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Application of the Enhanced Dynamic Causal Digraph Method on a Three-Layer Board Machine

Hui Cheng, Vesa-Matti Tikkala, Alexey Zakharov, Tommi Myller, and Sirkka-Liisa Jämsä-Jounela

Abstract

This brief presents an enhanced dynamic causal digraph (EDCDG) reasoning method for fault diagnosis. In order to improve the fault isolation ability of the dynamic causal digraph method, a new algorithm for separating the positive and negative fault effect contributions is proposed. The proposed method was tested with an application on a three-layer board machine process. The results show that the proposed method, compared to the conventional dynamic causal digraph method, is able to detect the correct nodes, to form a better fault propagation path and to identify the responsible arcs when the system is affected by a process fault.

Keywords

Board machine, causal digraph, fault diagnosis, industrial application, paper making.

1 Introduction

Owing to the increasing competition and complexity in the process industries, fault diagnosis systems that detect and locate the faults are needed to meet the requirements set on product quality, efficiency, environment, and safety. The fierce competition in the global market means that the processes have either to run more efficiently or to produce the same quality of products with less stringent raw materials using more complex processes. Meanwhile, the fault diagnosis tasks can no longer be carried out by operators or plant engineers due to their complexity.

According to the studies of Nimmo [1], the improper management of abnormal situations results in the loss of 20 billion U.S. dollars annually in the American petrochemical industry alone. For economic reasons, fault diagnosis systems are therefore needed to handle abnormal situations instead of human operators. By providing supportive information to the operators and/or recovering the process automatically, the fault diagnosis system keeps the complex processes running efficiently and safely [2]. This will bring enormous economical benefits to the industries.

Of the large number of fault diagnosis methods, causal digraph fault diagnosis methods are focused in this brief. The causal graph is an excellent modeling method for representing those physical cause-effect relationships between different variables that are meaningful for the human operators in understanding the process or crucial for the fault diagnosis. In the causal directed graph models, the nodes denote the variables while the directed arcs between the nodes represent the causal relationships between these variables, through which faults could propagate. However, different models can be used to explain the cause-effect relationships on the arcs depending on the nature and abstraction level of the model. This has subsequently led to the development of a range of different methods for fault diagnosis.

Since Iri *et al.* [3] introduced the signed digraph (SDG) to the field of process fault diagnosis in 1979, there has been considerable progress in research on fault diagnosis methods with causal digraph models. In the past 20 years, dozens of modified causal digraph methods have been created and applied in the industry. Especially during the last decade, fuzzy logic [4], [5] and dynamic models, such as qualitative transfer functions (QTF) [6] and difference equations [7], have been integrated into causal graph in order to increase the quantitative knowledge about the arcs and nodes for modeling a process. This, in turn, has provided space for developing new inference mechanisms for diagnosing the faults. The goals of reducing the uncertainty of the models and eliminating erroneous diagnosis results have been pursued along with the increase in quantitative knowledge. In fact, the history of the development of causal-directed graph fault diagnosis methods indicates a focus on increasing the quantitative knowledge in qualitative models and on the development of new inference mechanisms that improve the performance of fault diagnosis.

The basic SDG method proposed by Iri *et al.* [3] models the process in a purely qualitative way, and this gave rise to the problem of multiple diagnosis results. Furthermore, for the sake of simplicity the SDG failed to analyze the faults whenever an inverse response (non-minimum phase systems) or a compensatory response (systems under negative feedback) existed in a complex process [8]. This limited the quality of the fault diagnosis result and impaired its practical usability. In order to decrease the number of diagnosis results, a five-range pattern was applied to categorize the value of the variables by Shiozaki [9] that replaced the original three-suited threshold. Apparently the five-range pattern provided more quantitative information concerning the variables in the SDG, and this also led to progress in the inference mechanism.

Applications of the SDG have been reported in different processes such as the nuclear power plant [10], the multistage separation process [11], the flash vaporizer process [12]–[15], and the furnace process in the petrochemical industry [16]. Furthermore, the variations of the SDG method tried to gain new features by combining it with other methods. An application of PCA-SDG has been reported in a fluidized catalytic cracking unit [17], while the PLS-SDG and the dynamic PLS-SDG have been developed and applied in a pulp mill process [18] and a multistage flash desalination process [19].

