Applications of object-oriented Bayesian networks for condition monitoring, root cause analysis and decision support on operation of complex continuous processes

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Object-Oriented Bayesian Networks for Condition Monitoring, Root Cause Analysis and Decision Support on Operation of Complex Continuous Processes: Methodology & Applications

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Abstract: The increasing complexity of large-scale industrial processes and the struggle for cost reduction and higher profitability implies automated systems for processes diagnosis in plant operation and maintenance are required. We have developed a methodology to address this issue and have designed a prototype system on which this methodology has been applied. The methodology integrates decision-theoretic troubleshooting with risk assessment for industrial process control. It is applied to a pulp operation and screening process. The process is modeled using object-oriented Bayesian networks (OOBNs). Most abnormalities are derived from the context-adaptive signal classifications with their enable and action events. The system performs reasoning under uncertainty based on multi-sensor information extraction and presents to users corrective actions, with explanations of the root causes. It records users' actions with associated cases and the OOBN models are prepared to perform sequential learning to increase its performance in diagnostics and advice. The system allows modeling during the design phase of a new plant, can provide guidance already in the start up phase and allows adaptation to process changes during plant operation.

1. Introduction*

In large-scale and complex industrial processes, a failure of the equipment or abnormality in process operation due to equipment malfunctioning is usually detected by means of hardware sensors. The process operator has to isolate the cause of a failure or abnormality by analyzing many sensors' signals. The time until the failure source is identified and subsequently eliminated results in unplanned production interruption, which is the main source of cost increase due to lost production profit. The sheer amount of data and the continuity of the process require a high level of automation of operation and maintenance control. But not all operations can be completely automated. Often it is necessary to let a human operator steer the process in critical situations. This poses a formidable challenge on the concentration and capability of the human being and on the efficiency of his decisions. Therefore, the operator needs quick detection of early abnormal shifts, disturbance analysis of process operation and identification of the most probable root causes. Simultaneously, the process overview should be maintained and relevant explanations provided with an advice on corrective sequence of actions. Under such circumstances, the operator can make educated decisions, based both on artificial intelligence and human experience. This should help avoid unplanned production interruption or at least ensure that the lost production is minimal.

In general, a fault diagnosis system for industrial process operation should satisfy the following requirements listed in (Sohlberg, 1998; Vedam et al., 1999 and Dash et al., 2000): Early detection and diagnosis; Isolability; Robustness; Novelty identifiably; Multiple fault identifiability; Explanation facility; Adaptability; Reasonable storage and computational requirements. In the chapter "Validation with data", we summarize the techniques by which these requirements are fulfilled by the system presented here. In addition, once a (expected) failure is identified, the operator should be supported with causal interpretation of diagnostic conclusions and with advice on corrective actions. This will help to recover the normal operation of the process as soon as possible.

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Here, we focus on key aspects of process monitoring and root cause analysis and give concrete examples.

Box and Kramer (1990) have discussed the roles of Statistical Process Control for process monitoring and of Automatic Process Control for process regulation. If only a classification of the failure type is required, neural networks or statistical classifiers may be more adequate. However, if decision support is needed, Bayesian networks (BNs) for probabilistic reasoning in intelligent systems can be used to calculate the posterior probabilities, e.g. (Pearl, 88; Cowell et al., 1999; Jensen, 2001), and BNs have the ability to adapt to changes (Spiegelhalter et al., 1990; Olesen et al., 1992). In a pre-study, we have also considered neuro-fuzzy hybrid systems as an alternative approach. For an overview on the application of fuzzy systems for diagnosis and control of industrial processes see (Nauck et al., 1997). The neuro-fuzzy approach would not provide causal interpretation of diagnostic conclusions, which was one of the main system requirements for explanatory decision support on demand or continuously. The topic of supplying the user of a system performing reasoning under uncertainty using probabilistic reasoning in Bayesian networks with explanations has been considered by (Suermondt et al., 1993) who use an approach incorporating entropy-based explanations and by (Henrion and Druzdzel, 1999) who use an approach incorporating scenario-based explanations. A probabilistic approach to fault diagnostics in combination with multivariate data analysis was suggested in (Leung at al., 2000-2002). Moreover, (Arroyo-Figueroa and Sucar, 1999) have been using temporal (dynamic) Bayesian networks for diagnosis and prediction of failures in industrial plants. (Heger and Aradhye, 2002) have also applied Bayesian networks to diagnose sensor and/or process faults utilizing hardware and software redundancies.

This paper contributes a combined object oriented methodology, which meets the listed requirements and incorporates various modeling and cost issues in industrial process control. The analysis and decision system comprises three main steps as shown in Fig. 1: 1) root causes analysis (RCA) in case of expected process abnormality; 2) decision support (DS) on corrective actions for process operation and maintenance; 3) time-critical DS for alternative actions.

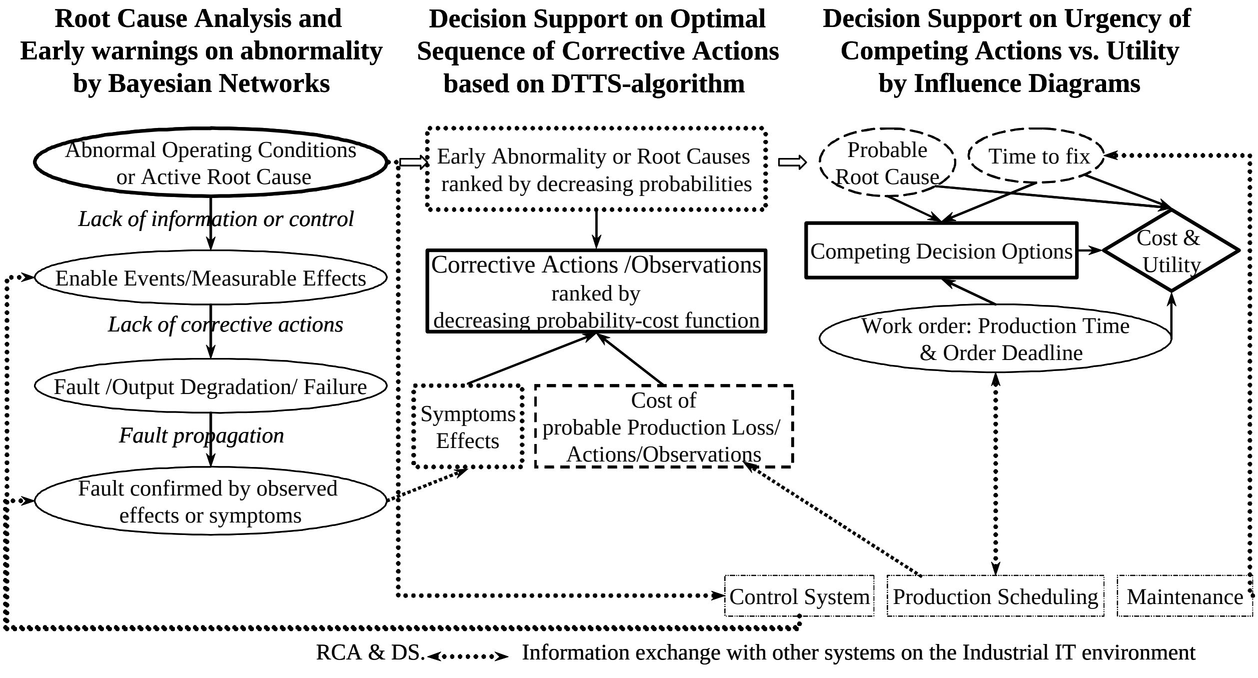

Fig. 1. The hybrid system for Root Cause Analysis, Decision Support on efficient sequence of Actions and Observations, and DS on Urgency of Competing Actions for the same root cause

The proposed methodology is developed for a RCA & DS system and integrated in the industrial IT-environment of the plant (Weidl et al., 2002a-2003a). Here, it is implemented on a prototype system and applied to real industrial processes (pulp digesting and screening).

