Cheng, H.; Nikus, M.; Jämsä-Jounela, Sirkka-Liisa

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CAUSAL MODEL BASED FAULT DIAGNOSIS APPLIED ON A PAPER MACHINE SIMULATOR

Hui Cheng, Mats Nikus, Sirkka-Liisa Jämsä-Jounela

Aalto University
Laboratory of Process Control and Automation
Kemistintie 1, FI-02150 HUT, Finland

Abstract: The aim of the work presented in this paper is to evaluate the ability of the causal digraph method to detect and isolate faults on a simulated paper machine process. A causal digraph model for the short circulation process of the paper machine was constructed, identified and used to detect and isolate artificial faults in the simulation environment. The fault of headbox slice opening was studied and diagnosed. Copyright © 2006 IFAC

Keywords: Fault detection, Fault isolation, causal digraph, papermaking, APROS simulator

1. INTRODUCTION

Due to the increasing competition in the process industries, there has been a strong need to detect, locate and estimate faulty states and recover the process from these states. By applying fault diagnosis, process safety, production quality and equipment maintenance could be improved remarkably.

Since Iri et al. (1979) introduced the Signed Directed Graph (SDG), the simplest causal digraph method, into the field of process fault diagnosis, it has made remarkable progress and been the most popular causal model based method for process fault diagnosis. In order to decrease the spurious results, fuzzy logic was used by Shih and Lee (1995) to represent both the variables and relations in causal digraph. However the method still kept as steady state based. Another big improvement for causal digraph was the introduction of the piece-wise linear transfer functions (QTF) by Leyval et al. (1994). Simplified transfer function provides dynamic information and new reasoning method for diagnosis purpose. Recently more quantitative models, such as difference-algebraic equations (Montmain and Gentail, 2000) have been used in causal digraph to make further improvement to the diagnosis result.

A set of inference diagnosis methods, such as causal digraph, Bayesian networks, Automata and Petri net were selected for fault detection and isolation on paper machines. The aim of this paper is to test the fault detection and isolation ability for one of these techniques – the causal digraph method. In this study, the APROS simulator developed by VTT (Technical research center of Finland) was used to build model for the papermaking process (APROS, 2005) and NNDT (Saxén B. and H. Saxén, 1994) was used to identify the relations in the causal digraph. The fault detection and isolation steps were performed in the Simulink environment.

The paper is organized as follows. In the next section the basic concepts about FDI, causal digraphs and the CUSUM method will be described. Section 3 describes the short circulation process in paper mills and the specific faulty case. In section 4, the causal digraph model construction is discussed. The results are presented in section 5 followed by the conclusions in section 6.

2. FAULT DETECTION AND ISOLATION (FDI)

In both process industries and the academic world, a fault is usually considered as an undesired deviation of the system structure and parameters from their nominal state. Fault detection and isolation refer to detecting the occurrence of a fault in a process and locating the faulty components respectively. Due to active research during the last two decades, dozens of new FDI methods have been developed. However,
most of the methods are carried out using a similar procedure entailing residual generation, residual evaluation and decision-making. In this paper, the residuals are generated using a causal digraph model and evaluated with the CUSUM method. The final decision is made according to the causal digraph reasoning rules.

2.1 Causal digraphs

Causal graphs provide a good way to represent physical cause-effect relations between different process variables that are of interest for fault diagnosis. In the causal directed graph models, the nodes denote the variables, while the directed edges between the nodes represent the causal relations between these variables, through which faults can propagate.

Different models can be used to explain the cause-effect relations on the edges depending on the nature and level of abstraction of the model, which subsequently leads to a variety of different methods for backward (diagnosis) and forward (simulation) reasoning. The Signed Directed Graph (SDG) method, the simplest causal directed graph method, uses pure qualitative information, which can give rise to ambiguous fault diagnosis. The uses of QTF and deference equation introduce more quantitative information and decrease the spurious results.

2.2 Residual generation

Causal digraphs produce two kinds of residuals to be used in fault detection and isolation. The global residuals are obtained as the difference between the measurement and the global propagation value shown below:

\[
\delta(t) = y(t) - \hat{y}(t)
\]

where \( y(t) \) is the measurement and \( \hat{y}(t) \) is the global propagation value obtained by

\[
\hat{y}(k+1) = Ax(k) + Bu(k)
\]

where \( u(k) \) is the global propagation value from the parents nodes in the graph model.

