series X and Y, each with N observations and $m = 4$. If the nearest neighbor of an embedded vector $y_4 = [y_4, y_3, y_2, y_1]$ is $y_{20} = [y_{20}, y_{19}, y_{18}, y_{17}]$, then according to (2), if the distance between $x4 + h$ and x_{20+h} is small, then Y can be considered as a good predictor of X [24]. The self-predictability of X is defined as

$$D_i(X) = \frac{1}{K}\sum_{j=1}^{K}|x_{i+h} - x_{r_{i,j}+h}| \tag{3}$$

where x_{i+h} is the prediction values of x_i and $x_{r_{i,j}+h}$ is the prediction of the jth nearest neighbor of x_i. The results are then scaled to give the predictability improvement measure [37]

$$H(X|Y) = \frac{1}{\tilde{N}}\sum_{i=1}^{\tilde{N}}\frac{D_i(X|Y)}{D_i(X)}. \tag{4}$$

In the same manner, $H(Y|X)$ is calculated to take into account the influence of X on Y. Finally, both $H(X|Y)$ and $H(Y|X)$ are compared in order to determine whether X influences Y or vice versa [24]

$$H_{x\to y} = H(X|Y) - H(Y|X). \tag{5}$$

A positive value indicates on a causal influence from X to Y, while a negative value implies on directionality from Y to X.

We propose the following MV directionality measure taking into account the effect of Y on X via n intermediate variables Z

$$H(X|Y, Z) = \frac{1}{\tilde{N}}\sum_{i=1}^{\tilde{N}}\frac{D_i(X|Y)}{D_i(X) + \sum_{j=1}^{n} D_i(X|Z_j)} \tag{6}$$

where $D_i(X|Z_j)$ is the mutual predictability from an intermediate variable Z_j to X and n is the total number of intermediate variables. One can think of the numerator as the directionality measure from Y to X which is scaled by the denominator representing the self-directionality of X and the sum of the directionality measure from each Z_j to X. Then, according to 5, a direct causality from X to Y can be established if the following term is greater than zero:

$$H_{x\to y,z} = H(X|Y, Z) - H(Y|X, Z). \tag{7}$$

If $H_{x\to y,z}$ is considerably higher than zero, then the directionality from x to y can be considered as direct. Note that the same parameters (m, k, and h) used for the bivariate directionality measure are used as well in the MV case.

III. Applications

In this section, we provide a few examples for the application of the nearest neighbors method. The first three examples consist of simulated data generated from simple mathematical equations. Those examples are aimed to demonstrate the application of the MV directionality measure proposed in (6) and (7). Finally, a case study of a drying section of an industrial board machine is investigated to demonstrate the overall methodology using the search algorithm.

TABLE I
RESULTS FOR CASE I

$H_{row \to column}$	x	z	y
x	NA	0.387	0.400
z	-	NA	0.084
y	-	-	NA

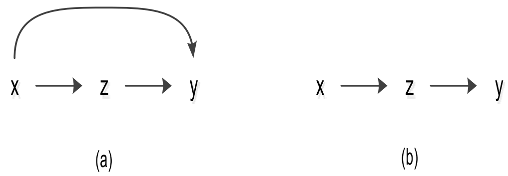

Fig. 2. Causal model according to (a) case I and (b) case II.

TABLE II
RESULTS FOR CASE II

$H_{row \to column}$	x	z	y
x	NA	0.367	0.265
z	-	NA	0.512
y	-	-	NA

A. Case I

Consider the following linear continuous system with the following variables:

$$\begin{cases} z(n+1) = 0.5x(n) + 0.3z(n) + \nu_1(n) \\ y(n+1) = z(n) + 0.8x(n) + \nu_2(n) \end{cases}$$

where $x(n) \sim N(0,1)$, $\nu_1(n), \nu_2(n) \sim N(0, 0.1)$, and $z(0) = 3$. 6000 samples were simulated while only the last 3000 samples were taken for the analysis to ensure stationarity. The following parameters were used in the calculations: $m = 4, k = 1, h = 1, \text{and} K = 20$. The results are summarized in Table I.

Note that only positive values are taken into account. Fig. 2(a) presents the causal model based on the results. According to the model, the directionality from x to y can be direct or indirect via z. Therefore, $H_{x\to y,z}$ should be calculated in order to determine the type of directionality. Since $H_{x\to y,z} = 0.182$ is fairly larger than zero, we can deduce that the causality from x to y is direct (we consider values >0.1 as indication for direct causality).

