Process Disturbance Cause & Effect Analysis Using Bayesian Networks

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Abstract: Process disturbances can propagate over entire plants and it can be difficult to locate their root causes from observed effects. Bayesian Networks offer a way to represent unit operations, processes and whole plants as probabilistic models which can be used to infer and rank likely causes from observed effects. This paper presents a methodology to use deterministic steady-state process models to derive Bayesian Networks based on alarm event detection. An example heat recovery network is used to illustrate the model building and inferential procedures.

Keywords: Alarm, Conditional Probability, Deterministic, Disturbance, Network, Process, Root Cause

1. INTRODUCTION

Modern process plants operate in demanding safety, environmental and economic conditions and comprise a range of interconnected chemical, mechanical, electrical and control operations and systems.

Process disturbances affect both short-term production and long-term equipment condition, and the complexity of process interactions means that their root causes can be difficult to unravel, isolate and repair (Thambirajah, Benabbas, Bauer, & Thornhill, 2008). Within the process engineering and control communities there are a number of approaches to cause and effect analysis and disturbance diagnosis (for a review see Thornhill and Horch, 2007, and Yang, Duan, Shah and Chen, 2014). These approaches include the use of graph theory to model causal and connectivity relationships using process and instrumentation diagrams (P&IDs) and other drawing information (e.g. Maurya, Rengaswamy and Venkatasubramanian, 2004; Jiang, Patwardhan and Shah, 2009).

Graph models are used in systems theory to demonstrate the existence of connectivity paths between distributed causes and effects (e.g. Deo, 1974). They can also be used in reverse to trace paths from effects to possible causes. This reversal property finds application in Bayesian Networks which model the probabilistic relationships between system variables as Directed Acyclic Graphs and are used to rank possible causes using observed effects (Murphy, 2012).

Bayesian Network models have been applied to engineering condition monitoring (Marwala, 2012) and process systems (Yang, Duan, Shah and Chen, 2014), where time series data are used to infer the existence of a causal structure connecting process variables and fault states. In addition Yang et al. note that the physical explanation of Bayesian Network probabilities is not straightforward. Medjaher, Gouriveau and Zerhouni (2009) use Bond graphs to model the forward information flow around a dynamic system and generate residuals – which account for the discrepancies between the predicted state of a system and its observed state – to derive a Dynamic Bayesian network for prognostic analysis.

Another research direction is based on the concept of structural equations (e.g. Lee, Christensen and Rudd, 1966) which illustrates an intuitive link between process unit operations, causality, and graphs.

This paper addresses the question of how to derive Bayesian Networks which can be used for both diagnostic and prognostic analysis from process flow diagrams, deterministic models and structural equations, and gives a physically intuitive meaning to network probabilities based on observing process alarms. Section 2 presents a practical definition of a plant disturbance and explains the basic principles behind Bayesian Networks. A deterministic heat exchanger unit operation model is used to illustrate the derivation of a corresponding Bayesian unit operation. Using these Bayesian unit operations Section 3 builds an example process heat recovery system as a probabilistic model. The corresponding deterministic process model is used to simulate a process disturbance and the ensuing alarms. It is shown that the Bayesian Network can use alarm information to identify the most likely root cause. Finally section 4 presents a brief discussion of the results.
2. METHODS

As a teaching example Figure 1 shows a section of a heat recovery network, adapted from Kemp (2007). This process system is useful to illustrate the rationale and methods of Bayesian Network process cause and effect analysis. The network comprises a set of heat transfer processes (circles) which act on the given upstream condition (boxes) to produce the required downstream conditions (arrowheads).

Fig. 1. Example Heat Recovery Network (Kemp 2007)

Hot streams which require cooling traverse from left to right, and conversely cold streams that require heating traverse from right to left; X2, X3, X5 and X6 are counter-current heat exchangers. S1 is a hot stream source stream, S4 is a cold source stream, and MX is a two stream mixer. The original unit operation numbering has been preserved for referencing. The network is designed to operate at a steady state, however in practice disturbances arise and propagate throughout the plant. Such disturbances result in downstream temperature changes and can come about because of variations in the upstream conditions, and the heat transfer performance of the individual exchangers. The operational problem is then to work out which upstream causes or heat exchangers contributed to the observed downstream effects using the available information.