The local residual is produced by a test using the local model as shown:

\[
\delta^l(t) = y^l(t) - \hat{y}^l(t)
\]

where \( y^l(t) \) is the local propagation value obtained by

\[
x^l(k+1) = Ax^l(k) + Bu^l(k)
\]

\[
y^l(k) = Cx^l(k)
\]

where \( u^l(k) \) is the measurement value from the parents nodes in the graph model. For the case that one node in the graph has more than one measured variables as parents, the local residual could be multiple. There are several rules concerning this:

i. In equation 4, rearrange \( u \) as \( u_1, u_2, \ldots, u_r, \)

\( u_{r+1}, \ldots, u_n \) such that \( u_1 \ldots u_r \) are measured parent nodes for \( y \) while \( u_{r+1} \ldots u_n \) are not.

ii. For all the measured parents nodes, \( u_i, u_2, \ldots, u_n \) use their measurement produce the local residual \( LR(u_i, u_2, \ldots, u_n) \)

iii. For \( u_i, 1 \leq i \leq r \), produce the local residual \( LR(u_i) \), using its measurement and the other parent nodes’ global propagation value.

iv. For the pair \((u_i, y_j), 1 \leq i \leq r, 1 \leq j \leq r \) and \( i \neq j \), produce the local residual \( LR(u_i, y_j) \), using their measurements and the global propagation values for the remaining inputs.

v. Produce the local residuals for all possible combinations of inputs.

2.3 Residual evaluation

The nature of the residual evaluation in this method is a mapping from the residual to the set \([0, 1]\). In the faultless case, the residuals are considered to be a zero mean random sequence, for which the statistical distribution will change when a fault occurs. Among all the possible changes in the signal distribution, a jump in the mean is considered as the most relevant one for fault detection and is hence used in this study.

For the detection of a jump in the mean of a noisy residual sequence, the CUSUM method by Page and Hinckley was implemented. For a positive mean jump, the following applies.

\[
SUM(n) = \sum_{k=1}^{n} (\delta(k) - \mu - fault_{min})
\]

\[
MinSUM = \min \sum_{k \in \mathcal{G}} (k)
\]

where \( fault_{min} \) is a user specified minimum jump that the method will be able to detect. When \( SUM(n) - MinSUM > \lambda \), a jump has been detected (Hinckley, D. V., 1971). The parameter \( \lambda \) provides some robustness to the fault detection but it will also delay the detection. Negative jumps are handled in a similar way.

\( fault_{min} \) and \( \lambda \) are design parameters, usually tuned according to the requirement for false alarm and missed alarm rates. Technically the CUSUM method can detect very small jump in the mean of a random sequence but in practice, \( fault_{min} \) is decided by the minimum fault the method should be able to detect and \( \lambda \) is usually set to 20\( fault_{min} \).

With the CUSUM method, the generated residuals are mapped into 0 or 1, which can be used in the fault isolation reasoning step with Causal digraphs.

2.4 Fault isolation reasoning

With the result obtained from residual evaluation, the structural information in the causal digraphs can be used to isolate faults. In most cases, the nature of the fault can also be inferred. Several rules concerning fault isolation reasoning are given below:

i. If the global residual \( GR(y) = 1 \) and local residual \( LR(u_1, u_2, \ldots, u_r) = 1 \), then the fault is
local or has propagated from the variables 
\(u_{1}, \ldots, u_{n}\).

ii. If \(GR(y) = 1\) and \(LR(u_{1}, u_{2}, \ldots, u_{r}) = 0\), then the fault is not local and propagated from the variables \(u_{1}, \ldots, u_{r}\).

iii. If the local residual \(LR(u_{i}) = 0\) for an individual parent node then the fault has propagated from the variable \(u_{i}\).

iv. If the local residual \(LR(u_{i}, u_{j}) = 0\) for the parent node combination then the fault is propagated from those combined variables.

v. After the location of fault, if it propagates through global propagation, it is a process variable fault.

vi. After the location of a fault, if it propagates through local propagation, it is a measurement fault.

Fig. 1 illustrates the basic ideas of the presented rules.

![Fault isolation scheme in CDG](image)

### 3. CASE STUDY

This paper provides a case study concerning fault detection and isolation on a paper machine simulator. The focus is on the short circulation process but paper quality variables are considered as well. For this study, the Advanced Process Simulator (APROS) was used to build the paper machine model. For a general description of the APROS simulator, the reader is referred to the APROS website (APROS, 2005). In the remainder of this section, the short circulation process is described together with a presentation of the studied fault.