A major step in improving the fault diagnosis resolution of causal digraph models was the introduction of fuzzy logic. Han *et al.* [20] and Wang and Huang [21] utilized fuzzy membership functions to represent the variables, while the fault propagation manner was still kept as consistency tables on arcs. Because the membership functions are related to the possibility distribution function, the results of the diagnosis have been evaluated on the basis of the degree of fuzzy set and the possibility of faults [20]. In the following year, Shih and Lee [4], [5] extended their idea to signal propagation on the arcs, as well. In their paper, a fuzzy relation matrix was used to represent the causal-effect relationship between the nodes. Even though the fault diagnosis results were still obtained from the graph search inference mechanism, the results were sorted by the fuzzy membership function value, the credible fault membership, and the frequency number. The number of multiple diagnosis results decreased considerably.

Several applications of the fuzzy causal digraph method (FCDG) have been reported. The application fields include the continuous stirred-tank reactor and the vaporizer [5], [20], the waste water treatment process [22], the propane evaporator [23], and the multistage flash desalination process [24].

When using the methods mentioned above, however, the graph search inference mechanism still had to be used to find the paths of the fault propagation. This inference mechanism has high computational demands and can produce multiple diagnosis results because of uncertainty. Due to their poor ability to deal with dynamic situations, these methods are called steady-state analysis methods. Even with the integration of fuzzy logic, the representation of the variables and the relationship between them is still static. In order to incorporate more quantitative information about the process and to improve the fault diagnosis results, a qualitative transfer function (QTF) was introduced by Leyval *et al.* [6]. In the QTF-causal digraph model, the trajectories of the variables were used for the nodes, and the qualitative transfer function parameterized

by a static gain, a delay, and a settling time were used to represent the relationship between the variables. In the QTF, the evolution of the variables was piecewise linear, and the event (the disturbance in a variable) was propagated through the arcs. However, the QTF-causal digraph has mainly been used for simulation purposes [6]. The inverse inference mechanism was developed later by Montmain and Gentil [7], with the difference and algebraic equations representing the cause-effect relationships. In this method, the behavior of the process could be simulated dynamically and the graph search inference mechanism was no longer needed. With the inverse inference mechanism, the results of the global and local simulations were compared with the measured values in order to locate the fault.

Applications of the dynamic causal digraph method (DCDG) in a nuclear fuel reprocessing plant have been reported by Montmain and Gentil in [7] and Evsukoff *et al.* in [25]. In the latter application a prototype graphical interface based on DCDG models, which illustrates the status of the plant to the operators, was developed.

However, there are also some disadvantages to DCDG, which reduce the applicability of the method. First, fault detection based on the simulation residual is not valid in certain special cases. It has been shown that the simulation residual for the node is the sum of the propagated fault effects from the predecessor nodes and the local fault [7]. The effects of different faults may be cancelled out when they are acting in different directions. Cheng *et al.* proposed a method in [26] to reduce problem by testing the fault effect cancelling and then reevaluating the corresponding nodes with modified residuals. The residuals are recalculated after excluding the propagated fault effects which cancel the local faults. The set of excluded nodes is formed by means of a qualitative rule. Second, the isolation of the fault origin node might not be sufficient to explain the faulty behavior, i.e., the fault might be caused by a change of consistency between the variables (an arc in the digraph), not by a change in a variable (node). This has increased interest in further diagnosis development. An inference mechanism between the arcs has also been developed in [26] in order to diagnose the process faults more accurately.

Due to the qualitative rules used for separation of the fault effects in [26] the statistic used in fault detection is not robust with respect to the fault effect values. In other words, a minor change in a fault effect value may vary the result of the detection of fault effect cancellation completely. As a consequence, the value of the statistic used in fault detection may be completely changed.

Due to the deficiency in the fault effect separation approach in [26], the investigation of fault effect separation is expanded in this brief to evaluate the fault effect contributions quantitatively. The positive and negative fault effects are separated and evaluated independently in order to achieve improved isolation and diagnosis. An application to a three-layered board machine is also presented in order to illustrate the performance of the proposed method. This brief is organized as follows. Section II presents the enhanced dynamic causal digraph (EDCDG) method, including a new algorithm for the separation of fault effects in residuals. The three-layered board machine and the simulation environment are introduced in Section III. The fault scenarios, description of the experiment and the fault diagnosis results for each fault scenario are given in Section IV followed by the conclusions in Section V.