2.1 Bayesian Modelling

Bayesian Networks (Koller and Friedman, 2009; Murphy, 2012) offer a way to model complicated systems probabilistically and use the evidence available in the downstream measurements to rank likely upstream causes for further investigation.

An example of a Bayesian Network is that introduced by Pearl (1988) and adapted in Figure 2. This shows the causal links and conditional probability relationships between causes and effects in a simple system where F = FALSE and T = TRUE.

From the conditional probability table associated with the “Wet Grass” variable, the probability of the grass being wet given that has been raining and the sprinkler has been on is 0.99 or 99%.

Fig. 2. Example Bayesian Network

Using the idea of structural equations (Lee, Christensen and Rudd, 1966) this probability network can be written as (1). The notation $\omega(\cdot)$ means the $\omega$ function has no external inputs so that $R$ is an independent variable with a corresponding stand alone conditional probability table.

$$ R = \omega(\cdot), \quad S = \xi(R), \quad G = \psi(R,S) $$

(1)

where $G$ = Grass Wet (TRUE/FALSE), $S$ = Sprinkler On (TRUE/FALSE) and $R$ = Raining (TRUE/FALSE). The probabilistic structural functions $\omega$, $\xi$ and $\psi$ are defined by the conditional probability tables for each variable of Figure 2.

Using the definitions of conditional probability and the probability chain rule the cause and effect question “Given that the grass is wet, what is the chance that it has rained?” can be modelled as (2) where details of how to evaluate the conditional probabilities are given in Pearl (1988).

$$ P(R = T | G = T) = \frac{\sum_{S,T} P(R = T, G = T, S)}{\sum_{S,R} P(G = T, S, R)} $$

(2)

This model does not account for the time sequence of the rain and sprinkler causes in generating the wet grass effect, and is said to be static (Murphy, 2012). Temporal information can be modelled using Dynamic Bayesian Networks to probabilistically relate time sequenced effects and causes (ibid). For both static and dynamic networks the primary source for building the conditional probability tables is experimental or observational data. For a process system, if these data are not initially available an alternative procedure is to generate the required statistics by driving deterministic models using noisy input data. In the case of dynamic...
systems this may involve the solution of a set of stochastic differential-transport delay equations (Jacobs, 2010).

If however the initial focus of an investigation is the likely occurrence of causes given a set of observed effects around the nominal plant design steady-state, irrespective of their timing, the construction of the conditional probability relationships is simplified by the use of deterministic steady-state models to derive static Bayesian Networks. A process operator can refine the results of a specific static Bayesian Network analysis by comparing the time-stamps of the potential causes with those of the observed effects.

2.2 Disturbance Modelling

Figure 3 shows a counter-current heat exchanger. Assuming that fluid heat capacities remain constant over the unit, (3), (4), (5) and (6) define a deterministic steady-state log-mean temperature model.

\[
\alpha = \exp\left( -UA \left( \frac{1}{CP_h} - \frac{1}{CP_c} \right) \right) \tag{3}
\]

\[
\beta = \frac{CP_h}{CP_c}, \quad \lambda = \frac{1-\alpha}{1-\alpha\beta} \tag{4}
\]

\[
\theta_o = \theta_i (1 - \lambda) + \lambda T_i \tag{5}
\]

\[
T_o = T_i + \beta \lambda (\theta_i - T_i) \tag{6}
\]

Table 1. Generalised Heat Exchanger Model Variables

| Variable | Units     | Type | Description                      |
|----------|-----------|------|----------------------------------|
| CP_c     | kW/^oC    | Input| Cold stream heat capacity        |
| CP_h     | kW/^oC    | Input| Cold stream heat capacity        |
| \theta_i | ^oC       | Input| Hot stream inlet temperature     |
| UA       | kW/^oC    | Input| Heat transfer coefficient        |
| T_i      | ^oC       | Input| Cold stream temperature          |
| \theta_o | ^oC       | Output| Hot stream temperature           |
| T_o      | ^oC       | Output| Cold stream temperature          |
| UA       | kW/^oC    | Input| Heat transfer coefficient        |
| \alpha, \beta, \lambda | ------ | ------ | Intermediate variables |

The suffix “i” denotes “inlet” and the suffix “o” denotes “outlet”.