#### 3.1 Short circulation process

The short circulation is a crucial part of the papermaking process, with several important functions. The dilution of the fibre-suspension entering the process to a suitable consistency for the headbox takes place in the short circulation, in a mixing process were low-consistency water from the wire-pit is mixed with high-consistency stock. The second important task of the short circulation is the removal of impurities and air. This task is performed in the hydro-cyclones, machine screens and the so-called deculator. The short circulation also improves the economy of the process because the valuable fibres and filler materials that pass through the wire are recycled. As the intermediate process between stock preparation and former, the short circulation process is very important for paper quality control, since the basic weight, ash consistency and stock jet ratio control are performed in the short circulation part.

The short circulation process starts after a machine chest. Usually the machine chest is followed by a thick stock pump and a basic weight valve, which is used for basic weight control. The thick stock is pumped to the wire pit and mixed with white water and filler controlled by the filler valve. The diluted stock is pumped by a fan pump via the hydro-cyclones to the deculator. The deculator has a continuous overflow to keep the inlet pressure constant for the head box feed pump. The diluted stock is then pumped into the hydraulic headbox and sprayed onto the wire at a constant speed. On the wire the stock is dehydrated to form a wet web. About 98% of the water and 54% of the filler and fibre go through the wire and flow to the wire pit as white water. The process is presented in Figure 2.

![Flow sheet of the short circulation process](image)

The variables shown in Figure 2 are important for building the causal digraph model. Table 1 gives a description of the variables.

#### Table 1 Description of the variables in the short circulation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>baval</td>
<td>Basic weight valve opening</td>
<td>-</td>
</tr>
<tr>
<td>wp fc</td>
<td>Filler consistency in the wire pit</td>
<td>%</td>
</tr>
<tr>
<td>wp fic</td>
<td>Fiber consistency in the wire pit</td>
<td>%</td>
</tr>
<tr>
<td>fival</td>
<td>Filler adding valve opening</td>
<td>-</td>
</tr>
<tr>
<td>de fc</td>
<td>Filler consistency in the deculator</td>
<td>%</td>
</tr>
<tr>
<td>de fic</td>
<td>Fiber consistency in the deculator</td>
<td>%</td>
</tr>
<tr>
<td>feedpump</td>
<td>Headbox feed pump rotation</td>
<td>%</td>
</tr>
<tr>
<td>totalflow</td>
<td>Mass flow into the headbox</td>
<td>kg/s</td>
</tr>
<tr>
<td>sliceopen</td>
<td>Headbox slice opening</td>
<td>mm</td>
</tr>
<tr>
<td>bw</td>
<td>Basic weight of paper</td>
<td>g/m²</td>
</tr>
<tr>
<td>ash</td>
<td>Ash consistency of paper</td>
<td>%</td>
</tr>
</tbody>
</table>

The APROS simulator provides first principle models for the necessary components, with which the model for the paper machine was construed and parameterized. Figure 3 shows the model used for this case study.
3.2 Faulty case

An artificial fault on the headbox slice opening was studied. In the APROS simulator, a zero mean noise signal with a 0.03 variation was added to the headbox slice opening signal. During the simulation, the fault was simulated by a jump in the mean of this noise from 0mm to 0.2mm when the operating point for the slice opening is 10mm. In this faulty case, the variables $baval$, $fival$ and $feedpump$ are not measurable while the other variables in Table 1 are measured. Especially for the variable slice open, the headbox provides a measurement for the actual slice open. In order to be able to detect and isolate this fault, the causal digraph model is constructed in the next section.

4. MODEL CONSTRUCTION

The model construction for causal digraphs has two steps: structure design and edge model identification.

Knowledge of the papermaking process and experience from operating the APROS model are useful for building the structure. In this case study the graph model is made up of the 11 important variables listed in Table 1 and structured as shown in Figure 4.

For identification of relations between the variables, experiments were carried out using the APROS simulator running under fault free conditions. The control loops for basic weight, ash consistency, and headbox jet ratio were running on manual control during the identification. The data was then imported to the NNDT software package, which besides neural network training also supports identification of linear structures such as discrete state-space models (Nikus, 1995). State-space models, as given in the below equation, were identified:

$$x(k + 1) = Ax(k) + Bu(k)$$

$$y(k) = Cx(k)$$

where $u(k)$ is the input from the parent nodes and $y(k)$ is the propagation value for the child node.

