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APPLICATION OF A CAUSAL DIGRAPH BASED FAULT DIAGNOSIS METHOD WITH STATE SPACE MODELS ON A PAPER MAKING PROCESS SIMULATOR

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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. In order to represent the causal relations between the variables using state space models, a linearity test was performed for the short circulation sub process in the papermaking simulator. The corresponding causal digraph model was constructed, identified and used to detect and locate the artificial fault in the simulation environment. The studied fault was a fiber retention rate drop on the wire.

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, product 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 alleviate the problem with spurious results, fuzzy logic was used by Shih and Lee (1995a, 1995b) to represent both the variables and the relations in the causal digraph. However the method itself still remained static. Another big improvement of the causal digraph was the introduction of the piece-wise linear transfer functions (QTF) by Leyval et al. (1994). The used simplified transfer function provides dynamic information. With the introduction of the QTF a new reasoning method for diagnosis purposes was based on residuals was needed. Recently more quantitative models, such as difference-algebraic equations (Montmain and Gentail, 2000) have been used in causal digraph to further improve the diagnosis results.

The aim of this paper is to test the fault detection and isolation abilities of the causal digraph method on paper machines. In this study, the APROS simulator developed by VTT (Technical research center of Finland) was used to simulate the papermaking process (APROS, 2005) and NNDT (Saxén B. and H. Saxén, 1994) was used to identify the causal relations in the causal digraph model. In this paper the causal relations are represented by state space models. The fault detection and isolation steps were performed using the developed MATLAB graphic user interface.

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 studied retention drop fault. In section 4, the linearity of the APROS paper machine model was proved and the causal digraph model is constructed using the MATLAB user interface. The fault diagnosis result is shown in section 5 followed by the conclusion 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 more recent use of QTF and difference equations has introduced more quantitative information into the model and consequently decreased the amount of spurious results.

2.2 Residual generation

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

\[
\delta(k) = y(k) - \hat{y}(k) \tag{1}
\]

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

\[
\hat{y}(k) = f(\hat{U}(k-1),\hat{U}(k-2),..) \tag{2}
\]

where in dynamic cases \(\hat{U}(k-1) = [\hat{u}_1(k-1),..\hat{u}_n(k-1)]\) is the lagged global propagation values from the parent nodes in the graph model and \(n\) denotes the number of the inputs for the variable \(y\).

The local residual can be further subcategorized into three types: individual local residual (ILR), multiple local residual (MLR) and total local residual (TLR).

The individual local residual can be produced by taking the difference between the measurement and the local propagation value with only one measured input while all the others are propagation value from parent nodes.

\[
ILR(m) = y(k) - f(U_m(k-1),U_m(k-2),..) \tag{3}
\]
where \(U_m(k-1) = [u_1(k-1),..u_m(k-1),..\hat{u}_m(k-1)]\), the \(\hat{u}_m(k-1)\) is the global propagate value from the parent node, and the \(u_m(k-1)\) is the measurement for the parent nodes. Usually the number of ILRs is the same as the number of inputs to the model for predicting the variable \(y\).

Similarly the MLR is produced by

\[
MLR(m,d) = y(k) - f(U_{m,d}(k-1),U_{m,d}(k-2),..)\tag{4}
\]

where \(U_{m,d}(k-1) = [\hat{u}_1(k-1),..u_m(k-1),u_j(k-1),..\hat{u}_m(k-1)]\) and \(m, d\) denote the inputs for variable \(y\) with measurement value. Generally the MLRs can be produced for all possible combinations inputs to the model for variable \(y\).

The TLR is produced by

\[
TLR = y(k) - f(U(k-1),U(k-2),..) \tag{5}
\]

where \(U(k-1) = [u_1(k-1),..u_j(k-1)]\) is the lagged measurement values for all inputs to the model for variable \(y\).

2.3 Residual evaluation

The nature of the residual evaluation in this method is a mapping from the residuals to the set \{0,1\}. In the faultless case, the residuals are considered to be a zero mean random sequence signal, for which the mean value will change when a fault occurs.

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

\[
SUM(k) = SUM(k-1) + \delta(k) - \mu_y - minfault / 2 \tag{6}
\]

\[
MinSUM = \min_{\alpha = 1}^{n} SUM(\alpha) \tag{7}
\]

where \(minfault\) is a user specified minimum detectable jump. When \(SUM(k) - MinSUM > \lambda\), 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. A more general procedure can be developed based on the simple positive jump case for detecting two-directional jumps and residual recovery back to the normal situation.

\(minfault\) and \(\lambda\) are design parameters, usually tuned according to the requirement for false alarm and missed alarm rates. Theoretically the CUSUM method can detect very small jumps in the mean, but in practice, \(minfault\) is decided by the minimum detectable fault and \(\lambda\) is usually set to 10-20 times of \(minfault\).
With the CUSUM method, the generated residuals above are mapped into 0 or 1, which can be used in the fault diagnosis reasoning with the rules presented in the following section.

### 2.4 Fault diagnosis reasoning

With the results obtained from the residual evaluation, the structural information in the causal digraphs can be used to diagnose faults. There are two types of rules concerning fault diagnosis: fault location rules and fault nature rules.

For a specific node \( y \) in the causal digraph, the fault location rules can locate the fault on the variables even in the presence of multiple alarm variables. The reasoning rules for faults location are shown in the Table 1.

<table>
<thead>
<tr>
<th>GR</th>
<th>TLR</th>
<th>ILR(m)</th>
<th>MLR(m,d)</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>No fault</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>Upstream</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Upstream</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>Local</td>
</tr>
</tbody>
</table>

After the locating the fault origin, in most cases the nature of the fault can be identified by fault nature rules, which are given in the following table.