![Fig. 3. Heat Exchanger Unit Operation](image)

Equations (5) and (6) can be written as the deterministic structural equations (7) and (8) which make clear the input-output causality of the heat exchanger.

\[
\theta_o = f(\theta_i, T_i, CP_c, CP_h, UA) \tag{7}
\]

\[
T_o = g(\theta_i, T_i, CP_c, CP_h, UA) \tag{8}
\]

A two-stream stream mixing model is defined by (9)

\[
T_3 = \frac{(T_1)(CP_1) + (T_2)(CP_2)}{CP_1 + CP_2} \tag{9}
\]

where \( T \) denotes stream temperature [^oC] and \( CP \) denotes stream heat capacity [kW/^oC]

Equation (9) can be remapped to the structural form of (10) to highlight the input-output causal relationships.

\[
T_3 = h(CP_1, CP_2, T_1, T_2) \tag{10}
\]

A deterministic process system model can now be built by interconnecting unit operation models and stream properties.

Moreover, such deterministic unit operations can be used to derive corresponding probabilistic disturbance models by using a Monte Carlo procedure whereby each unit operation function is evaluated using randomly sampled input data.

In this work the values of the variables are modelled as normal distributions, although it is noted that Bayesian networks are distribution-independent.

For a process variable \( x \) the set of measurements \( x(j) \) is assumed to be normally distributed about its set-point with a maximum range of \( r_{m,x} \) % such that

\[
x(j) = x \left( 1 \pm \frac{r_{m,x}}{100} \right), \quad j = 1, 2, \ldots n \tag{11}
\]
where $\bar{x}$ is the set-point of $x$.

If the population standard deviation of $x$ is denoted by $\sigma_x$ then assuming that a six sigma confidence interval accounts for practically all the data $\sigma_x$ can be found from (12) and (13).

$$\bar{x} \pm 6\sigma_x = \bar{x} \pm \left( \frac{r_{m,x}}{100} \right) \bar{x}$$  \hspace{1cm} (12)

$$\sigma_x = \left( \frac{r_{m,x}}{600} \right) \bar{x}$$  \hspace{1cm} (13)

Defining an alarm range variable $r_{a,x}$ the control objective is to keep the process variable $x$ within an alarm range bounded by $\bar{x} \pm r_{a,x}\sigma_x$. For each measurement $x(j)$ an associated binary alarm variable $a_x(j)$ is defined by (14)

$$a_x(j) = \begin{cases} 0, & \bar{x} - r_{a,x}\sigma_x \leq x(j) \leq \bar{x} + r_{a,x}\sigma_x \\ 1, & \text{otherwise} \end{cases}$$  \hspace{1cm} (14)

Further, from $n$ measurements of $x$ the probability that any randomly selected measurement $x(k)$ is in alarm is found from (15).

$$P(a_x(k) = 1) = \frac{1}{n} \sum_{j=1}^{n} a_x(j)$$  \hspace{1cm} (15)

The procedure thus outlined can be applied to all the process variables that characterise Figure 1. In this paper for all such variables $x$, $r_{m,x} = 15$ and $r_{a,x} = 2$.

The models defined by (3) – (15) are implemented in MATLAB. A sample size of $n = 8000000$ is chosen to generate statistically significant samples. Figure 4 and Tables 2 and 3 illustrate the procedure for example data.

The five input values in each column of Table 3 form $2^5 = 32$ possible distinct binary patterns, which can be denoted as $b01,b02,...,b32$.

These data can now be used to form the conditional probability tables for the input-output alarm variables. As an example, for the binary pattern $b01 = (0 \ 0 \ 0 \ 0 \ 0)^T$ and the hot-side output temperature alarm variable $a_{\theta_o}(j)$ the conditional probability for the state $(b01 = \text{TRUE}) \& (a_{\theta_o}(j) = 1)$ is given by (16), (17) and (18) where & is the logical AND function.