B. Case II

Consider the same system as case I, however, this time the influence from x to y is removed

$$\begin{cases} z(n+1) = 0.5x(n) + 0.3z(n) + \nu_1(n) \\ y(n+1) = z(n) + \nu_2(n) \end{cases}.$$

Using the same parameters as in case I, the directionality measure is calculated once again (see Table II).

However, in this case $H_{x\to y,z} = 0.029$, we can conclude that the causality from x to y is via z [Fig. 2(b)].

TABLE III
RESULTS FOR CASE III

$H_{row \to column}$	x	z	r	y
x	NA	0.461	0.226	0.144
z	-	NA	0.512	0.342
r	-	-	NA	0.128
y	-	-	-	NA

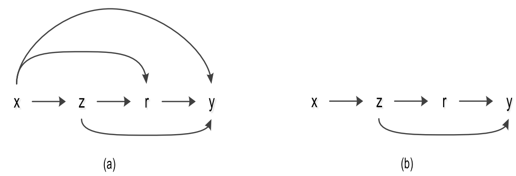

Fig. 3. (a) Initial causal model and (b) final causal model for case III.

TABLE IV
INDIRECT PATHS FOR CASE III AND THEIR DIRECTIONALITY MEASURE

Indirect Path	The MV directionality measure
$x \to z \to r$	-0.0044
$x \to z \to r \to y$	0.0095
$x \to z \to y$	-0.0037
$x \to r \to y$	0.058
$z \to r \to y$	0.151

C. Case III

Consider the following nonlinear system:

$$\begin{cases} z(n+1) = 1 - 2|0.5 - (0.8x(n) + 0.4\sqrt{z(n)})| + \nu_1(n) \\ r(n+1) = 0.45r(n-1) + 2\sqrt{|z(n)|} + \nu_2(n) \\ y(n+1) = 0.5z(n)^2 + \sqrt{|r(n)|} + \nu_3(n) \end{cases}$$

where x is a uniform distributed signal in the interval [1, 2], $\nu_1(n), \nu_2(n) \sim N(0, 0.05)$, and $z(0) = 0.5$. The following parameters where used in the calculations: $m = 4$, $k = 1$, $h = 1$, and $K = 20$. 6000 samples were simulated while the last 3000 were taken for the analysis. Table III presents the directionality measure for case III.

The initial causal model based on the results is shown in Fig. 3(a). Next, it is necessary to establish whether the directionality from x to r, from x to y, and from z to y is direct. Therefore, the MV directionality between those variables is calculated. The results for each indirect path are given in Table IV.

The results indicate that the only directionality which can be considered as direct is $z \to y$ since all the other measures are either negative (directionality is inconclusive in this case) or close to zero. Accordingly, the final model is presented in Fig. 3(b).

D. Industrial Case Study

The industrial case study is a drying section of a large-scale board machine that produces liquid packages. This section consists of six consecutive drying groups (DGs). Each group consists of steam-filled cylinders that are used to evaporate the excess water in the web and a tank where the condensate is collected by siphons. Each group has its own controllers