With the discrete state space models representing the relations between variables, residuals were generated in the Simulink environment.

5. RESULTS

The causal digraph model presented in the previous section was subsequently simulated in Simulink and applied for fault detection and isolation. The test starts from the quality variables and goes back to the root cause for the deviation of the paper quality.

5.1 Tests for the basic weight variable

Firstly global and local residual tests using all the measured inputs were performed as shown in Figure 5.
For the test, the parameters for the CUSUM method were $\text{fault}_{\text{min}} = 0.15 \text{ g/m}^2$ and $\lambda = 3$, which means that a deviation in the basic weight above $0.15 \text{ g/m}^2$ can be detected. From the result in Figure 5, the global residual evaluation is 1 after the sample point 880, which indicates the occurrence of a fault. However the local test using all the three measured inputs gives no alarm, which implies that the fault has propagated from the upstream variables. In order to find out the fault propagation path, individual local tests for a single measured input were performed first. The $bw$ variable has three inputs, $\text{totalflow}$, $\text{de\_fc}$, $\text{de\_fic}$, as shown in Figure 4. So the local residuals $LR(\text{totalflow})$, $LR(\text{de\_fic})$, $LR(\text{de\_fc})$ were tested for individual inputs. The results are shown in the Figure 6.

![Fig. 6. Local tests for individual inputs with measurement](image)

From Figure 6, it can be seen that the evaluation for all individual local residuals are one, which means the single fault propagation path cannot explain the faulty situation. Multiple fault propagation paths were considered by doing the two-input combination local residual tests ($LR(\text{totalflow, de\_fc})$, $LR(\text{totalflow, de\_fic})$, and $LR(\text{de\_fic, de\_fc})$). The results are shown in Figure 7.

![Fig. 7. Local tests for two-input combinations](image)

Figure 7 shows that the evaluation for the local residual $LR(\text{de\_fic, totalflow})$ is zero all the time which indicates the fault propagated from those two variables. The result shows the explanation for the fault propagation is consistent with the process knowledge. The fiber consistency in the deculator and the mass flow to the headbox affect the final basic weight for paper much more than the filler consistency in the deculator does. Since the fault propagates from both $\text{de\_fic}$ and $\text{totalflow}$, tests for these two were performed as illustrated in the following subsections.

5.2 Tests for the deculator fiber consistency

The global and local tests for all the measured inputs have been done for the deculator fiber consistency. Since the input variable $baval$ is not measured, its global value was used in the local test. The results are shown in the Figure 8.

![Fig. 8. Global test and the local test for all the inputs with measurement](image)

Figure 8 indicates that the fault in this variable is not local. Since the, $de\_fic$ variable has two measured input variables, further local tests for individual inputs were performed as shown in Figure 9.

![Fig. 9. Local tests for individual inputs](image)

As seen in the above figure, the local tests for the individual inputs indicate the fault cannot be explained by only one of the inputs. Considering the fact shown in Figure 8, it is concluded that the fault propagated from the variables $\text{totalflow}$ and $wp\_fic$.

5.3 Tests for the wire pit fiber consistency

Similar tests as shown above were performed for the variable $wp\_fic$. The results shown in the following figures indicate that the fault in $wp\_fic$ propagated from $de\_fic$, which makes the $\text{totalflow}$ the only variable to be tested.
5.4 Tests for the total mass flow to headbox

The global and local tests are done for the variable totalflow as shown below. For the local residual test, the only measured input, sliceopen, was tested.

The local test indicates that the fault originates from the sliceopen variable. Since the slice opening is the boundary of the causal digraph, we locate the fault origin in the sliceopen variable as shown in the Figure 13.

Apparantly the CUSUM method can detect the deviation of the slice opening too. However with a causal digraph, the nature of the fault can be identified. Since the slice opening is the fault origin and the fault propagated via a global model to the totalflow variable, it is considered to be a process variable fault rather than a measurement fault. The fault also propagated to the variables ash, de_fc, and wp_fc. The fault propagation path in the causal digraph is shown in Figure 13.

6. CONCLUSIONS

In this paper, the ability of the causal digraph method for fault detection and isolation was tested in a simulation environment. Linear discrete state space and algebraic equations were used to describe the causal relations in the graph. The CUSUM signal-based method was applied to evaluate the generated residuals. The results shown and discussed prove that the causal digraph is a useful fault diagnosis tool. Fault diagnosis inside control loops and nonlinear cases using causal digraphs are left as topics for future research.

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