The industrial IT-integration allows efficient communication with other IT-applications and with agents providing information from first level diagnostic solutions and physical models. This hybrid information is used for automated reasoning on abnormality in process operation

The developed methodology is based on the combination of RCA and DS for operation of industrial processes. A precise description of RCA and DS is given in section 2.2, and the combination we have developed is given in section 4.4.1. For DS, (Weidl et al., 2002b) have combined the algorithm for decision theoretic trouble-shooting (DTTS) with time critical decision support. DTTS was first proposed in (Kalagnanam et al., 1990) and further analyzed in (Heckerman et al., 1995). (Weidl et al., 2002b) have applied an Influence Diagram (ID) for time critical decision support on the urgency of competitive actions for the same root cause. An ID is an extension of a BN with utility nodes and decision nodes, which are ordered in a directed path (Jensen, 2001); alternatively one can use LIMIDs (new feature of Hugin™, which allows unordered decisions and “limited” memory).

The main contributions of this work include:

- The system design for RCA & DS, incorporating the probabilistic reasoning agents for handling of uncertainties and reflecting the information flow.
- The development of a pressure-flow network as a physical (non-causal) model of the process behaviour. It provides soft sensor (non-measurable) information for evidence in the reasoning under uncertainties.
- The use of OOBNs for RCA & DS in process operation to ensure causal modeling of interdependency of events and to provide explanations with overview at different levels of industrial plant hierarchy; Models reusability, simple construction and modification of generic BN-fragments, reduction of the overall complexity of the network for better communication and explanations, were other selection criteria in favor of OOBNs (Koller et al., 1997).
- The development of an OOBN model for adaptive signal classification by mixture models and prediction of the development of signals' level-trend.
- OOBN for risk assessment of disturbances, estimation of their most probable root causes for predictive maintenance on demand.
- The construction of OOBNs for RCA of process operation.
- A case study with real process data
- The RCA System integration in the industrial IT platform for efficient data exchange with DCS (Distributed Control System) and various IT packages.
- The methodology for decision support including corrective actions and cost issues
- The adaptive learning from feedback and its associated cases on process condition.

2. Targeted Problem

Disturbance analysis or Root Cause Analysis (RCA) in industrial process control can be a time-consuming task leading to big production losses. The overall goal of RCA and Decision Support (DS) is to extract from DCS-data volumes the necessary information for early assessment of abnormalities and provide efficient troubleshooting advice in process operation and for maintenance on demand.

The following issues are treated in the developed methodology, which is applied on a prototype system. The disturbance analysis system should provide reliable handling of uncertainties in acquisition of knowledge and data, including both discrete and continuous signals. The signal classification should be adaptive to changes in process operation mode and account for both normal and abnormal/faulty operation conditions. Prediction of the level-trend development should ensure early risk assessment and warning on abnormality in order to be able to propose early treatment using efficient sequences of actions. Therefore, for predictive maintenance on demand, the cost estimations should also anticipate the potential production losses.

The system performance should adapt to natural process changes and support user interaction. An operator steering a complex process will prefer a transparent decision support system to a black box system. If the system explains the underlying mechanism for its suggestions and conclusions, the operator can compare these with his experience and take the needed corrective actions with confidence.

2.1. Conditions for a process or device

Conditions are the process states at a particular time. Conditions are used to determine whether a plant-wide disturbance analysis should run or not. Process condition is a condition that depends on the state of a production process. The state is affected by external factors. An abnormal condition is a condition caused by disturbances that prevent the process parameters to stay within control limits that define the range of normal process operation. It causes degradation of targeted process performance, resulting in the inability to deliver a pre-specified state of output. A critical condition is a condition that causes failure to meet targets, unexpected process destructive effects or dangerous consequences. It requires urgent corrective actions.

2.2. Relation of Condition Monitoring, RCA and DS

RCA (root cause analysis) is a structured procedure, which guides the failure analyst from the disturbance or failure event to its cause(s). In our methodology, RCA refers to the procedure of searching for the source of a problem, while automatically collecting findings on its effects and reasoning on the base of the causality mechanism that has enabled a failure or undesired events. Moreover, root cause analysis is expected to interact with condition monitoring and early risk assessment of abnormality or process disturbances.

In standard process control the deviation of a single parameter outside its normal range will trigger an alarm. To prevent a large number of false alarms, the thresholds of the variables should not be too sensitive. But this approach will indicate failures only late at an advanced stage.

Process condition monitoring interacting with RCA will use more sensitive thresholds. The large number of triggered “alarms” is first analyzed internally by the RCA system. Only if the change of some variables in context with the behavior of all other process parameters suggests the development of a failure, the operator is informed and advised on actions.

3. Preliminaries

3.1. Bayesian Networks

A Bayesian network (a.k.a. belief network, Bayesian belief network or causal probabilistic network) is a probabilistic graphical model for reasoning under uncertainty. For industrial processes, the uncertainty can be originating from incomplete understanding of the complexity of the domain, from stochastic events leading to randomness in the process behaviour, from the process condition at the time a given control or maintenance actions is to be performed, or a combination of these.

A Bayesian network $N=(G,P)$ consists of a set of nodes (vertices V) representing random variables, a set of links L connecting these nodes to form an acyclic, directed graph (DAG) $G=(V,L)$, and P - a set of conditional probability distributions $P(X|\ pa(X))$, see (Jensen, 2001; Jensen et al., 2002). Here, X denotes a discrete random variable with n states $x_1,\ldots,x_n$; $pa(X)$ denotes the parents of X in G, i.e. the random variables on which X is conditionally dependent. The nodes correspond one-to-one with the domain variables of the probability distributions such that there is one conditional probability distribution (CPD) function $P(X|$

pa(X)) for each node given its parents in the DAG. The CPD expresses the strengths of the (causal) dependency relations of the child node given its parents.

An acyclic, directed graph *G=(V,L)* induces a set of (conditional) independence and dependence relations between the nodes of *V*. The set of independence and dependence relations of *G* changes when the states of a subset of the nodes of *G* are known or observed events (called evidence). Evidence on a variable provides information on its states. Conditional dependence and independence relation between nodes given a (possibly empty) set of evidence can be read from the DAG G using linear complexity algorithms.

3.1.1. Object-Oriented Probabilistic Graphical Models

An object-oriented probabilistic graphical model $N=(G,P)$ is a network (i.e., Bayesian network or influence diagram) that, in addition to the usual nodes, contains instance nodes. An instance node, e.g. see the node "class signal" in Fig. 3, represents an instance of another network (called model class, e.g. ***Fig. 2***). The fundamental unit of an object-oriented probabilistic graphical model is an object. An object represents either a node (i.e. a variable) or an instantiation of a network class (called an instance node). An instance node is an abstraction of a network fragment into a single unit. A network class is a named and self-contained representation of a network fragment with a set of interface and hidden nodes. As the network (e.g. Fig. 3) of which instances exist in other networks (e.g. ***Fig. 4***) can itself contain instance nodes (***Fig. 2***), an object-oriented network can be viewed as a hierarchical description (or model) of a problem domain.