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

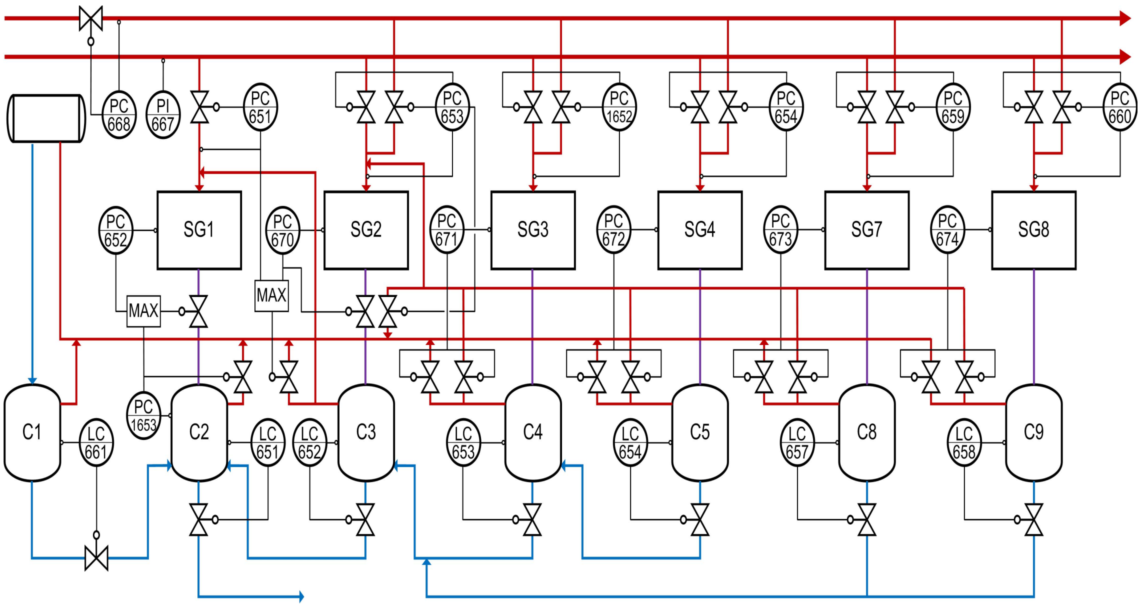

Fig. 4. Flowsheet of the drying section. Red lines: steam pipes. Blue lines: condensate pipes. Purple lines: mixed flow of steam and condensate (PI = pressure indicator, PC = pressure controller, LC = level controller, SG = steam group, and C = condensate tank).

to control the steam pressure, the steam pressure difference between the steam and the condensate headers, and the level of the condensate tanks. The steam pressure of each DG is regulated using 5 and 10 bar steam headers. The pressure difference is maintained using control valves in the steam outlet of the condensate tank while the level of each tank is regulated using the outlet flow control valve. The process scheme is shown in Fig. 4. The case study investigates the propagation path of oscillation as a result of valve stiction in pressure controller PC1652. Oscillations in control valves can easily propagate due to the process connectivity, and therefore, it is of major importance to detect the root cause and identify the propagation path as early as possible. In this paper, the stiction was initially detected using the detection system proposed in [38] and was later confirmed using the maintenance records of the plant. The outcome of the analysis is a causal model of the controllers in the drying section depicting the propagation path of the oscillation generated by PC1652.

The time series corresponding to the measured variables are illustrated in Fig. 5 and their corresponding spectra are shown in Fig. 6 (the measurement and spectra of PC1652 are shown in red). The samples were recorded with 10-s sampling interval and 3000 samples were taken for the analysis. Initially, it is essential to select the subset of variables with a common oscillation frequency. This step is important in order to focus on the variables that are pertinent to the fault, to reduce the dimensionality of the analysis, and to provide a better understanding of the process behavior [39], [40]. Several clustering methods for isolating the faulty variables for diagnostic purposes are reported in [4], [29], and [39]–[42]. In this case, the spectra of the series are examined to select the series with similar oscillating features. The spectra of the series (Fig. 6) reveal that the control loops which oscillate at the same

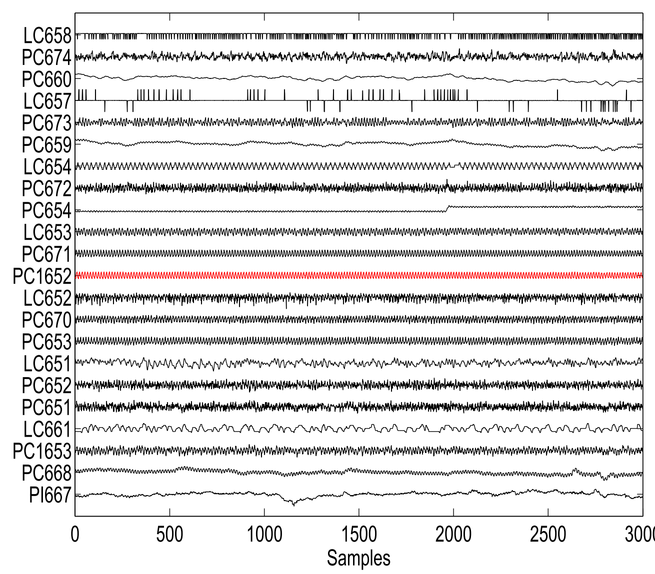

Fig. 5. Measured process variables in the drying section of the board machine.

frequency (0.007 Hz) are PC668, PC1653, PC651, PC652, PC653, PC670, LC652, PC1652, PC671, LC653, PC672, and PC673.