2 Enhanced dynamic causal digraph method and its application procedure

The enhanced dynamic causal digraph method employs the process knowledge formalized as a causal digraph model in order to perform the ordinary process monitoring tasks. Fault detection in the EDCDG method is performed with the residuals of the nodes in the digraph, while the isolation is carried out by applying a set of rules to the residuals in order to extract the fault propagation path. The diagnosis is based on identification of those arcs in the digraph that explain the faulty behavior.

2.1 Fault detection

The fault detection is performed in two steps: residual generation and change detection in residuals using the CUSUM method.

1) *Residual generation with the dynamic causal model*: The dynamic causal digraph produces two kinds of residuals to be used in fault detection and isolation: global (GR) and local residuals (LR). The global residual is produced by a difference between the measurement and the global propagation value

$$GR(Y) = Y(k) - \hat{Y}(k) \quad (1)$$

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

$$\hat{Y}(k) = f_Y(\hat{U}(k-1), \hat{U}(k-2), \dots) \quad (2)$$

Where f_Y is a discrete-time model describing the cause-effect relationship from n predecessor nodes U_i to node Y . $\hat{U}(k-\tau)$ are the lagged global propagation values from the predecessors with time lags $\tau = 1, 2, \dots$ depending on the system order.

The local residuals are subcategorized into three types: individual local residuals (ILR), multiple local residuals (MLR), and total local residuals (TLR) [7].

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

$$\begin{aligned} ILR_Y^m &= Y - \bar{Y} \\ \bar{Y}(k) &= f_Y(\bar{U}(m, k-1), \bar{U}(m, k-2), \dots) \end{aligned} \quad (3)$$

where

$$\begin{aligned} \bar{U}(m, k-\tau) &= \{\bar{u}_i(k-\tau)\bar{u}_i(k-\tau) \\ &= \begin{cases} \hat{u}_i(k-\tau), i \neq m \\ u_i(k-\tau), i = m \end{cases}, 1 \leq i \leq n \end{aligned} \quad (4)$$

$\hat{u}_i(k-\tau)$ is the lagged global propagated value from the predecessors, and $u_i(k-\tau)$ is the measurement for the i th parent node.

Similarly, the $MLR_Y^{P_Y^l}$ is produced as

$$\begin{aligned} MLR_Y^{P_Y^l} &= Y - \bar{Y} \\ \bar{Y}(k) &= f_Y(\bar{U}(P_Y^l, k-1), \bar{U}(P_Y^l, k-2), \dots) \end{aligned} \quad (5)$$

where

$$\begin{aligned} \bar{U}(P_Y^l, k-\tau) &= \{\bar{u}_i(k-\tau)\bar{u}_i(k-\tau) \\ &= \begin{cases} \hat{u}_i(k-\tau), i \notin P_Y^l \\ u_i(k-\tau), i \in P_Y^l \end{cases}, 1 \leq i \leq n \end{aligned} \quad (6)$$

P_Y^l is the set of indices of the predecessors which use the measurement as an input. The $(TLR(Y))$ is produced with $P_Y^l = P_Y$, where P_Y is the set of indices of all the predecessors of Y .

The residual generation scheme follows the DCDG method developed in [7].

2) *Fault detection with the CUSUM method:* Next, the inconsistent nodes are detected with the CUSUM method which is constructed by applying statistical Wald's rule to the "presence of fault" hypothesis check. The CUSUM algorithm [27] for a positive mean change is given by the following equations:

$$\begin{aligned} U_0 &= 0 \\ U_n &= \sum_{k=1}^n r(k) - \mu_0 - \frac{\beta_0}{2} \\ m_n &= \min_{0 \leq k \leq n} U_k \end{aligned} \quad (7)$$

Where β_0 is a user-specified minimum detectable change, $r(k)$ is a residual signal, and μ_0 is the mean value of the residual. Whenever $u_n - m_n > \lambda$, a change is detected, where λ is a design parameter, usually tuned according to the requirements for the false alarm and missed alarm rates. The statistic (7) may be interpreted as a logarithm of a likelihood ratio, if the residuals are independent, normally distributed variables with a mean of μ_0 for normal conditions and of $\mu_0 + \beta$ for faulty conditions.

The CUSUM method may be modified for detection of negative changes in the mean of the residual signal. Thus, the residual signals produced by the method are mapped to the set $\{0, 1, -1\}$. In the rest of the brief, the result of the CUSUM calculation will be denoted as a function: $CU(r)$.