### Table 2. Example Input-Output Data

| Variable | Type  | Sample j |
|----------|-------|----------|
| $\theta_i$ | Input | 161.1 ... 167.2 ... 155.4 |
| $T_i$ | Input | 36.93 ... 36.78 ... 37.19 |
| $C_P h$ | Input | 2.214 ... 2.346 ... 2.356 |
| $C_P c$ | Input | 0.947 ... 0.972 ... 0.953 |
| $U_A$ | Input | 1.226 ... 1.195 ... 1.172 |
| $\theta_o$ | Output | 126.2 ... 132.4 ... 124.6 |
| $T_o$ | Output | 118.6 ... 120.6 ... 113.4 |

**Fig. 4. Heat Exchanger X3 Steady-State Design Basis**

### Table 3. Example Input-Output Alarms

| Variable | Type  | Sample j |
|----------|-------|----------|
| $a_{\theta_i}$ | Input | 0 ... 1 ... 0 |
| $a_{T_i}$ | Input | 0 ... 0 ... 0 |
| $a_{C_P h}$ | Input | 0 ... 0 ... 0 |
| $a_{C_P c}$ | Input | 0 ... 0 ... 0 |
| $a_{U_A}$ | Input | 0 ... 0 ... 0 |
| $a_{\theta_o}$ | Output | 0 ... 0 ... 0 |
| $a_{T_o}$ | Output | 0 ... 0 ... 0 |

This procedure is applied to all the input patterns and output alarms states of Table 3 to derive a conditional probability table for the heat exchanger, and extended to all the unit operations of Figure 1 to derive a static Bayesian Network of the complete system.
\[
X = \sum_{j=1}^{n} (b_{01} \& a_{\theta}(j)) \\
Y = \sum_{j=1}^{n} (b_{01}) \\
P(b_{01} \& a_{\theta}) = \frac{X}{Y}
\]

(16) \hspace{1cm} (17) \hspace{1cm} (18)

2.3 Static Bayesian Network Implementation

For this investigation the Microsoft Bayesian Belief Toolkit MSBNx (Microsoft Research, 2010) is used.

For ease of implementation the mathematical notation of Table 1 is mapped onto one compatible with the MSBNx user interface as per Table 4, where the prefixes v, p and a refer to the deterministic process variable, the Bayesian probability that the variable is in alarm, and its actual deterministic alarm state respectively.

In the heat recovery process variables are always associated with four basic physical quantities:

- \( CP \equiv \text{Heat Capacity} \)
- \( TH \equiv \text{Hot Stream Temperature} \)
- \( TC \equiv \text{Cold Stream Temperature} \)
- \( UA \equiv \text{Heat Transfer Coefficient} \)

Table 4. Heat Exchanger 3 Bayesian Nomenclature

| Generic Process Variable | Heat Exchanger 3 Specific Instantiation |
|--------------------------|----------------------------------------|
|                          | Process | Probability | Alarm   |
| \( CP_c \)               | \( c \)  | \( S4CP \)  | \( aS4CP \)  |
| \( CP_h \)               | \( h \)  | \( S1CP \)  | \( aS1CP \)  |
| \( \theta_i \)           | \( i \)  | \( S1TH \)  | \( aS1TH \)  |
| \( UA \)                 | \( X3UA \)| \( X3UA \) | \( aX3UA \)  |
| \( T_i \)                | \( X2TC \)| \( X2TC \) | \( aX2TC \)  |
| \( \theta_o \)           | \( o \)  | \( X3TH \)  | \( aX3TH \)  |
| \( T_o \)                | \( X3TC \)| \( X3TC \) | \( aX3TC \)  |

The same principles are applied at the mixer MX downstream of the cold-side outlets of heat exchangers X5 and X6. The Bayesian representation of Heat Exchanger 3 can now be written as (19) and (20)

\[
pX3TH = \Phi \left( pS1TH, pX2TC, pS1CP, pS4CP, pX3UA \right) \quad (19)
\]
\[
pX3TC = \Gamma \left( pS1TH, pX2TC, pS1CP, pS4CP, pX3UA \right) \quad (20)
\]

where \( \Phi \) and \( \Gamma \) are defined by conditional probability tables generated using the procedure of Section 2.2.

The Bayesian Network for Heat Exchanger 3 is shown in Figure 5 highlighting the connections to \( pX3TH \).

![Fig. 5. Heat Exchanger 3 Bayesian Network Connections](image)

The static Bayesian Network for the complete heat recovery system is now derived by building conditional probability tables for each process output alarm variable using the techniques just described, and interconnected in the same way as the deterministic network.

![Table 5. Conditional Probability Table for pX3TH](image)
Having built a complete heat recovery Bayesian Network its use as a diagnostic tool is now explored in Section 3.