1) Parameter Settings: The parameters were selected based on the guidelines provided in [24]. The embedding dimension m was selected by plotting $H_{x\rightarrow y}$ while m was varied from 1 to 10 and $k = h = 1$. The value of m for which $H_{x\rightarrow y}$ is maximized was selected for each pair of variables. Next, the same procedure was repeated while varying k when $h = 1$ and m was set according to the previous step. Finally, h was varied while m and k were retained at their optimal

TABLE V
RESULTS OF PHASE I: INITIAL CAUSALITY MATRIX

$H_{row \to column}$	PC1653	PC651	PC652	PC653	PC670	LC652	PC1652	PC671	LC653	PC673
PC1653	-	-	-	-	-	-	-	-	-	-
PC651	-	-	0.082	-	-	-	-	-	-	-
PC652	-	0.178	-	-	-	-	-	-	-	-
PC653	-	-	-	-	0.978	-	-	-	-	-
PC670	-	1.802	1.384	0.572	-	1.261	-	-	-	-
LC652	-	0.217	0.101	-	-	-	-	-	-	-
PC1652	-	-	-	-	-	-	-	1.206	2.593	-
PC671	-	-	-	-	0.326	-	-	-	0.738	-
LC653	-	1.792	0.587	-	-	1.556	-	-	-	-
PC673	-	-	-	0.448	-	-	-	-	-	-

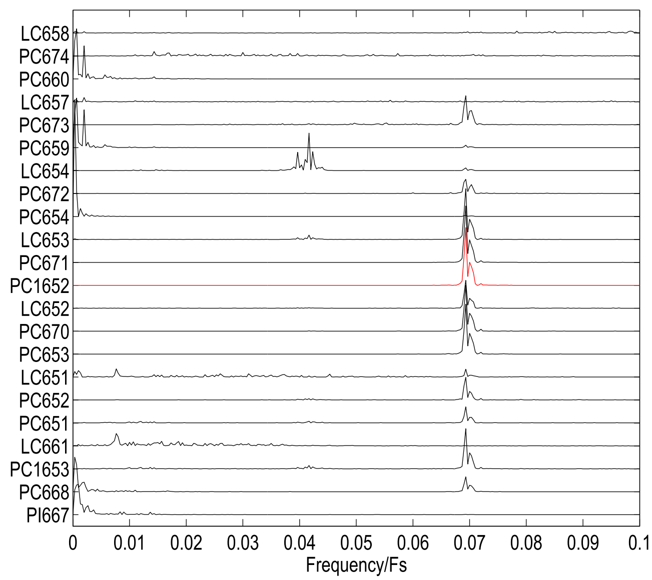

Fig. 6. Spectra of the process measurements.

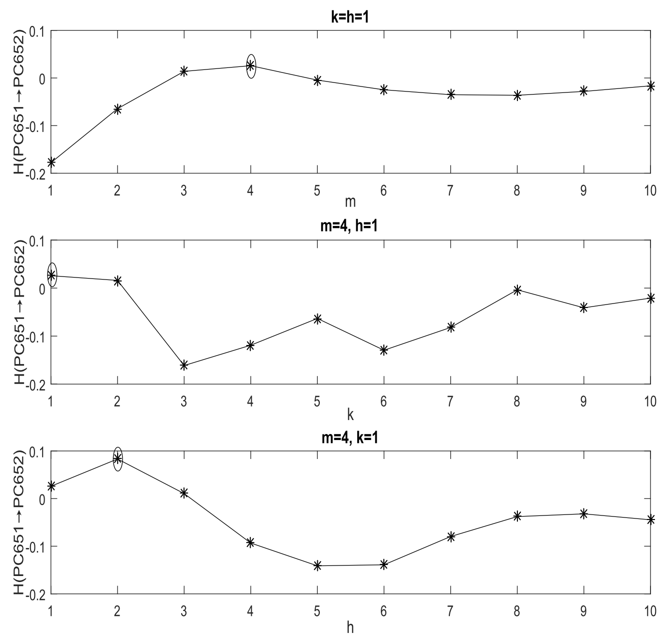

Fig. 7. Parameter setting for PC651 → PC652 ($N = 3000$ and $K = 200$). $H_{\mathrm{PC651 \to PC652}}$ is plotted when m, k, and h are varied (top, middle, and bottom, respectively). The chosen parameters are circled.

settings. An example for setting the parameters of the pair $PC651 \to PC652$ is presented in Fig. 7. Fig. 7 shows $H_{\mathrm{PC651 \to PC652}}$ when m is varied and h and k are fixed (top), the selection of k (middle), and the selection of h (bottom).