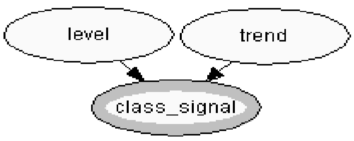

Fig. 2. Simplified BN class for signal classification, based on the signal level and its trend

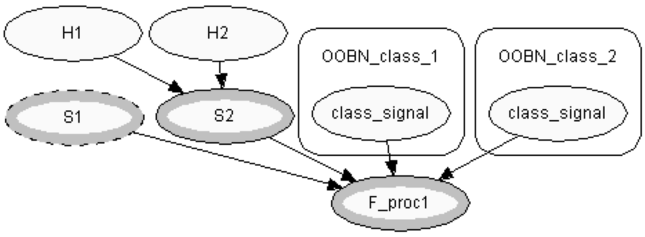

Fig. 3. Simplified OOBN for modeling of "Failure in subprocess" and containing "class signal" as instance, S1 as input interface node and {S2, F_proc1} as output interface nodes.

An instance node connects to other nodes via *interface nodes*. An instance node of a network class hides detailed information on the structure of its network class inside the encapsulating network class. Therefore, the interface nodes usually comprise a strict subset of the nodes of the instance. Interface nodes are subdivided into *input nodes* and *output nodes*.

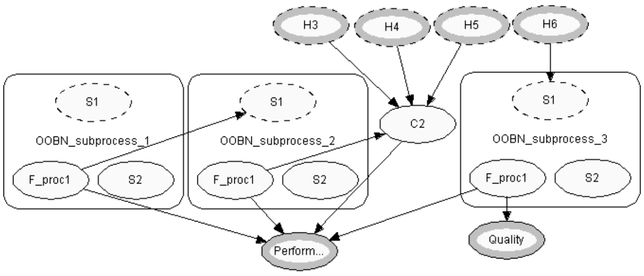

Fig. 4. The network of which the node "Failure in subprocess" is an instance

Input nodes are placeholders for (basic) nodes outside the instance (i.e. an input node is a placeholder for a node of the encapsulating network class).

An output node extends the scope of a node of the instance node to the encapsulating network class. An output node can be specified as parent of nodes in the network containing the instance node or can be bound to an input node of another instance node of the network.

In an OOBN, we use the following *notations:* instance nodes are squares with input and output interfaces: input nodes are ellipses with shadow dashed line borders and output nodes are ellipses with shadow bold line borders, as shown in Fig. 3, Fig. 4.

In this work, we have used the Hugin software (Andersen et al., 1990; Jensen et al., 2002), which supports the construction of *hierarchical network structures*. In the Hugin tool, any OOBN has an equivalent “run-time” BN. A run-time domain is the domain, where the BN is compiled and probability update is performed, based on the propagation of the effects of new evidence.

3.2. Object-oriented Modeling

In general, object-oriented (OO) constructs incorporate encapsulation, inheritance and hierarchy. Its common purpose is efficient modelling and simulation, providing a convenient language for reuse and exchange of models.

Examples of non-causal object-oriented languages for modelling of physical and chemical systems and processes include: Modelica, gPROMS, ASCEND, NMF/IDA, Omola, etc. As compared to the known simulation languages, these object-oriented languages offer several advances: 1) non-causal modelling based on differential and algebraic equations, describing the physics of the domain, provided it is well understood; 2) multi-physics domain modelling within the same application model, incorporating a combination of electrical, mechanical, thermodynamic, hydraulic etc. sub-models; 3) a general type system that unifies object-orientation, multiple inheritance, and templates within a single class construct, see (Fritzson et al., 1998).

Thus, the main difference in our OOBN approach (exploiting hybrid information obtained from both measured and calculated variables from physical models) is in the causal probabilistic handling of uncertainties, while the above mentioned OO languages are using non-causal modelling, based on differential and algebraic equations of the problem domain. On the other hand, we use a hybrid approach, which is a combination of OOBNs with first level statistical diagnostic packages and physical models (e.g. pressure-flow nets) serving as agents in the system design and providing evidence for automated reasoning on abnormality in process operation.

The main advantage due to the Bayesian network approach is much faster operator guidance, *without limiting* the failure analysis to only one possible root cause. Instead, a list of root causes ranked after probabilities will give quick and flexible decision support to the operator with explanation facility based on causality.

We have previously developed a number of generic OOBNs for signals classification, process performance monitoring and diagnosis (Weidl et al., 2002b -2003b). Some of these models have been further extended and for methodology consistency - described in section 4.3.

4. Methodology

The task of failure identification during production breakdown, its isolation and elimination is a troubleshooting task. On the other hand, the task of detecting early abnormality is a task for adaptive operation with predictive RCA and maintenance on demand. Therefore, these two tasks have different probability-cost function. We combine both tasks under the notion of asset management. It aims at predicting both process disturbances and unplanned production stops, and to minimize production losses. Thus, the priority is to determine an efficient sequence of actions, which will ensure the minimal production losses and will maximize the company profit. To provide a solution to troubleshooting, predictive RCA and maintenance on demand, we have developed an extended methodology. The combined methodology incorporates:

1. Detection of a failure at an early abnormality stage with a reduced number of hardware sensors
2. Identification of the most likely root causes of abnormality and of observed or predicted disturbances.
3. Advice on an efficient sequence of corrective actions and observations, under the assumptions of order independent costs, which ensures an optimal sequence of actions

(Heckerman et al., 1995). Methodology extension to pro-active solutions with early treatment of abnormality in order to avoid potential losses of production is due to (Weidl et al., 2003c) and uses the maintenance model of (Wang et al., 2003) for the estimated average cost.

4. Time critical decision support on alternative actions and their urgency, as described in (Weidl et al., 2002b).

4.1. An Overview of the Modeling Process

4.1.1. Monitoring of the Plant Performance

One can undertake a top-down approach, if monitoring and analysis of the plant performance are of interest. This approach is utilizing an OOBN. The structure of the OOBN is reflecting the plant hierarchy and can also be used to understand how the modeling process evolves.

The knowledge-based library of RCA models could be in the form of hierarchically structured and interconnected failure trees, as shown in Fig. 5. At the top are abnormalities in process operation and output quality, which can originate from abnormalities in equipment or in process conditions possibly due to basic failures.

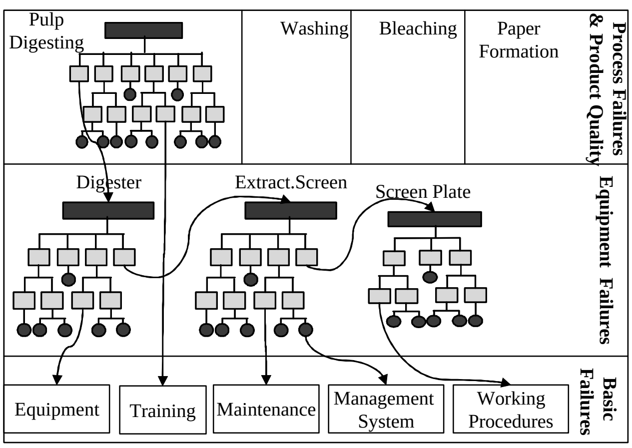

Fig. 5. Failure trees interconnections as a knowledge base for RCA of digesting and its process performance analysis

In the main stream of a pulp and paper mil, the wood chips are digested to become pulp. The washing is removing the impurities and is preparing the pulp for bleaching. The paper formation is flattening the paper into the desired thickness and fiber orientation, which ensures certain paper properties such as stiffness, etc.

Examples of performance parameters are: availability of machines; speed in factory; production rate; quality of output; cost efficiency.

This approach has been applied in a case study of RCA and performance monitoring for a cutting process in hot rolling mils. As a natural modeling language of the interconnections of failure trees has been applied an OOBN (Weidl et al., 2003b).