4.2 Fault isolation

The fault isolation step consists of two steps: isolation on variables and the separation of the fault effects.

1) *Fault isolation on variables:* Fault isolation is performed recursively for the nodes in the detection set by using a set of rules. These isolation rules, developed by Montmain and Gentil [7], are converted into a table for the convenience of implementation, as shown in Table 1. After the isolation the nature of the fault is determined by using rules in Table 2.

2) *Separation of the fault effects:* In order to manage the specific cases where GR becomes too small to detect due to the cancellation of different fault effects, the fault effects with different directions are taken into account and separated. Thus, the aim of the following step is to detect fault in the nodes where GRs have been canceled. The proposed approach performs the separation of the fault effects in the following four steps.

Table 1

Fault isolation rules of the dynamic causal digraph

$CU(GR(Y))$	$CU(TLR(Y))$	$CU(ILR_V(m))$	$CU(ILR_V(i))$	$CU(MLR_V(P_1))$	$CU(MLR_V(P_2))$	Decision
0	0	0	0	0	0	No fault
1/-1	0	0*	1/-1*	0*	1/-1*	Fault propagates from the parent node m
1/-1	0	1/-1**	1/-1**	1/-1**	0**	Fault propagates from the nodes with subscript P_2
1/-1	1/-1	1/-1	1/-1	1/-1	1/-1	Local fault on variable Y

* $\forall i \neq m, i \in P_Y, m \in P_1, m \notin P_2, P_Y$ is the set of subscripts of parent nodes of the node Y .

** $\forall i, m, i \in P_Y, m \in P_Y, \forall P_1, P_2 \subseteq P_Y$.

Table 2

Fault nature rules of the dynamic causal digraph

$CU(GR(X))^*$	$CU(TLR(X))$	Fault nature
1/-1	1/-1	Local fault for that child node
1/-1	0	Process fault for the faulty node
0	1/-1	Measurement fault for the faulty node

* X is the subscript of any child node of the Y .

1) **Form the fault separation set (FSS)** consisting of the variables, for which different fault effects in the GRs need to be separated

$$FSS = \{Y | \text{Index}U_Y \neq \phi \text{ and } |CU(GR_Y)| = 0\} \quad (8)$$

where $\text{Index}U_Y$ is the set of the indices of the node Y 's predecessors, the global residuals of which have been identified in the fault detection. The symbol ϕ denotes the empty set.

2) **Calculate the fault effect contributions** for each variable in the FSS from its detected parent nodes and its local fault effect

$$\begin{aligned} \text{contp}_Y^i &= GR_Y - ILR_Y^i, Y \in FSS, i \in \text{Index}U_Y \\ \text{contl}_Y &= TLR_Y \end{aligned} \quad (9)$$

where contp_Y^i is the fault effect contribution from the i th predecessor, while the contl_Y is the local fault effect contribution.

3) **Separate and sort the fault effect contributions** according to the sign and magnitude in a decreasing order

$$\begin{aligned} PFE_Y &= \{\text{contp}_Y^i | \text{contp}_Y^1 > \text{contp}_Y^2 > \dots > 0, i \in \text{Index}U_Y\} \\ NFE_Y &= \{\text{contp}_Y^i | \text{contp}_Y^1 < \text{contp}_Y^2 < \dots < 0, i \in \text{Index}U_Y\} \end{aligned} \quad (10)$$

4) **Fault detection of fault effect contributions.** Both local and propagated fault effects are considered. The algorithm is illustrated in Fig. 1.

- Apply the CUSUM method to the local fault effect contribution contl_Y , the sum of the positive fault effect contribution $\sum_{i=1}^{lp} PFE_Y(i)$ and the sum of the negative fault effect contribution $\sum_{i=1}^{ln} NFE_Y(i)$, where $PFE_Y(i)$ and $NFE_Y(i)$ denote the i th element in the sets PFE_Y and NFE_Y , respectively. lp and ln are the numbers of the elements in these two sets. If none of these three contributions have been detected, the node Y is fault free, otherwise go to Step b).
- If the local fault effect contribution contl_Y is detected, then the node Y is the fault origin.
- If the sum of the positive fault effect contribution $\sum_{i=1}^{lp} PFE_Y(i)$ is detected, then the CUSUM method is applied to each positive fault effect contribution $PFE_Y(i)$, otherwise go to Step e). If a set of elements $PFE_Y(i)$ are detected, then the fault is considered as detected and propagated from the corresponding parent nodes, otherwise go to Step d).
- The CUSUM method is applied to the combined fault effect contributions $PFE_Y(1) + PFE_Y(2)$, $PFE_Y(1) + PFE_Y(2) + PFE_Y(3)$ and so on, until the first combined fault effect contribution is detected. The fault is then considered as detected and propagated from the corresponding parent nodes.
- For the negative fault effect set NFE_Y , repeat Steps c)–d).