The number of nearest neighbors, K, is typically set to be equal to the number of cycles that are analyzed in the case of an oscillatory disturbance [24]. In this case, the oscillation period is 14 samples while 3000 samples were analyzed; hence, K was chosen as 200.

2) Results: The results obtained in phase I are given in Table V. Empty cells indicate either that there is not a direct physical connectivity from the raw element to the column element according to the search algorithm or that the directionality is in the opposite direction (i.e., only positive values are considered).

In phase II of the analysis, each nonzero element in the matrix is further investigated to ensure that causality can be considered as direct. First, a new connectivity matrix is constructed from the initial causality matrix, where each nonzero element is replaced by "1." Based on the new connectivity matrix, the MV directionality measure is calculated for all the indirect paths according to the search algorithm. The outcome is a new causality matrix where "1"s indicate on direct causality based on the new connectivity matrix, while the rest of the numeric values correspond to the mean MV directionality measure for the indirect paths based on the new connectivity matrix [calculated according to (6) and (7)]. The outcome of phase II is presented in Table VI.

As an example, consider the directionality from PC670 to PC651. According to the initial causality matrix (Table V) $H_{\mathrm{PC670 \to PC651}} = 1.802$, however, it is essential to confirm whether the causality is direct or indirect. According to the initial causality matrix, the search algorithm finds three possible indirect paths between these controllers. Next, for each path, the MV directionality measure is calculated according to (6) and (7) (see Table VII). Finally, the mean of all the results is calculated ($H_{\mathrm{PC670 \to PC651}}$ in Table VI). In this case, the mean value is significantly higher than zero (0.282), thus we can deduce that the causality from PC670 to PC651 is direct.

The results of phase II show that $H_{\mathrm{PC670 \to PC651}}$, $H_{\mathrm{PC670 \to PC652}}$, $H_{\mathrm{PC1652 \to LC653}}$, and $H_{\mathrm{LC653 \to PC651}}$ are much

TABLE VI
RESULTS OF PHASE II

$H_{row \rightarrow column}$	PC1653	PC651	PC652	PC653	PC670	LC652	PC1652	PC671	LC653	PC673
PC1653	-	-	-	-	-	-	-	-	-	-
PC651	-	-	1	-	-	-	-	-	-	-
PC652	-	1	-	-	-	-	-	-	-	-
PC653	-	-	-	-	1	-	-	-	-	-
PC670	-	0.282	0.270	1	-	1	-	-	-	-
LC652	-	0.084	0.017	-	-	-	-	-	-	-
PC1652	-	-	-	-	-	-	-	1	0.673	-
PC671	-	-	-	-	1	-	-	-	1	-
LC653	-	0.148	0.078	-	-	1	-	-	-	-
PC673	-	-	-	1	-	-	-	-	-	-

TABLE VII
INDIRECT PATHS FROM PC670 TO PC651 AND THEIR DIRECTIONALITY MEASURE

Indirect Path	**The MV directionality measure**
$PC670 \rightarrow PC652 \rightarrow PC651$	0.339
$PC670 \rightarrow LC652 \rightarrow PC651$	0.338
$PC670 \rightarrow LC652 \rightarrow PC652 \rightarrow PC651$	0.169

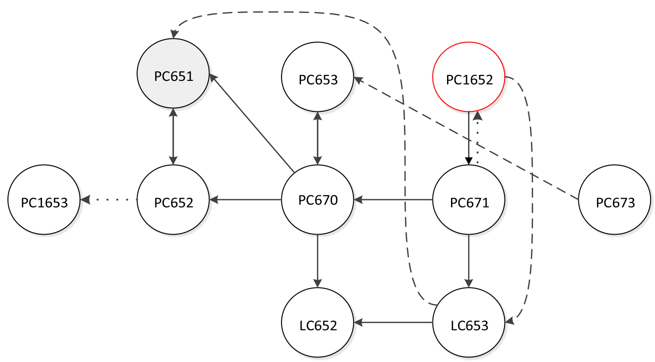

Fig. 8. Final causal model. Dashed arcs: causality which is indirect or spurious. Dotted arcs: causality which is direct but had not been identified).

