Fault propagation analysis of oscillations in control loops by combining process causality and topology

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ABSTRACT

Disturbances in large-scale industrial systems can easily propagate through the process units and thereby adversely affect the overall process performance. In particular, oscillations in control loops are very common in industrial processes and lead to poor control performance, an excessive energy consumption and deteriorate the product quality. Identifying the propagation path of oscillations is of great importance due to its ability to disclose the root cause and identify the process units of concern which should be monitored closely.

This paper presents a technique for identifying the propagation path of oscillations in control loops using a dedicated search algorithm. The algorithm combines the quantitative results from the data-driven causal analysis and the topology-based model in the form of a connectivity matrix in order to yield an enhanced causal model which illustrates the propagation path. The algorithm has two functionalities: one is finding feasible propagation paths among two elements and second is determining whether each path which had been found is direct or indirect. The analysis is demonstrated on an industrial paperboard machine with multiple oscillations in its drying section due to valve stiction. First, the connectivity matrix is extracted from a P&ID. Secondly, the causality matrix is obtained using the Granger causality method which is then refined using the search algorithm based on the connectivity matrix. Finally, the causal model illustrating the propagation path is given and the results are evaluated.

1 INTRODUCTION

In large-scale chemical processes, disturbances can easily propagate through the process units and thereby adversely affect the overall process performance. In particular, oscillations in control loops are very common inindustrial processes and lead to poor control performance, low product quality and excessive energy consumption /14/. In large-scale systems with a high degree of connectivity, it is a difficult task to determine the most probable propagation path. In recent years, capturing causality between different process variables has become a vital tool in the diagnosis of faulty systems due to its ability to identify the propagation path of disturbances /12/.

Causality can be captured from process knowledge and/or process data. Models which are based on the physical layout of the process are typically referred to as topology-based models or process connectivity models /3/.

Several techniques for extracting plant connectivity information from piping and instrumentation diagrams (P\&IDs) have been developed in recent years /10,11,13/. On the other hand, data-driven causal analysis utilizes historical process data in the form of time series and measures to what extent the time series corresponding to specific variables influence each other. The main difficulty in data-driven causal analysis is in establishing the statistical significance of the results, hereby eliminating redundant links from the causal model. Consequently, several attempts have been made in recent years to combine data-driven causal analysis with topology-based models /11, 12/. However, in cases where the system has a high degree of connectivity among the process units, finding feasible propagation paths among the process components might not be sufficient to capture precisely the causal topology.

The present study was designed to identify the propagation path of oscillations in control loops by utilizing a dedicated search algorithm which validates each entry in the causality matrix obtained from the data-driven analysis using the connectivity matrix extracted from the P&ID. The search algorithm has two main functionalities: finding feasible propagation paths between two control elements and determining whether a path is direct or indirect. The outcome is a refined causality matrix which contains the structural information of the propagation path. The efficiency of the analysis is successfully demonstrated on an industrial board machine utilizing the Granger causality (GC) while the connectivity matrix was captured from an AutoCAD P\&ID as an XML schema. This paper is organized as follows. Section 2 describes how to generate a topology-based model. Section 3 presents the fault propagation analysis including the data-driven analysis and the search algorithm. Section 4 describes the process case study and the results of the fault propagation analysis. The paper ends with concluding remarks in Section 5.

2 GENERATION OF TOPOLOGY BASED MODELS

There are two types of topology-based models: causal digraph and connectivity matrix which can be considered as a graphical and a numerical representation of the process schematics, respectively. The digraph reflects physical or signal flows between the equipment and instruments based on the physical layout of the components it represents. Similarly to the digraph, the connectivity matrix indicates the relationships between process components in the form of a binary matrix whose elements are assigned according to the existence of a directional connection from the row header component to the column header component /9, 11/ .

In this study, topology data was extracted from an electronic P\&ID which is drawn by the specialized Autodesk AutoCAD P\&ID drafting application that has been developed based on Autodesk AutoCAD. In the developed application, the topology data is exported in the format of ISO 15926-compliant XML scheme XMpLant /1/.

The automated generation of topology information includes the following tasks. First, the schematic information on the initial component and the terminal component of every line segment, such as pipes and control signals is included in the drawing. Secondly, this information is attained through the database object of the drawing which includes all the topology information, namely, the names of the process components, the coordinates of the components and the connections among them. Finally, this data is further processed by MATLAB program and converted into connectivity information which includes the tags, coordinates, and the connectivity between process components /9/.

3 FAULT PROPAGATION ANALYSIS

This section first provides an overview on the Granger causality method and then proceeds by describing the search algorithm which is utilized in order to combine the connectivity information with the results of the causal analysis.

3.1 Granger causality

Granger causality has received great attention in many areas due to its ease of implementation and efficiency when investigating causal relationships /7, 14/. Moreover, the method has been extended to multivariate (MV) time series analysis /4/ which makes it highly beneficial when investigating large-scale systems.