Next, each set of suspected arcs is tested in order to determine whether the fault may be caused exactly by the current set of arcs. In order to do it the matrix $\mathbf{M}$ is multiplied with a vector representing the suspected arc set, which is defined as follows:

$$\mathbf{sv}(i) = \begin{cases} 1, & \text{if } \text{ARC}(\mathbf{M}, i) \in S, 1 \leq i \leq N_a \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

where $\text{ARC}(\mathbf{M}, i)$ gives the arc corresponding to the i th row in the matrix $\mathbf{M}$. S is the set of suspected arcs. If the number of non-zero elements of $\mathbf{sv} \cdot \mathbf{M}$ is different from that of $\mathbf{sv}$, the current suspected set of arcs must be excluded.

3 Description of the process and test environment

This test focuses on the stock preparation, short circulation and forming sections of a board machine at Stora Enso's Kaukopää mills in Imatra, Finland. The simulation tests are run on a board machine simulator model in APROS simulation environment.

3.1 Board machine process

The board making process begins with the preparation of raw materials in the stock preparation section, as shown in the flowsheet in Fig. 2. Different types of pulp are refined and blended according to a specific recipe in order to achieve the desired properties and composition for the board grade to be produced. The consistency of the stock is controlled with dilution water.

Fig. 2. Flowsheet of stock preparation of layer 2 of the Stora Enso board machine (Stora Enso Oyj, 2002)

The blended stock passes from the stock preparation to the short circulation, see Fig. 3. First, the stock is diluted in the machine chest to the correct consistency for web formation. The diluted stock is then pumped with a fan pump, which is used to control the basis weight of the board, to cleaning and screening. Next,

the stock passes to the head box, from where the stock is sprayed onto the wire in order to form a solid board web.

Fig. 3. Short circulations of the three-layered board machine (Stora Enso Oyj, 2002)

The excess water is first drained through the wire and later by pressing the board web between rollers in the press section. The rest of the water is evaporated off in the drying section using steam-heated drying rolls.

In a board machine producing three-layered boards, such as the one examined in this brief, the stock is prepared in two different stock preparations (top and bottom layers have a similar composition which, however, differs from that of the middle layer) and then passed to three short circulations—one for each layer. After web forming the layers are combined to form the end product.

In these test scenarios the process is limited to the two stock preparations, the three short circulations and the forming sections of the board machine. The variables of interest are listed in Table 3. The measurement signals and the actuator signals are denoted with M and A, respectively, and E denotes a variable, which is estimated from another variables.

3.2 Simulation Environment

The Imatra board machine model was developed by Stora Enso and VTT in the APROS environment. It was originally constructed on the basis of modeling and simulation studies carried out during 1998–2002 for Stora Enso's Kaukopää mills. It has been previously used for grade change simulations and in studies reported by Lappalainen *et al.* [28].