higher than zero (>0.1); therefore, they can be considered as direct. However, $H_{LC652 \rightarrow PC651}$, $H_{\mathrm{LC652} \rightarrow \mathrm{PC652}}$, and $H_{\mathrm{LC653} \rightarrow \mathrm{PC652}}$ are considerably low; therefore, they are either indirect or their level of interaction is very weak. (The corresponding values are highlighted in yellow in Table VI.) Based on these results, the final causal model can be obtained (Fig. 8). The causal model depicts the propagation path of the oscillation originated in PC1652. The dotted arcs correspond to interactions that are considered as spurious or indirect based on our process knowledge and previous investigations [8], [10]. For instance, the directionality from PC673 to PC563 has been identified as direct by the search algorithm since one of its manipulating valves discharges steam from C8 into SG2. However, typically, the PCs in the drying section manipulate two valves, whereas only one valve is constantly open while the other valve is opened only when a higher pressure is needed. Hence, PC673 essentially affects the level in C8 rather than PC653. This case exemplifies that the physical connectivity does not necessarily indicate on information transfer. In addition, the causality from PC652 to PC1653 and from PC671 to PC1652 had not been identified. However, overall, the results demonstrate a high level of accuracy (∼90%).

3) Comparison With Other Methods: The authors carried out several investigations into the current case study using different data-based methods [8], [10]. The proposed methodology has shown several advantages compared with the one implemented in our previous study using the TE method [10]. The two methodologies have similar features: they are implemented as a two-phase analysis wherein bivariate analysis is implemented in phase I, while MV analysis is implemented in phase II as a tool for discriminating indirect connectivity. Both the methods are nonlinear and require estimation of prediction horizon, embedding dimension, and time delay. Thus, they are sensitive to parameters changes which affect the results and the computational burden. However, the TE requires estimation of the probability density function whose complexity increases with the dimensionality of the analysis. Wherefore, from computational point of view, the TE method is more difficult to implement. In both studies, the statistical significance was determined according to the magnitude of the results instead of computationally expensive methods involving the surrogate data [43]. Although the TE and the nearest neighbors methods produced a fairly accurate causal model, the TE yielded more spurious result and required more computational effort compared with the nearest neighbors method.

On the other hand, there was no significant difference in the ability to identify the propagation path when applying the conditional GC [8] and the nearest neighbors method. Unlike the nearest neighbors method, the GC is linear and based on fitting MV AR (MAR) models to the time series. Essentially, it is less computationally heavy than the nearest neighbors method and the statistical significance can be simply determined via the F-statistic test [7]. However, its performance is dependent on the model estimation and the linearity between the process variables. In this case, the GC method produced similar results to the nearest neighbors method, which implies on somewhat linear interactions between the controllers in the drying section.

With respect to the frequency-domain methods, the partial directed coherence (PDC) [12] and the directed transfer function (DTF) [14] are particularly useful when investigating an oscillatory disturbance. The PDC and the DTF represent the normalized measure of the direct and the total energy transfer between two variables [3]. Similar to the GC, the DTF and the PDC are linear methods which are based on the estimation of MAR models of the time series and their Fourier transform to the frequency domain. The frequency-domain methods measure the magnitude of the energy transfer at each frequency, and therefore, they are able to quantify rather accurately the causal dependence between oscillating signals as demonstrated in [8]. However, the methods require surrogate data to evaluate the significance of the measure at each frequency which makes them more time-consuming and computationally complex to implement compared with the nearest neighbors and the GC methods. Therefore, in our previous study [8], frequency-domain analysis was used as a supplementary method to the GC.

IV. Conclusion

The problem of identifying the propagation path of a fault in a highly interconnected system is a demanding task whose complexity increases with the number of variables involved and the level of interactions. This paper proposes a new methodology for retracing the propagation path based on the nearest neighbors method. The methodology is implemented in two phases. In phase I, an initial causality matrix is obtained according to the paths that are considered as direct based on the process topology. In phase II, a new MV directionality measure is used in order to exclude indirect interactions from the model. In both the phases, a unique search algorithm is used in order to facilitate the analysis.