An application of condition monitoring and RCA for digesting process operation will be given in section 5.

4.1.2. Causal Domain Modeling using Bayesian Networks

An example of hypotheses, symptoms, and faults can demonstrate the scenario for causal modeling of malfunctioning in a screen (i.e. pulp filter) operation. Assume, a process operator is observing changes in process variables: increased pressure ($\Delta p\uparrow$) and reduction of accepted flow ($F_{accept}\downarrow$) after the filtering equipment. This malfunctioning could be either due to clogging of the filter (screen plate) or due to decreased flush flow. Filter clogging could occur due to either decreased number of the round per minutes (rpm) of the rotor or due to increased concentration of the filtered flow. The low revolution of the rotor could be caused by a malfunctioning motor or due to skidded strap. Other root causes of the observed changes in process variables could be simply due to malfunctioning valves on the accept side or reject side of the screen. If we follow the causal mechanism behind the development of the observed fault (screen malfunctioning), one can express this scenario with its hypotheses on possible root causes of the problem as a graphical model as shown in Fig. 6, where the last step is deduction on the fault, based on the observations.

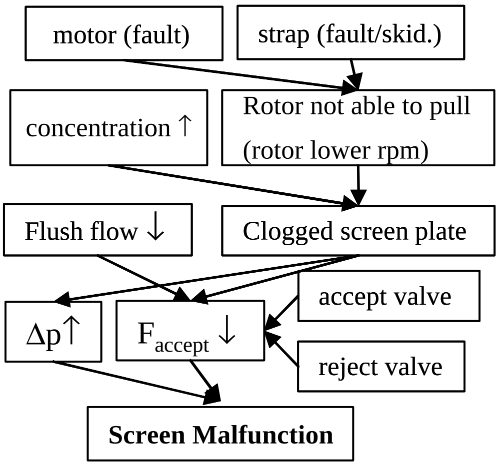

Fig. 6. Example on the causal mechanism behind the development of an observed fault (screen malfunctioning)

The generic mechanism of disturbance (or failure) build up includes a root cause activation, which causes abnormal changes in the process conditions. The latter represents effects or symptoms of abnormality. Abnormal changes in process conditions are registered by sensors and soft sensors. If not identified and corrected, these abnormal conditions can enable events causing an observed failure. A causal representation of the above factors gives the following chain of events and *transitions*, which is of interest for RCA under uncertainty and for the purpose of decision support on corrective actions, as shown in the left part of Fig. 7.

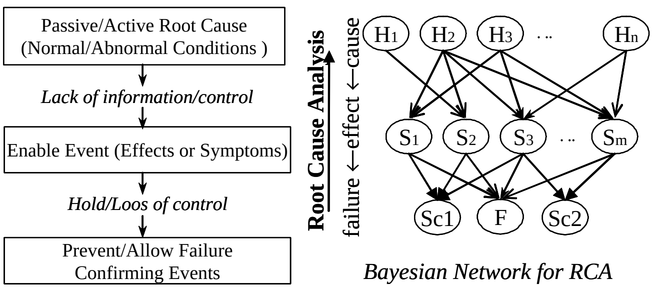

Fig. 7. The conceptual layers of the BN for RCA (column 1) and the corresponding variables in each layer of the BN

The BN model for Root Cause Analysis reflects the causal chain of dependency relations as shown in right part of Fig. 7. The dependency relations are between three symbolic (conceptual) layers of random variables in the problem domain:

(1) $\{H_i\}$, $\{S_j\}$, $\{F\}$, where $i = 1... n$, $j = 1 \dots m$

In eq. (1), the set of root causes $\{H_i\}$ contains all possible hypotheses on failure sources or conditions, which can enable different events S_j, which precede a failure F or its confirming events Sc_k. The set of variables $\{S_j\}$ contain also early abnormality effects and symptoms, which are observed, measured by sensors, or computed by simple statistical or physical models (e.g. mass and energy balances). The word “symptoms” refer to changes in the process operation conditions, which are affecting the equipment performance or the final output.

The BN model (right part of Fig. 7) is assuming single cause, i.e. everything was properly functioning before the first symptoms were observed. This is modeled by adding a constraint node as a child of all possible root causes $\{H_i\}$. Moreover, in the BN models, we assume explicitly that all variables are discrete.

The developed methodology is presented in section 4 as a mixture of two concepts. Subsection 4.2 provides a description of the system to be modeled and how to handle uncertainties, whereas subsection 4.3 outlines the modeling process in detail and subsection describes the basic algorithm for RCA and DS, including also the cost issues.

4.2. Handling of Uncertainties

The necessary data to determine the condition of a process and its devices is provided by DCS-signals, alarms, event lists, equipment data, maintenance reports, and a number of first level diagnostic packages (Fig. 8). Thus, the knowledge acquisition for the CPDs of the BN models is a mixture of different acquisition strategies for different fragments of the network, as discussed in (Olesen et al., 1992).

4.2.1. Agents for Handling of Uncertainties

First level asset diagnostic packages serve as agents in the RCA-system architecture. These include diagnostics of small asset units, e.g. sensors, actuators, control loops, soft sensors, see Fig. 8.

They provide information on the degree of reliability of sensors readings (by data reconciliation), sensor status (by sensor diagnosis), calculated signal-trends (by trend diagnosis), actuators and other process assets conditions. Thus, it reduces the degree of uncertainty in the acquired evidence. The term asset is used here as a collective notion to include actuators (valves, pumps), other process assets (e.g. digester screens; pipes, can be represented as fake valves) and in general, even equipment failures as a root cause of signal deviations. More details on the system architecture are given in (Weidl, 2002).

In Fig. 8, the Dynamic Data Reconciliation Agent is utilizing simulations from a Pressure-Flow Network, which we describe in the following sub-section.