Table 3

Description of the variables in the studied board machine

Stock preparation 2			
Variable	Description	Type	Unit
<i>broval2</i>	valve opening for the broke line	A	%
<i>broflow2</i>	mass flow of the broke	M	kg/s
<i>brodval2</i>	dilution water valve opening for the broke line	A	%
<i>brodflow2</i>	dilution water flow for the broke line	E	kg/s
<i>brocon2</i>	broke consistency	M	%
<i>pspeed2</i>	pine pump rotation speed	A	%
<i>pflow2</i>	mass flow of the pine stock	M	kg/s
<i>pdval2</i>	dilution water valve opening for the pine line	A	%
<i>pdflow2</i>	dilution water flow for the pine line	E	kg/s
<i>pcon2</i>	pine consistency	M	%
<i>cspeed2</i>	CTMP pump rotation speed	A	%
<i>cflow</i>	mass flow of the CTMP	M	kg/s
<i>cdval2</i>	dilution water valve opening for the CTMP line	A	%
<i>cdflow2</i>	dilution water flow the CTMP line	E	kg/s
<i>ccon2</i>	CTMP consistency	M	%
<i>mcval2</i>	dilution water valve opening for the machine chest	A	%
<i>dflow2</i>	dilution water flow for the machine chest	E	kg/s
<i>conm2</i>	consistency before the machine chest	M	%
<i>ppress2</i>	pressure before the pine valve	M	kg/s
<i>cpress2</i>	pressure before the CTMP valve	M	kg/s
<i>sccon2</i>	consistency of the machine chest	M	%
Short circulation 2			
Variable	Description	Type	Unit
<i>bwspeed2</i>	basis weight pump rotation speed	A	%
<i>scflow2</i>	flow from the machine chest (thick stock flow)	M	kg/s
<i>wpcon2</i>	wire pit consistency	M	%
<i>acceptcon2</i>	consistency of accept flow from the hydrocyclone	M	%
<i>headspeed2</i>	headbox feed pump rotation speed	A	%
<i>headflow2</i>	mass flow through the headbox	M	kg/s
<i>headcon2</i>	headbox consistency	M	%
<i>sliceopen2</i>	slice opening of the headbox	A	mm
<i>drybw2</i>	dry basis weight of the layer 2	M	g/m2

4 Testing of the EDCDG using the three-layer board machine simulator

In this section, the proposed EDCDG method is tested on the three-layered board machine simulator constructed in the APROS simulation environment.

4.1 Dynamic causal digraph modeling

The dynamic causal digraph model of the board machine was obtained by constructing the causal structure of the process and then identifying the cause-effect models representing the relationships between variables, see Table 3. Also, the inter-arc knowledge matrix was constructed based on the process knowledge presented in Section III and the construction procedure given in [26]. The causal digraph model of the stock preparation 2 of the board machine is shown in Fig. 4.

Fig. 4. Causal digraph structure of the three-layer board machine

4.2 Fault scenarios

Two fault scenarios were selected for the study on the basis of an interview with the plant operators. The scenarios were a sensor fault in a consistency sensor in the stock preparation and a retention drop fault in the short circulation of the layer 2.

1) *Consistency sensor fault in the stock preparation of the layer 2:* Consistency sensors are some of the most important process instruments in paper making. They are used in many parts of the process, primarily in stock preparation and in the short circulation, where the quality of the stock and paper are controlled. For example, one of the main quality variables, the dry basis weight, is controlled with measurements from the mass flow and consistency sensors in the thick stock flow out of the machine chest.

The performance of the consistency sensors also plays an important role in the economics of paper mills. In the stock preparation, as seen in Fig. 2, the consistency of each individual pulp line is controlled with dilution water, while the setpoint of the mass flow for the each pulp line is calculated from the recipes and the measured consistencies. Thus, accurate measurement of the individual stock components before mixing is crucial in guaranteeing that the correct recipes are prepared.

A fault in the consistency sensor of the pine line in the stock preparation of layer 2 was studied, see Fig. 2. Using the board machine model in APROS, the fault was simulated by introducing a 0.1% negative bias to the selected sensor. The total simulation time was 720 min (12 h) with 10 s as the sampling time. Grade 1 was produced in the first 5 h and grade 2 in the last 7 h. The fault was introduced during the time period 60–180 min and the time period 480–600 min, respectively, for the two different board grades. Due to the effect of the controller for pine consistency, a faulty measurement tries to track its setpoint, which makes it difficult to notice the occurrence of a fault. Furthermore, the controller will drive the real value of the pine

consistency higher than the setpoint due to the faulty measurement, which lead to an increase in the ratio of pine in the final stock. Since the pine pulp is usually more expensive than CTMP, more money will be spent on manufacturing the same amount of production.

2) *Retention drop fault in the short circulation of the layer 2*: Retention is a measure of how much of the solid material is retained on the wire while the flow from the headbox is spread on the wire. It is mainly dependent on the structure of the wire, the composition of the stock, e.g., the level of flocculation, and the chemical state of the process. A sudden drop in retention can occur in the process due to a change in the chemical state or misoperation of the former.

Using the board machine model in APROS, the fault was simulated by changing the retention rate of the former from 90% to 87%. The total simulation time was 720 min (12 h) with 10 s as the sampling time. Grade 1 was produced in the first 5 h and grade 2 in the last 7 h. The fault was introduced during the time period 60–180 min and the time period 480–600 min, respectively, for the two different board grades. Due to the effect of the fault, the fiber transport ability was impaired, which means a lower percentage of the fiber can reach the final production. Although the quality control for the dry basis weight maintained the paper quality in accordance with the setpoint, the board machine was running inefficiently.