The methodology was successfully demonstrated on an industrial case study of a board machine exhibiting oscillations in its drying sections. The methodology offers several advantages. First, the automated integration of the data-based analysis with the connectivity information using the search algorithm produces an efficient analysis which is suitable for industrial applications. Second, the methodology only considers direct interactions when obtaining the initial causal model, thus not all pairs of variables are tested in order to obtain the causal model. Therefore, the computational load is reduced and the results are easier to interpret. Moreover, the newly proposed measure for estimating the direct causality in MV cases proved to be beneficial in excluding indirect interactions in phase II of the analysis. Although the results of phase I might be sufficient to obtain an adequate causal model, phase II is essential since physical connectivity does not necessarily imply on direct causality. Consequently, the two-phase analysis yields a casual model with a high degree of credibility, although the significance level of the results was not tested. This enables to retrace the propagation path with less computational effort compared with other data-based methods that require surrogate data for statistical significance testing or are more computationally complex, e.g., TE. On the other hand, the GC method was able to produce just as reliable results in the same case study [8]. In general, therefore, it seems that in the future cases, straightforward linear methods such as the GC should be tried at first, while if the system is highly nonlinear, the nearest neighbors method would be an appropriate selection.

The main weakness of this paper is that it does not take into account a variety of case studies. Further studies need to be carried out in order to estimate the efficacy of the proposed methodology using other case studies with different types of disturbances. In particular, it would be interesting to test the proposed methodology on a highly nonlinear system or with nonoscillatory disturbances. An important limitation of this approach is that the directionality measure relies on the physical connectivity of the process. On the one hand, the possibility to easily capture the plant topology using a CAD tool offers a practical method for automated causal analysis [32]. On the other hand, the connectivity matrix is a simple qualitative representation of the process schematic which does not include any information on the process itself such as the chemical composition of the components, reactions rate, and so on. Thus, it is problematic, for example, to retrace the propagation of disturbances that cause variations in the composition of a stream. One possibility to tackle this issue could be labeling the contents of vessels and pipes with the attribute of composition [22]. Addressing these kinds of limitations is further discussed in [22] and [32]. Future studies should therefore concentrate on automatic technique to deal with disturbances in unmeasured variables. Another problem with this approach lies in the fact that the results are not evaluated by a statistical threshold. Consequently, several indirect/spurious results were obtained in the final model. Therefore, it is advised to verify the results using process knowledge or plant personnel if available. Alternatively, several data-based methods can be applied in parallel to reinforce the analysis.

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Rinat Landman received the B.S. degree in chemical engineering from Technion—Israel Institute of Technology, Haifa, Israel, in 2007, and the M.S. degree in process systems engineering from Aalto University, Espoo, Finland, in 2013, where she is currently pursuing the Ph.D. degree in process control and automation with the School of Chemical Technology.

Her current research interests include a variety of different topics such as causality, data-driven techniques for process monitoring, and machine learning methods.

Sirkka-Liisa Jämsä-Jounela received the master's degree in process engineering from the University of Oulu, Oulu, Finland, in 1978, and the Ph.D. degree in process engineering from the Helsinki University of Technology, Espoo, Finland, in 1990.

She joined Kemira Engineering, Siilinjärvi, Finland, in 1983, where she was a Control Engineer with Siilinjärvi Phosphate Plant. From 1987 to 1991, she was a Research Scientist (Industrial Researcher) with the Academy of Finland, Helsinki, Finland, and Kemira Oyj, Helsinki. In 1991, she joined the Outokumpu Group, where she was a Senior Consultant and also received practical experience in international automation projects. In 1994, she was a Professor of process control with Aalto University, Espoo. From 2005 to 2008, she was a Vice President of the International Federation of Automatic Control (IFAC), Laxenburg, Austria. From 2008 to 2010, she was a Board Chair of the Nordic Process Control Group. Since 2015, she has been a Vice Dean (Research) of the School of Chemical Technology, Aalto University. She has supervised 15 Ph.D. students, over 200 M.Sc. students, and published over 200 publications in international conference and journal papers.

Prof. Jämsä-Jounela is a member of Research Council for Natural Sciences and Engineering, Academy of Finland. She is the Chair of the Technical Committee on Automation in Mining, Mineral, and Metal Processing, IFAC.