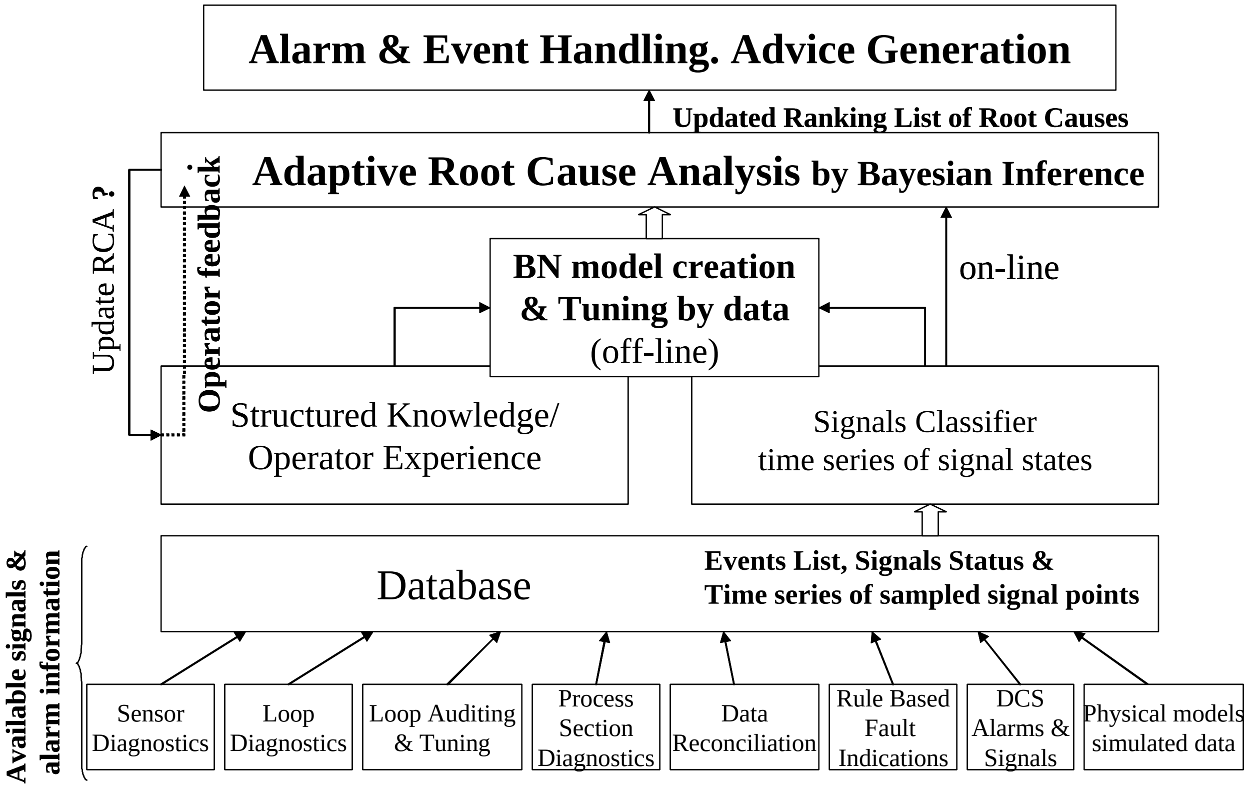

Fig. 8. System architecture for RCA

4.2.2. Agents for handling of uncertainties in fluid dynamics modeling

The idea is to use the simulations provided by a fluid dynamic model (e.g. pressure-flow net) as soft sensors' evidence from thereof computed (non-measurable) process variables. A pressure-flow model can provide for example estimates on some parent configurations in the BN, if there is no database to extract such dependency relations. There are several sources of uncertainties in this physical model estimation, since modeling inputs for the actual valve openings might be different than the ones indicated by DCS measurements. Moreover, the state of the screening plate (normal, clogged, hole or cracks) will still represent uncertainty of the outcome of such estimations. This is because clusters of small particles or long fibers in the pulp flow can clog part of the plate screening area, which is not directly considered in the flow dynamics model. One can also model this effect in the fluid dynamics simulations by a function expressing the gradual reduction of a plate screening area.

A pressure-flow model (see Fig. 9) can be used to specify a mathematical expression of the relation between a node *(flow_accept or flow_reject)* and its parents. Two types of equations can be used to build the pressure-flow equation system of the screening process:

- Mass conservation equations for all flow splitting-points

(2) $$S\ In\_flow = S\ Out\_flow$$

this for the screen becomes

$$flow\_inject + flush\_flow = flow\_accept + flow\_reject$$

- Pressure drop equations at all pressure changing components of the network. Three types of pressure changing components *D(Pressure_at_component)* are considered: pumps, valves and screening plate

$$Pressure\_after = Pressure\_before + D(Pressure\_at\_component)$$

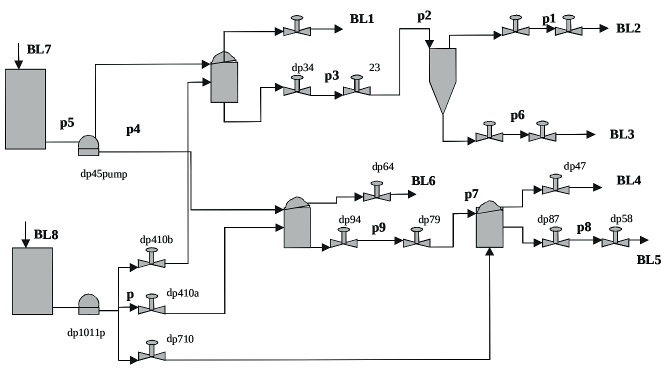

Fig. 9. Pressure-flow network of pulp screening process with screens in different process sections and series connection of screens

The pressure change due to a pump is given as:

(3) $$Dp\_pump = dp_0 - [\ (dp_0 - dp_n) \cdot q^2 / q_n^2\ ]$$

where dp_0 , dp_n , q_n are the dimensioning parameters of the pump, i.e. dp_0 - the pressure at flow $q=0$ through the pump; dp_n the pressure at normal flow $q = q_n = [N\ kg/h]$.

The pressure change due to a valve is given as:

(4) $$Dp\_valve = r \cdot q^2 / (a^2 v^2)$$

where q is the flow, r is the density of pulp, a is the admittance factor and v is the valve opening in % units. Due to non-measurable process disturbances, the parameters r, a and v incorporate uncertainties in the expressions for Δ*p_accept_valve*, *Dp_reject_valve and Dp_screen_plate.*

Usually, the pulp flow concentration (density) measurements are unreliable. The building and dynamics of fibers and clusters in the pulp flow are not modeled by physical models, or even if modeled - not calculated on-line since they are computation time expensive to determine. The active screening area in relation to the clogged plate surface is difficult to estimate. The flow of accepted pulp consistency can be reduced due to many other factors, besides screen plate clogging. Uncertainty in measurements is one of the motivations for adaptation.

Uncertainty in computed pressure-flow balance is another argument for adaptation. The pressure-flow equation system build from (2), (3), (4) can be expressed as: $f(x) = 0$, where the vector $x = \{q, p\}$ is its solution with components $q = \{ q_1, q_2, \ldots, q_n\}$ for the flow and $p = \{ p_1, p_2, \ldots, p_m \}$ for the pressure.

We use the Newton's iteration method to find the solution $x=\{p, q\}$ of the pressure-flow equation system, as follows:

(5) $$x^k = x^{k-1} - J^{-1}(x^{k-1})\, f(x^{k-1}), \quad k = 1, 2, 3, \ldots$$

where the Jacobian of the system is given by

$$J(x) = \{¶f_i(x)/¶\ x_i\}.$$

At $k = 1$, $x^{k-1} = x^0$ is the *initial guess* of the iteration procedure. Since the Newton's iteration method represents tangential search, the closer the initial guess is to the real solution, the higher the chance to find the correct pressure-flow net configuration is and thus to keep the system control in balance.

The above provides good motivation for using adaptation. Adaptation will be discussed in section 7. The Newton iteration provides a good mathematical model for estimates on $x = \{q, p\}$. The pressure-flow balance should hold at each time step and is computed in quasi-stationary regime (by use of the general purpose software *Maple*), since there is a possibility to change at each time step the initial flow entering the system by taking into account process input changes. The adaptation will then compensate the classification of those states of the system, which the models do not fully capture, since the domain changes over time.

Physical simulations models (like fluid dynamics, or integrated fluid dynamic models with built-in control strategies) are more rigorous, although computational time consuming and sometimes unsuitable for on-line use. In this respect, we have with advantage used the knowledge of process physics for causal probabilistic modeling, which allows (time efficient) on-line exploitation. In cases, where the underlying physics of the problem domain is not well understood, one possible alternative is to use simplifying assumptions in BN as described in (Weidl, 2002).

4.2.3. More sensitive internal thresholds of abnormality

A conventional Distributed Control System (DCS) provides alarms at extreme process conditions. For the purpose of RCA more sensitive signal thresholds and internal RCA system alarms are needed, especially if the process deviations and faults are to be found and corrected at an early stage of fault development.