<table>
<thead>
<tr>
<th>GR for any child node</th>
<th>TLR for any child node</th>
<th>Fault nature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Local fault for that child node</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Parameter fault</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>Sensor fault</td>
</tr>
</tbody>
</table>

### 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 fiber-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 1.

The variables shown in Figure 1 are important for building the causal digraph model. Table 3 gives a description of the variables.

### Table 3 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>Basis 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>bw</td>
<td>Basis 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 constructed and parameterized. Figure 2 shows the model used for this case study.
3.2 Faulty case

As a serious fault in the paper making industry, wire retention drops can cause serious problems even though the quality control loop could compensate the fault effect on the final product quality. The low retention rate will make it difficult to transfer fiber or filler from wire section to the press section decreasing the efficiency significantly. The corresponding artificial fault was simulated in the APROS model were the retention dropped from the nominal value 85% to 84.6%. In the faulty case, the value of fiber consistency in deculator, headbox and wire pit will all increase over the thresholds and cause alarm. The need to find the fault origin as well as the nature of the fault in these situations is well met by causal digraphs.

4. MODEL CONSTRUCTION

4.1 Linearity test

In this paper dynamic models were used to describe the relations between the variables of equation 2. Before the dynamic modeling the linearity of the APROS paper machine model was tested, since the detailed mathematical model for it was unknown.

Among all the variables in Table 3, baval, fival and feedpump are actuator input signals corresponding the input nodes in the causal digraph. By opening the control loop for the paper machine and manipulating the actuator signal manually, the data of 64 different steady states was collected from the simulator. From the knowledge of the process and the collected data, the structure of the causal digraph can be defined and shown as in figure 3.

The linearity between related variables is tested in two ways. For those variables that have only one input in the digraph in figure 3, the steady points (input vs. output) was plotted and tested. One example is given in figure 4 for the fiber consistency in the wire pit.
Another way to test linearity is to build a steady state static model for the tested variable with 32 steady states data using the least square method, and test the model with the remaining 32 steady states. One example is shown in figure 5 for the basis weight variable.

The test result shows that the APROS paper machine model is relatively linear, which gives us a reason to use state space models when representing causal relations according to equation 2.

4.2 MATLAB graphic user interface

The inputs and outputs variables for state space models were selected according to the structure of digraph in figure 3. New training data and validation data for state space model identification were collected from the APROS simulator under fault free and open loop conditions. 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 and Bulsari, 1995).

In order to apply the causal digraph method for fault diagnosis more easily, a MATLAB graphical user interface was developed to have such functionalities as: specify the graph, generate the residuals (GR, ILR, MLR, TLR), detect the change with CUSUM and diagnose the fault according to the reasoning rules.

In the interface, nodes and connections between nodes can be specified for the digraph structure. A from the specifications automatically generated digraph is shown in figure 3.

5. RESULTS

The causal digraph for the short circulation is constructed in the graphical user interface, and the diagnosis was performed for the faulty data which was collected during closed loop operation of the APROS model. The residuals, alarms, the fault origin and the fault nature were generated and shown by the MATLAB graphic user interface automatically. An example for the global residual for the filler consistency in headbox and basis weight is shown in figure 6.

Similar results can be obtained for the variable totalflow, de_fc, hb_fc and wp_fc, which give no alarm for those variables.

In spite of the above results, several interesting implications can be noted. First of all, the global residual of basis weight has smaller mean deviation than minfault during most of faulty period (260-660), while the beginning and ending have bigger deviation. The CUSUM method didn’t give alarm even for the beginning and ending part of fault, which provides better detection result in the sense of decreased false alarm rated as compared to fuzzy or normal threshold residual evaluation.

The second implication it that, the small deviation of the basis weight during faulty period implies that the controller for the basis weight is not perfect, even though basis weight global residual didn’t fire alarm.

Finally we can note that the controllers will hide some faults that could be important for the process and this gives rise to the demand to detect and locate faults even though the quality of final product doesn’t decrease significantly.

There are also variables that have alarms for the global residuals. The following figure shows that the alarms are fired for the variable de_fic, hb_fic and wp_fic.

As shown above, the multiple alarms fired also result in the problem to find the real origin that cause the fault. The local residuals (ILR, MLR, TLR) are usually tested to solve those problems stated above.

It can be seen clearly in figure 3, variable de_fic, hb_fic and wp_fic form a loop in the graph, which implies the fiber circulation in the short circulation process. Since all these three variables have global alarms and are in the graph loop, one of them could be chosen arbitrarily for the local residual test. The variable hb_fic is selected first and the result is shown below.
The result shown above implies the fault propagates from the upstream variable \textit{de\_fic} according to the fault location rules presented in section 2. Further tests for the variable \textit{de\_fic} is hence required.

From the above figure, one of the individual local residual removes the alarm by using measurement value, which implies to do further test for \textit{wp\_fic}.

The TRL for \textit{wp\_fic} finally locates the position of the fault on itself. The fault nature rules further tells that this is a process parameter fault since it propagates to the process globally. The final fault diagnosis is presented by the MATLAB graphical user interface shown in the following figure.

6. CONCLUSIONS

In this paper, the ability of the causal digraph method for fault detection and isolation was tested in a simulation environment. The linearity of APROS paper machine model was tested and linear discrete state space models 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 on arcs and nonlinear cases using causal digraphs are left as topics for future research.

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REFERENCES


All in-text references underlined in blue are linked to publications on ResearchGate, letting you access and read them immediately.