3. A WORKED EXAMPLE

A useful property of a Bayesian model is that given a set of observed effects, also known as evidence, it can be applied to infer and rank possible causes (Pearl, 1988). A modelling demonstration based on the operation of Heat Exchanger 3 is now used to illustrate the principles of evidence and inference.

For a process operator the state of the plant alarm log provides the evidence snapshot for use in the static Bayesian Network so as to work out the likely cause of a plant disturbance.

In each of four example cases the full deterministic process model of Figure 1 is used to set the upstream source temperature \( vS1TH \) such that it is in alarm itself (\( aS1TH = \text{TRUE} \)), and is therefore a disturbance cause, and calculate the resulting process and alarm conditions in and around Heat Exchanger 3.

The inference test is to use the observed process alarms to identify which of the possible process inputs is the probable source of the disturbance.

However it is assumed that only a subset of the possible alarms can actually be observed so that knowledge of the process is limited. In the following analysis, the abbreviations O and U denote Observed and Unobserved alarms respectively.

If an alarm can be observed then its state – TRUE or FALSE - is used as disturbance effect evidence and the Bayesian Network alarm probabilities recalculated to generate a relative ranking \( RR_i \) for each possible causal alarm probability variable \( aX_j \) as defined by (21)

\[
RR_i = \frac{pX_i}{\min(pX_k)}
\]

where \( i, k = 1,..5 \).

Possible downstream alarm observations are constrained to be at \( aX3TC \), \( aX6TH \) and \( aMXTC \) only, which denote the cold-side outlet temperature alarm of Heat Exchanger 3, the hot-side outlet temperature alarm of Heat Exchanger 6 and the outlet temperature alarm of the cold-stream mixer MX.

The first case is a control experiment in which the process is in normal operation and no alarms are available for observation. In the second, third and fourth cases the temperature \( vSITH \) is set so as to trigger alarm effects throughout the process. In each of these cases a set of alarms is available for observation and use in the Bayesian Network to generate hypotheses about the state of the process.

### 3.1 Case No. 1

For Heat Exchanger 3 in undisturbed operation the process state and possible observations are given in Tables 6 and 7.

| Variable | Type   | Status | Value  |
|----------|--------|--------|--------|
| \( vSITH \) | Cause  |        | 159°C  |
| \( vX2TC \) | Cause  |        | 38°C   |
| \( vS1CP \) | Cause  |        | 2.285 kW/K |
| \( vS4CP \) | Cause  |        | 2.285 kW/K |
| \( vX3UA \) | Cause  |        | 1.180 kW/K |
| \( vX3TC \) | Effect |        | 117°C  |
| \( vX6TH \) | Effect |        | 77°C   |
| \( vMXTC \) | Effect |        | 53°C   |

The given probability values of \( pSITH \), \( pS1CP \) and \( pX3UA \), are close to those expected from a 2\( \sigma \) confidence interval on a normal distribution so that for a random measurement of \( vSITH \) the chance of it being in alarm is around 4.6 %. The tabulated values of \( pX6TC \) and \( pMXTC \) are both forward calculated from the Bayesian Network.

### 3.2 Case No. 2

The source stream temperature \( SITH \) is now increased from 159°C to 170°C. Table 8 shows the resulting process state. The deterministic alarm variable \( aX6TH \) is now observed to be TRUE, the corresponding Bayesian variable \( pX6TH \) set to 100% and the Bayesian Network recalculated in Table 9.
The probability of $vS1TH$ being in alarm has now increased to 24.8% and $vS1TH$ is ranked as being the most probable disturbance cause with an RR of 5.3.

Table 8. Case No. 2: $vS1TH$ Increase

| Variable | Type | Status | Value |
|----------|------|--------|-------|
| $vS1TH$ | Cause | 170°C  |
| $vX2TC$ | Cause | 38°C   |
| $vS1CP$ | Cause | 2.285 kW/K |
| $vS4CP$ | Cause | 2.285 kW/K |
| $vX3UA$ | Cause | 1.180 kW/K |
| $vX3TC$ | Effect | 124.2°C |
| $vX6TH$ | Effect | 81.6°C |
| $vMXTC$ | Effect | 54.9°C |