When only one signal in a problem domain exhibits a tendency of abnormality, it is usually due to sensor fault. This incorporates that, besides RCA, we also consider monitoring of the system. Another argument for monitoring is: even though no sensor is in DCS-alarm state, the system may be malfunctioning, e.g. the sensor, which should raise the alarm, could be broken. On the other hand, the DCS alarm thresholds (e.g. Fig. 10) serve for detection of really critical process conditions and not for early detection of abnormality, which RCA is aiming for. These reasons strongly motivate the combination of monitoring and RCA. If the alarm thresholds in the DCS system were set as low as needed to detect early deviations and perform RCA, the operator would be exposed to alarm signals overflow, since there is no alarm filtering in a standard DCS.

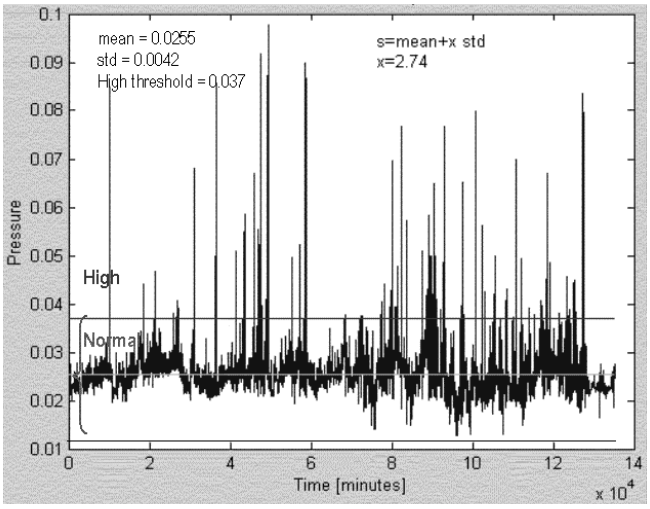

Fig. 10. RCA Alarm Threshold and Mean for Pressure

Signal classification into Discrete States

For industrial processes, the effect of a root cause is often recognized in abnormal variations of system parameters. Many of these process deviations are quantified by both DCS-signals (sensor readings, computed variables) and trends. The signals and their trends are conditionally dependent on the root causes H_i, as incorporated in the model structure in *Fig. 7*. Fig. 5 and *Fig. 7* show how the modeling process evolves. Since not the absolute value, but the level-trend pattern of the signal is considered to be a valuable information/evidence, it is sufficient to classify the input signals into discrete mutually exclusive intervals or states.

In this section we consider the classification of a continuous signal into level and trends with a minimal number of classes (states of a discrete variable), while in the next section we consider more refined classification, based on mixture models.

Suppose a DCS-signal S_k has Gaussian distribution during normal process operation. Its mean value can be equal to the (DCS) controller set-point or averaged over a certain time period to remove measurement noise. For the purpose of reasoning under uncertainties and to be able to distinguish the risk of abnormality from an alarm situation, the signal level S_k and the signal trend $\partial S_k/\partial t$ are discretized into a number of predefined states.

For the signal levels, the sum of probability on level states: *low (l), normal (n), high (h),* is expressed according to the definition of mutually exclusive and exhaustive states as:

(6) $$P(X=l|A, B)+P(X=n|A, B)+P(X=h|A, B) =1$$

where A and B are events causing changes in the signal.

The high and low states are defined as the ones outside the scaled standard deviation (i.e. $x_{abnormal} \times s$ from the mean) during normal process operation.

The signal trends are classified into *decreased (d), steady (s), increased (i)* states, i.e.

$$P(X=d|A,B)+P(X=s|A,B)+ P(X=i|A,B) =1$$

For many process signals under normal process behaviour, one can employ the Gaussian distribution

(7) $$S = m \pm x_{abnormal} \times s$$

where m is the mean and s is the standard deviation. We define as $x^H_{abnormal} = (q_{High} - m) / s$ where $s^H = q_{High}$ is the signal's high threshold obtained from data analysis. The low threshold is defined as $s^L = q_{Low}$, $x^L_{abnormal} = (m - q_{Low})/s$. From data analysis, we have found that, the ($x_{abnormal} \times \sigma$) variation of signals covering the different operation modes is in the interval 1σ-5σ. For more analysis and examples, see (Weidl, 2002). The most informative signals for RCA are the signals of predictive (e.g. pressure) and confirming (e.g. lignin content) character with respect to a certain failure event (e.g. digester screen clogging).

The ($x_{abnormal} \times \sigma$) variation provides *robustness* in the signal classification and reduces the number of false alarms Actually, according to the generic BN model for RCA, even if a false alarm is passing through this classification as abnormal, it would require a certain combination (Fig. 7) of several signals' alarms (internal for RCA) in order to trigger an operator alarm or warning, pointing at one or several root causes.

A prior probability distribution for measured process parameters can be obtained from their normal and abnormal frequencies in the time series of signal sampling points, e.g.

(8) $$P(X=low)=\frac{n_{low}}{n_{tot}};P(X=high)=\frac{n_{high}}{n_{tot}};$$
$$P(X=normal)=1-P(X=low)-P(X=high)$$

where n_{tot} is the total number of signal sampling points, n_{low} and n_{high} denote the number of *low* and *high* signal values respectively.

4.2.4. Continuous Distributions on Soft Range of States

The system is receiving as evidence both discrete and continuous signals. The DCS provides an event list on critical process variables, which contains only Boolean variables. The variation range of a continuous signal (DCS-measured or thereof computed signal (e.g. from a physical model)) is discretized into a number of soft numeric intervals, represented as states of a BN-variable. We use discretization and not continuous variables explicitly, since we want to capture both the continuous variation of the signal during normal process operation, as well as its non-continuous disturbances (or discrete faulty deviations outside normal variations). This is realized by use of mixture models, e.g. (McLachlan et al., 1988), (Holst, 1997).

Let S be a continuous variable. Assume that S can be partitioned into sets $s_1 \ldots s_n$ such that the discretized probability density function $P(S)$ can be approximated by a finite sum over its n soft interval states s_i

(9) $$P(S) = S_{i=1..n} P(s_i) P(S|s_i)$$

i.e. $P(S)$ is partitioned into n sub-CPD $P(S|s_i)$, each with probability $P(s_i)$ as a "root cause" of S, as shown in Fig. 11.

The sub-distribution of each soft interval state is chosen as a localized function with one peak and it is decreasing monotonically with the distance from the peak. Gaussian mixtures are used most commonly, since they allow approximating any other probability distribution. The use of mixture models for soft interval coding of a signal range reminds of the fuzzy sets representation (Zadeh, 1965) as membership functions. The difference is in their interpretation as CPD in the terminology of Bayesian networks.

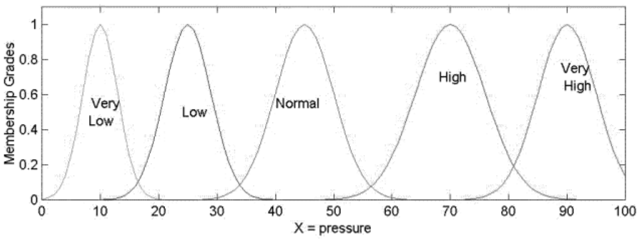

Fig. 11. “Soft interval coding” = Discretization of continuous signals into soft range of states within the same process operation mode

We also use the Gaussian distribution as the CPD on selected soft interval states to represent the most characteristic values of a continuous signal during normal and faulty operation, see also Fig. 15. The Gaussian peak is then localized at the signal set-point or at the mean of variables affected from the set-point change, as applied in (12) and (14).

The assumption of *soft interval coding* is reasonable, if it preserves the initial information contained in the signal, i.e. when the discretization intervals are selected proportional to the *std* for each set point (or mean) of a signal, so that outside of soft interval the CPD should decrease sufficiently fast to become negligible. Thus, this assumption provides natural signal classification into characteristic states over a signal range. As pointed out in (Holst, 1997) if the mixture is not used as natural categorization, but only as approximation of the real CPD, the intervals should be selected “close enough” in order not to distort the classification too much.