The basic notion of the GC is that if one time series affects another series, then the knowledge of the former series should help to predict the future values of the latter one /5/. To illustrate the concept of the method, consider two time series $X_1(t)$ and $X_2(t)$ and their corresponding autoregressive (AR) model:

$$(1)\quad X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + \epsilon_1(t)$$

$$(2)\quad X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + \epsilon_2(t)$$

where p is the model order and ϵ_1, ϵ_2 are the residuals for each series. (1) is typically referred to as the *unrestricted mode* /2/ . The GC from X_2 to X_1 is defined as:

$$(3)\quad F_{x2\to x1} = ln\left[\frac{var(\epsilon_1')}{var(\epsilon_1)}\right]$$

where $\epsilon_1{}'$ is obtained from (1) by omitting all A_{12} coefficients for all j /8/. The model after omitting all A_{12} coefficients is typically referred to as the *restricted model* /2/. For MV processes the MV (conditional) GC /6/ can be used.

3.2 Refinement of the causality matrix

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

- In matrix X, select the next non-zero *(i,j)*th element that has not been tested.
- Check if there is a direct physical path from controller *i* to controller *j* using the search algorithm.
- If there is no direct path from controller *i* to *j*, set *X(i,j)* to zero.

Note that we define a direct path from controller *i* to controller *j* if it does not transverse any other controller other than *j*. The search algorithm first finds if a physical path between two control elements exists. It is performed using a generic algorithm which is based on a graph traversal which searches a series of nodes, ensuring that each node is only traversed once /11/. Once a physical path between the 'cause' variable and the 'effect' variable is found, an additional unique algorithm is employed to find if it is direct or not. The algorithm checks the type of each element in each physical path that had been found in the previous step. If it finds a control element (i.e., valve, controller or sensor) which belongs to a control loop that is neither the 'cause' nor the 'effect', the corresponding path is considered as indirect. Otherwise, if the component belongs to the 'effect' control loop, the path is considered as direct.

4 PROCESS CASE STUDY

In this section, we first provide the process description. Next, spectral analysis is applied to identify the variables associated with the fault. Finally, the fault propagation analysis is applied to obtain the causal model depicting the propagation path.

4.1 Process description

The process case study is a large-scale board machine (BM) which produces a three-layer liquid packaging boards and board cups. The analysis is focused on the drying section of the BM where the remains of excess water in the web are evaporated to achieve the desirable moisture content in the board using steam-filled drying cylinders. The condensing steam in the cylinders releases latent heat which is used to evaporate the bound water in the web. The condensate from the cylinders is collected by siphons to condensate tanks where steam and condensate are separated. Steam is then delivered back to the process and condensate is returned to a power plant. A scheme of the drying section and its control loops can be seen in Figure 1. The cylinders in the drying section are divided into six steam groups (SG). Each SG and its corresponding condensate tank (CT) form a single drying group (DG). Each DG has its own controllers to control the steam pressure, the steam pressure difference between steam and condensate headers and the level of the condensate. The present case study entails a valve stiction in the pressure controller PC1652 and its effect on the interacting loops of the drying section of the board machine. The stiction diagnosis is based on the long-term maintenance records of the plant.

The power spectra of the series were examined in order to detect measurements with similar dynamic behavior. The power spectra of the controlled variables (*PVs*) are shown in Figure 2 where the measurement of PC1652 is colored in red. The loops oscillating at a common frequency are: PC668, PC1653, PC651, PC652, PC653, PC670, LC652, PC1652, PC671, LC653, PC672 and PC673. Thus, the disturbance is mainly affecting SG1, SG2 and SG3.

4.2 The results of the GC analysis

The GC method was applied by evaluating the influences of the controllers outputs (*OP*s) on the process controlled variables (*PVs*) and included only the control loops which were found to be oscillating at the same frequency based on the spectral analysis. The time domain MV (conditional) GC analysis was applied according to /6/. The MAR model estimation was performed using the least squares method and model order was chosen based on the AIC criteria (p=10). The statistical significance was determined via the F-statistic test /5/ and the results were corrected using the Bonferrori correction for multiple comparisons with a p-value of 0.01 /8/. The initial causality matrix is shown in Figure 3.