4.3 Fault diagnosis results with the enhanced dynamic causal digraph method

The proposed EDCDG method was applied using the causal digraph model, the inter-arc knowledge matrix and the faulty data obtained from the fault scenario simulations in APROS as described in Section 4.2. The results for the fault scenarios are presented in the following.

1) *Fault diagnosis results for the consistency sensor fault in the stock preparation*: The first fault scenario is a sensor fault for the fiber consistency in the pine line of the stock preparation for the layer 2. The GRs were first generated using the data collected from the simulation of fault scenario 1. Next, residual detection was performed using the CUSUM method with parameters $\beta = 0.01, \lambda = 0.1$ for consistency variables, $\beta = 1, \lambda = 2$ for flow variables and $\beta = 2, \lambda = 5$ for basis weight. The parameter values for β and λ were adjusted to the noise levels in the plant measurement data. In addition, similar noise levels were also used in the simulation.

The only detected variable was $pcon2$, whose global simulation value, global residual, and the detected results are illustrated in Fig. 5. Third, the fault isolation rules clearly inferred that the fault was local, and the fault nature rules that it was a sensor fault according to the local residuals shown in Fig. 6. Finally, the fault propagation path for the fault period is shown as the result of fault diagnosis in Fig. 7. Due to the nature of the fault, neither fault separation nor inference between the arcs was performed.

Fig. 5. Global residual of $pcon2$ (left y-axis) and its detection results (right y-axis)

Fig. 6. Total local residuals TLR_{pcon2} (top panel) and TLR_{conm2} (bottom panel) with the respective detection results (right y-axes)

Fig. 7. Fault diagnosis results for the fault scenario 1

2) *Fault diagnosis results for the process fault in the retention drop:* In the fault detection stage, the GRs were first generated using the data collected from the simulation. Next, the global residual detection was performed using the CUSUM method with parameters $\beta = 0.01, \lambda = 0.1$ for consistency variables, $\beta = 1, \lambda = 2$ for flow variables and $\beta = 2, \lambda = 5$ for basis weight. The parameter values for β and λ were

adjusted to the noise levels in the plant measurement data. In addition, similar noise levels were also used in the simulation.

The detection set was formed by the variables: *acceptcon2*, *headcon2*, and *wpcon2*, whose global residuals and detection results are shown in Fig. 8. Next, the local residuals were generated for the variables in the detection set, some of which are shown in Fig. 9.

Fig. 8. Global residuals of *acceptcon2* (top panel), *headcon2* (middle panel), *wpcon2* (bottom panel) with the respective detection results (right y-axes)

Fig. 9. Local residuals $ILR_{acceptcon2}^{wpcon2}$ (top panel), $MLR_{acceptcon2, wpcon2}^{headcon2}$ (middle panel), and TLR_{wpcon2} (bottom panel) with the respective detection results

In the fault isolation stage, the isolation rules and fault nature rules were applied to the generated LRs. The origin of the fault was located on the variable *wpcon2*, while the nature of the fault was identified as a process fault. The preliminary fault propagation path was therefore formed, as shown in Fig. 10.

Fig. 10. Preliminary fault propagation path of fault scenario 2

Since the identified fault was a process fault, the approach for separating fault effects was applied to those variables whose parent nodes had global detections. The fault separation set $FSS = \{drybw2\}$ was first

formed according to (8), provided $\text{Index}U_{\text{drybw2}} = \{\text{headcon2}\}$. The different fault effects were then calculated as

$$\text{contp}_{\text{drybw2}}^{\text{headcon2}} = \text{GR}_{\text{drybw2}} - \text{ILR}_{\text{drybw2}}^{\text{headcon2}} \quad (13)$$

$$\text{contl}_{\text{drybw2}} = \text{TLR}_{\text{drybw2}} \quad (14)$$

and they are presented in Fig. 11.