In addition, for cases with low frequency of abnormal events, we have used a mixture of Poisson distribution to represent the signal deviations during faulty operation of the process and Gaussian distribution, on soft interval states, during normal process behavior, see eq. (15).

The use of mixture models in a BN allows also predicting a continuous value of a process variable, given some evidence on other variables, as discussed in subsection 4.3.2.

4.3 Generic OOBN Models

The use of OOBN models facilitates the construction of large and complex domains, and allows simple modification of BN fragments. We use OOBN to model industrial systems and processes, which often are composed of collections of identical or almost identical components. Models of systems often contain repetitive pattern structures (e.g. models of sensors, actuators, process assets). Such patterns are network fragments. In particular, we use OOBNs to model (DCS and computed) signal uncertainties and signal level-trend classifications as small standardized model classes (a.k.a. fragments) within the problem domain model, see sections 4.3.1 - 4.3.3.

We also use OOBNs for top-down/bottom-up RCA of industrial systems in order to ease both the construction and the usage of models. This allows different levels of modeling abstraction in the plant and process hierarchy, see sections 4.3.4 - 4.1.1. A repeated change of hierarchy is needed partly due to the fact that process engineers, operators and maintenance crew discuss systems in terms of process hierarchies and partly due to mental overload with details of a complex system in simultaneous causal analysis of disturbances. It also proves to be useful for explanation and visualization of analysis conclusions, as well as to gain confidence in the suggested sequence of actions.

4.3.1. Adaptive signal classification

Dependent on operation mode and set-points of parameters, the signal's level and trend have different normal and abnormal states. Normal operation mode is characterized by a number of set-points c_p and their typical signal variations during normal and abnormal process operation.

The process is usually operated at several normal operation modes dependent on production rate, process load, etc. During normal operation modes, the variations of process variables are inside their boarders allowed from process control. Faulty change of operation mode, faulty process operation, as well as equipment faults can be the root causes of abnormal process deviations. This can cause degradation of process output (e.g. quality) or failure in process assets, when exploited under improper conditions.

The BN model of Fig. 12 provides information on the degree of reliability of sensor readings and reduces the degree of sensor uncertainties. The variable *sensor_reading* s_r represents the continuously measured value (signal) of a process variable. The variable *sensor_status* s_s represents the condition of the sensor instrument used to perform the measurement of a process variable (i.e. true for working properly and false for malfunctioning sensor). The variable *real_value* R_t represents the actual development of the process variable at time *t*. The time aspect plays an important role, while forecasting the development of the signal and the expected process behavior, as will be shown in subsection 4.3.2. The variable *sensor_diagnosis* s_d represents the input from the sensor diagnostics agent.

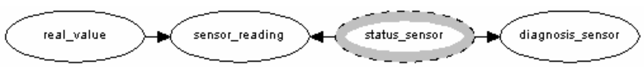

Fig. 12 General BN fragment of sensor readings uncertainties as part of any BN model for RCA.

It is obvious that if the measurement instrument is not properly functioning, then the real-value and the sensor_reading need not be the same. Therefore, the sensor reading from any DCS-measurement is conditionally dependent on random changes in two variables: real value under measurement and sensor status of the instrument. Its probability distribution is expressed as a mixture (10) of normal and uniform distributions for the real value when the sensor status is true and false, respectively.

$$(10) \qquad P(s_r | R_t, s_s) = \begin{cases} Normal(R_t, x_{abn} \cdot s), & s_s \\ Uniform(y_{\min}, y_{\max}), & o.w. \end{cases}$$

where the uniform distribution is defined on the entire interval (y_{min}, y_{max}) of signal variation, For more details and examples, see (Weidl, 2002).

The sensor diagnostics conclusions are affected by the sensor status (true/false), while the real value can be restored by use of information from the dynamic data reconciliation agent (Fig. 8).

From data analysis, we have found that certain failure events are enabled during process transition between consequent operation modes (e.g. mode change for increase of production rate). For such cases, it might be preferable to use signal classification, which is adaptive to change in normal process operation.

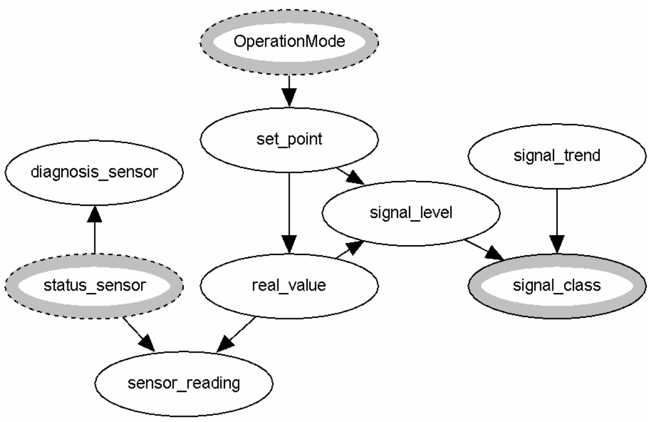

Fig. 13 Generic BN model for Signal Classification into levels and trends. Adaptive to change of Operation Mode

An extension of the BN model in Fig. 12 will provide classification of the signal, which takes into account changes in the process operation mode, see Fig. 13 representing the BN model structure. The signal level s_l is directly influenced by random changes in two variables: real value R_t and set point c_p of the process variable. The states of the signal level s_l are given in its probability distribution by the following qualitative decision rule, which is also used to compute the corresponding probabilities:

$$(11)\quad P\left(s_l \middle|\; c_p, R_t\right) = \begin{cases} low, & R_t < c_p \cdot n_- \\ high, & R_t > c_p \cdot n_+ \\ normal, & o.w. \end{cases}$$

where according to (7) $v_\pm = \pm s\ /m$ is specific for each operation mode and it is expressing the percentual variation around the mean.

Suppose a DCS-signal S is discretized over soft interval states as given in (9), subsection 4.2.4. The prior probability of the real value R_t is given then by (12).

For variables, which are directly manipulated in process control loops, the set point serves as mean m in the Gaussian distribution with the respective scaled variance $x_\pm \times s$ around the set-point of the operation mode. The variance is scaled by a factor $x_\pm$ in order to avoid too many *"internal alarms"* for RCA.

$$(12)\quad P(R_t|\, c_p)\ \tilde{}\ \ Normal\ (c_p,\, x_\pm \times s)$$

For all other process variables, (12) is modified to incorporate (7) as follows

$$P(R_t|\, c_p)\ \tilde{}\ \ Normal\ (m,\, x_{\text{abn}} \times s)$$

For variables without set-point, but which covariate with controlled variables, we calculate the mean of the relation (real value/set point) or alternatively any physical or statistical function expressing their correlation.

For the example of Fig. 10, the flow F is a control loop variable with set point $c_p(F)$, the pressure p is covariating parameter with real value $R_t(p)$ and one can use their physical pressure-flow relation p/F^2 to specify the CPD:

$$P(R_t(p)\ |c_p(F))\ \tilde{}\ \ Normal\ (m(p/F^2),\, 3s(p/F^2))$$

The signal class s_c is conditionally dependent on random changes in two variables: signal_level s_l and signal_trend $trend_s$. The states of its probability distribution are then defined to adapt the classification to changing operation mode and are given as

$$(13)\ \mathrm{P}(\mathrm{s_c}\,|\,\mathrm{s_l}\,,\mathrm{trend_s}) = \begin{cases} alarm, (\mathrm{s_l} = \text{"high"} \wedge \mathrm{trend_s} = \text{"increasing"}) \\ \quad \vee (\mathrm{s_l} = \text{"low"} \wedge \mathrm{trend_s} = \text{"decreasing"}) \\ warning, (\mathrm{s_l} = \text{"high"} \wedge \mathrm{trend_s} = \text{"steady"}) \\ \quad \vee (\mathrm{s_l} = \text{"low"} \wedge \mathrm{trend_s} = \text{"steady"}) \\ normal, o.w. \end{cases}$$

The generic BN model for adaptive signal classification into levels and trends (Fig. 13) is one of the generic building blocks in any RCA model of monitored industrial process with its equipment and asset components in every process section.