4.3 The refined causality matrix and the causal model

The refined causality matrix is shown in Figure 4a. All the GC values which correspond to non-direct interactions based on the process connectivity have been set to zero. The causal model based on the refined causality matrix is shown in Figure 4b. The search algorithm was able to eliminate most of the redundant results from the GC analysis, however the model was still assumed to have few redundant arcs (denoted by the dashed

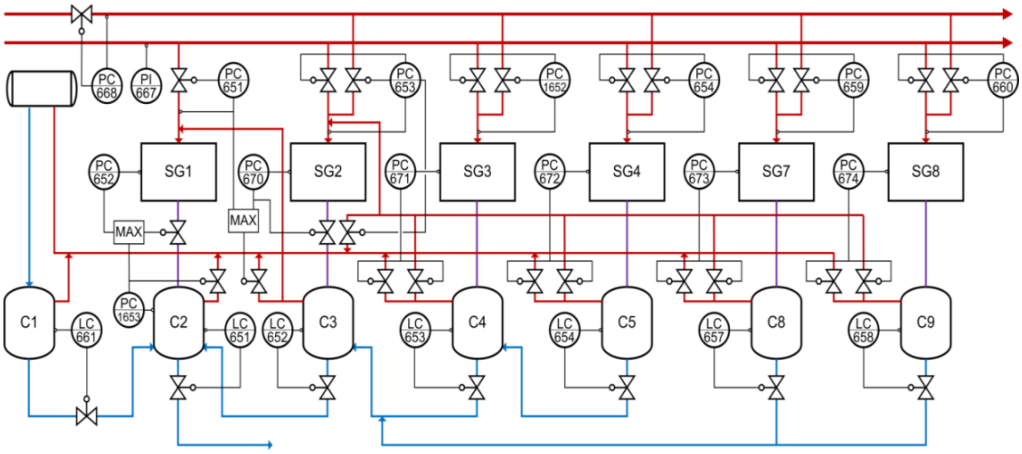

Figure 1. Flowsheet of the drying section. Red lines indicate steam pipes, blue lines are condensate pipes and purple lines indicate mixed flow of steam and condensate.

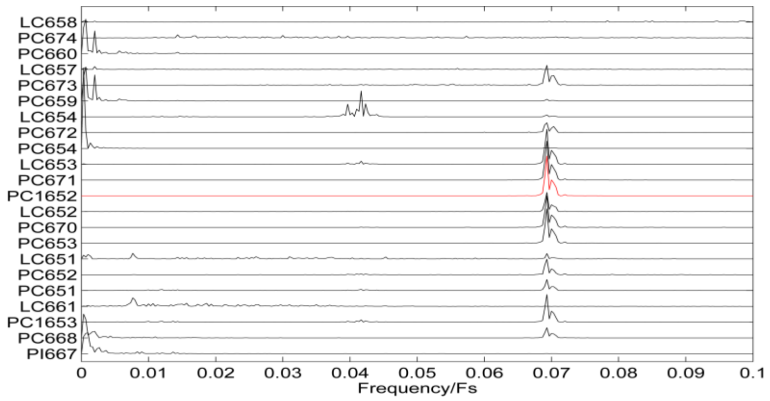

Figure 2. The power spectra of the time series

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

Figure 3. The initial causality matrix

arcs in Figure 5 and the highlighted values in Figure 3) based on process knowledge. Those types of ambiguous results are sometimes inevitable and in-depth process knowledge is needed to detect them. Nonetheless, the search algorithm was able to eliminate approximately 88% of the spurious results obtained from the GC analysis, herewith affirming the efficacy of the refinement procedure.

	PC1653	PC651	PC652	PC653	PC670	LC652	PC1652	PC671	LC653	PC673
PC1653	-	0	0	0	0	0	0	0	0	0
PC651	0	-	0.056	0	0	0	0	0	0	0
PC652	0.065	0.016	0	0	0	0	0	0	0	0
PC653	0	0	0	-	0.017	0	0	0	0	0
PC670	0	0.029	0.031	0	-	0	0	0	0	0
LC652	0	0	0	0	0	-	0	0	0	0
PC1652	0	0	0	0	0	0	-	0.113	0.044	0
PC671	0	0	0	0.016	0.029	0	0.144	-	0.074	0
LC653	0	0.013	0.014	0	0	0.068	0	0	-	0
PC673	0	0	0	0	0	0	0	0	0	-

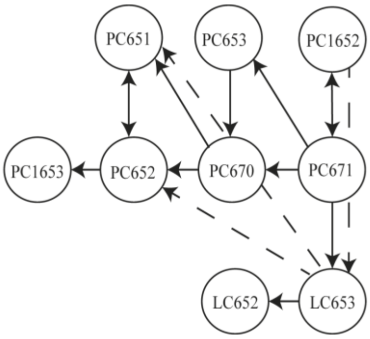

Figure 4. (a) The refined causality matrix (b) the corresponding causal model

5 SUMMARY AND CONCLUDSIONS

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

Yet, several redundant links remained in the causal model in spite of the refinement procedure, thus, process expert knowledge was essential in eliminating those. Alternatively, numerous data-driven methods can be employed in order to construct the causality matrix prior to the refinement procedure, particularly, in cases where the system is with a high degree of connectivity among variables.

In the future, the proposed fault propagation analysis can be used to study how different types of faults propagate in a system and accordingly select the critical variables for monitoring.

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