Fig. 11. Fault effects on $\text{contp}_{\text{drybw2}}^{\text{headcon2}}$ (top panel) and $\text{contl}_{\text{drybw2}}$ (bottom panel) with the respective detection results (right y-axes)

Next, the set $\text{PFE}_{\text{drybw2}}$ was formed as $\{\text{contp}_{\text{drybw2}}^{\text{headcon2}}\}$, while the set $\text{NFE}_{\text{drybw2}}$ was an empty set. Then, the CUSUM method was applied to the local fault effect contribution $\text{contl}_{\text{drybw2}}$ and the element in the set $\text{PFE}_{\text{drybw2}}$, according to the algorithm in Fig. 1. The detection results shown in Fig. 11 indicate that there are two fault effects on the variable drybw2 . The first one is the fault effect propagated from the variable headcon2 with a positive direction, while the second fault is the local fault on the variable drybw2 with a negative direction. Cancellation of these two fault effects makes the global residual of the variable drybw2 disappear, as shown in Fig. 12.

Therefore, the preliminary fault propagation path in Fig. 10 was modified as shown in Fig. 13.

Since the identified fault was a process fault, the fault diagnosis stage performed in order to find the responsible process component. However, there are multiple possible results due to the multiple fault origins and the multiple input arcs for each fault origin. In Fig. 13 the input arcs for fault origin nodes wpcon2 and drybw2 are $\{\langle \text{headcon2}, \text{wpcon2} \rangle\}$ and $\{\langle \text{headcon2}, \text{drybw2} \rangle, \langle \text{headflow22}, \text{drybw2} \rangle, \langle \text{matchspeed}, \text{drybw2} \rangle\}$, respectively. Thus the number of sets of suspected arcs is $1 \cdot (2^3 - 1) = 7$. After testing all the sets of suspected arcs, the number of possible results was reduced from 7 to 4: $\{\langle \text{headcon2}, \text{wpcon2} \rangle, \langle \text{headcon2}, \text{drybw2} \rangle\}$, $\{\langle \text{headcon2}, \text{wpcon2} \rangle, \langle \text{headcon2}, \text{drybw2} \rangle, \langle \text{headflow22}, \text{drybw2} \rangle\}$, $\{\langle \text{headcon2}, \text{wpcon2} \rangle, \langle \text{headcon2}, \text{drybw2} \rangle, \langle \text{matchspeed}, \text{drybw2} \rangle\}$ and $\{\langle \text{headcon2}, \text{wpcon2} \rangle, \langle \text{headcon2}, \text{drybw2} \rangle, \langle \text{headflow22}, \text{drybw2} \rangle, \langle \text{matchspeed}, \text{drybw2} \rangle\}$.

Fig. 12. Global residual GR_{drybw2} (left y-axis) and its detection results (right y-axis)

Fig. 13. Fault propagation path of the fault scenario 2

The fault diagnosis results, i.e., the four sets of suspected arcs, provide valuable information needed in identifying the faulty process component in the case of a process fault. The four sets consist of the common arcs $\langle headcon2, wpcon2 \rangle$ and $\langle headcon2, drybw2 \rangle$. The first arc corresponds to the process components: a former section and the white water tray, while the second arc, $\langle headcon2, drybw2 \rangle$, corresponds to the process components: a former section, a wet press and a drying group. Thus, the suspected process component is the former section, since it is located on both arcs. The result is illustrated in Fig. 14. Moreover, the direction of the TLR_{wpcon2} , as shown in Fig. 9, implies that the direction of the fault is a drop in fiber retention, rather than an increase in fiber retention.

detected in the second fault scenario with the help of the fault effects separation approach. Moreover, the results for the latter scenario were further improved in the fault diagnosis by locating the process fault on the arcs using the proposed inference mechanism between the arcs. The possible fault process component could be identified by carrying out further analyses. The improvements offered by the enhanced method are highlighted as a summary of a comparison of the results in Table 4.

Table 4

Comparison of the results between the proposed method and the conventional method

Fault	Fault type	Dynamic causal digraph		Enhanced dynamic causal digraph	
		Fault detection set	Fault isolation	Fault detection set	Fault isolation
1	Sensor fault	Nodes: <i>pcon2</i>	Fault origin: <i>pcon2</i>	Nodes: <i>pcon2</i>	Fault origin: <i>pcon2</i>
2	Process fault	<i>acceptcon2</i> , <i>headcon2</i> , <i>wpcon2</i>	Fault origin: <i>wpcon2</i>	<i>acceptpcon2</i> , <i>headcon2</i> , <i>wpcon2</i> , <i>drybw2</i>	Faulty arc sets (4): {< <i>headcon2</i> , <i>wpcon2</i> >}, < <i>headcon2</i> , <i>drybw2</i> >}, etc. Possible faulty component: Former section

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