Table 9. Case No. 2: $aX6TH$ Evidence

| Variable | Type | Status | Value |
|----------|------|--------|-------|
| $pS1TH$ | Cause | U | 24.8% |
| $pX2TC$ | Cause | U | 4.68% |
| $pS1CP$ | Cause | U | 13.9% |
| $pS4CP$ | Cause | U | 4.75% |
| $pX3UA$ | Cause | U | 4.82% |
| $pX3TC$ | Effect | U | 16.2% |
| $pX6TH$ | Effect | O | 100% |
| $pMXTC$ | Effect | O | 4.75% |

3.2 Case No. 3

In this case the mixer outlet temperature $vMXTC$ is observed to be not in alarm ($aMXTC = FALSE$). Therefore $pMXTC$ can be set to 0% to yield Table 10. Again $vS1TH$ is ranked first, where RR = 4.99.

Table 10. Case No. 3: $aX6TH$ & $aMXTC$ Evidence

| Variable | Type | Status | Value | RR |
|----------|------|--------|-------|----|
| $pS1TH$ | Cause | U | 23.3% | 4.99 |
| $pX2TC$ | Cause | U | 4.67% | 1  |
| $pS1CP$ | Cause | U | 14.1% | 3.02 |
| $pS4CP$ | Cause | U | 4.74% | 1.01 |
| $pX3UA$ | Cause | U | 4.80% | 1.03 |
| $pX3TC$ | Effect | U | 15.3% | - |
| $pX6TH$ | Effect | O | 100% | - |
| $pMXTC$ | Effect | O | 0% | - |

3.3 Case No. 4

Finally assume the cold-side outlet temperature of heat exchanger 3, $vX3TC$, is in observable alarm to yield Table 10. From Table 11 $pS1TH$ is still ranked first. In addition its RR is now 17.0, an increase of over threefold on the previous cases. This suggests that variable $vS1TH$ is the most likely source of the disturbance.

3.4 Hypothesis Testing

The hypothesis that $vS1TH$ is the most likely disturbance cause can be tested using the Bayesian Network in forward mode using the following procedure: build a Bayesian Network noisy logic gate (NLG) from the observed alarm states as per the specific example screenshot of Table 12.
For each candidate root cause \( vX_i \) (e.g. \( vS1TH \), \( vS1CP \) & \( vS4CP \)) set \( pX_i = 1 \). The NLG then calculates the probability of all the observed alarms occurring when the candidate root cause is in alarm, with the other candidate root causes are unobserved, so that the network is being used in a prognostic sense. The base case is the prior state of the NLG when the set of three candidate causes are all unobserved.

### Table 12. Bayesian NLG for observed alarm states

| Parent Node(s) | NLG        |
|----------------|------------|
|                | TRUE | FALSE |
| pX3IC          | TRUE | 0.0   | 1.0  |
|                | FALSE | 1.0   | 0.0  |
| pX6TH          | TRUE | 0.0   | 1.0  |
|                | FALSE | 0.0   | 1.0  |
| pMXTIC         | TRUE | 0.0   | 1.0  |
|                | FALSE | 0.0   | 1.0  |

### Table 13. NLG output for given alarm states

| p(aNLG = TRUE ) | 1.06% |
|-----------------|-------|
| p(aNLG = TRUE | aS1TH = TRUE) | 19.8% |
| p(aNLG = TRUE | aS1CP = TRUE) | 1.53% |
| p(aNLG = TRUE | aS4CP = TRUE) | 1.52% |

These data support the hypothesis that \( vS1TH \) is the most likely root cause.

### 4. DISCUSSION

The methods and results presented suggest static Bayesian Network analysis can be applied to disturbance cause and effect analysis of process systems. The Bayesian Network is constructed directly from the process configuration so that physical causality is inherent within the modelling. Moreover the network conditional probabilities are assigned based on the chance that a given process variable is disturbed with respect to easily defined and understood alarm limits.

Because Bayesian Networks are distribution independent, a plant model can be primed with simulated data which is augmented with operational data as it becomes available. In this paper such prior data were calculated using steady-state process unit operation models driven by noise data to derive static Bayesian Networks.

The use of the actual process configuration and the identification of probabilities with process alarm effects lends itself to the possible use of static Bayesian Networks at the process operator display level, making use of disturbance cause relative probability rankings to prioritise further investigation.

In conclusion static Bayesian Networks derived from process configurations have a natural interpretation in relating observed causes to likely effects, and can be presented in a way that is useful to plant operators and engineers.

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