Such generic building blocks (as Fig. 13) are typical examples of repetitive patterns in the BN model development. It is natural to represent them as OOBNs. A specification of the interface nodes of Fig. 13 is shown in Fig. 14.

As (Weidl et al., 2002b) have proposed, the BN model of Fig. 13 can be extended further to incorporate also the information output from loop diagnostics (Fig. 8), process section diagnostics and controller mode diagnostics, as shown in Fig. 14.

In cases of faulty operation or root causes originating from abnormal condition of process assets, the real value of a process variable is dependent on the set-points of different operation modes and on the status of the asset, denoted as "problem_Asset" A_s.

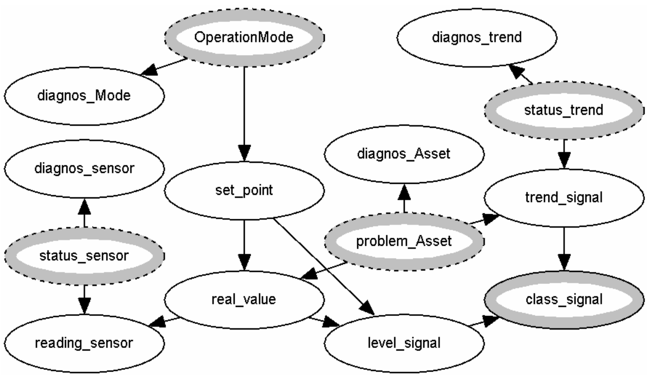

Fig. 14. A generic OOBN model for Signal Classification into levels and trends, within a control loop. The classification is adaptive to both normal and faulty changes in process operation mode.

Then, the conditional probability distribution (CPD) of the real value becomes a mixture of Gaussian and Uniform distributions around the set point during normal (no asset problems) and the mean during abnormal process operation

$$(14)\quad P(R_t \mid c_p, A_s) = \begin{cases} Normal(c_p, x_{\pm} \cdot s), & \neg A_s \\ Uniform(m_{abn}, x_{abn} \cdot s_{abn}), & o.w. \end{cases}$$

where $\neg A_s$ denotes "no problem_Asset".

Here, the reasoning is similar as for (12). The dependence on the status of the asset is expressed with a Gaussian distribution, where m_{abn} is the real alarm threshold and $x_{abn} \cdot s_{abn}$ is the scaled variance which lower variation limit provides more sensitive alarm threshold for early risk assessment of abnormality.

Alternatively, for signals deviation, which is characterized by low frequency of failure events (e.g. Fig. 10), we use a mixture consisting of a Gaussian distribution on normal operation behaviour and a Poisson distribution during faulty operation. Thus, the probability of the real value can be modified from (14) as a random variable on discretized soft intervals

$$(15)\quad P(R_t \mid c_p, A_s) = \begin{cases} \text{Normal}\ (c_p, x_{\pm} \cdot s), & \neg A_s \\ \text{Poisson}\ (m_{abn}), & \text{o.w.} \end{cases}$$

The CPD of the signal trend takes also into account problems with process assets and considers also the possibility of a novel situation expressed by "other root cause" (e.g. valve open by mistake).

$$P(\text{trend}_s \mid A_s) = \begin{cases} increasing, & A_s = \text{"clogging"} \\ low, & A_s = \text{" valve\_open "} \\ steady, & o.w. \end{cases}$$

In this case, a high and increased pressure signal is one of the symptoms of screen clogging.

In Fig. 14, signal_trend has two parents: problem_Asset and status_trend. This allows to use evidence on the trend and its status and to conclude on the state of the asset (e.g. actuator).

For robustness, the evidence on the trend is calculated as the derivative on the averaged time history of the signal sampled with a time step $Dt = t_i - t_{i-1}$:

$$(16)\quad trend_s = \frac{\Delta S}{\Delta t} = \frac{m(R_t(t_i)) - m(R_t(t_{i-1}))}{t_i - t_{i-1}}$$

where the mean

$$(17)\quad m(R_t(t_i)) = \frac{1}{N} \sum_{j=(i-N)\dots i} R_t(t_j)$$

is averaged between the time points t_{i-N} and t_i ($i=0$ current time) over the real value $R_t(t_i)$ of a signal at time point t_i.

This provides a simple filter of the noise in the signal behavior. To model the degree of uncertainty in the signal trend, we use a diagnosis trend agent. In this case, we use the uncertainty (historically calculated) for each of the N historical points and base on this the diagnosis of the derivative variable.

We consider in equ.(17) a floating time window with N = 20 historical values, sampling rate 30 sec and unit time interval of 1 minute for probability update, which is sufficient for processes of slow dynamics.

To summarize, Fig. 15 shows an example of prior probability distribution of a typical process variable in the BN model

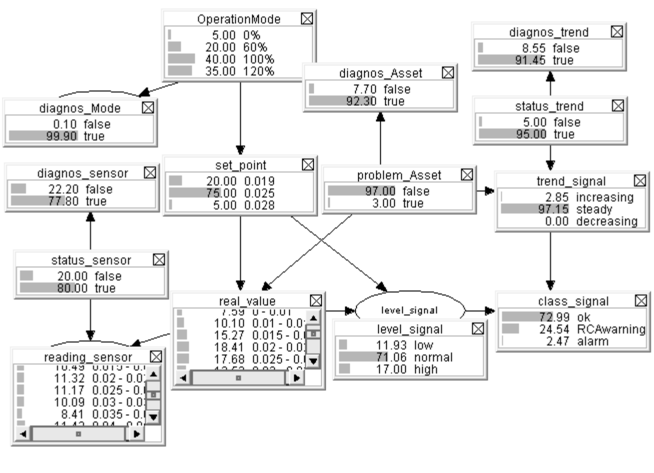

Fig. 15. BN with DAG structure and CPD for adaptive signal classification

4.3.2. Temporal BN for Predictions & Risk Assessment

For predictions and risk assessment of events in the process operation, we use dynamic Bayesian networks (a.k.a. temporal BN or time sliced models). In particular, we use a special kind of strictly repetitive time stamped models, like in Fig. 16, called hidden Markov[1] models of first order. The term *hidden* refers to a hidden activity in the process, e.g. the non-measurable disturbances in the industrial system.

Actually, there exist adaptive control techniques using extended Kalman filter to estimate both the process state and the unknown parameters of process parts subject to wear, e.g. (Sohlberg, 1998). In general, Kalman filter is a hidden Markov model, where exactly one variable has relatives outside the time slice.

The underlying assumptions of hidden Markov models are: 1) the property of Markov chain process: the future is independent of the past given the present. 2) we assume the process to be stationary (distributions are fixed over time). The last assumption is probably invalid, if the CPDs change over time.

The model in Fig. 14 is a general model for adaptive signal classification and can be extended to several time steps back and forward from present time in order to predict the development of process variables with time, as shown in Fig. 16.

One can also use the model in Fig. 16 to calculate the needed set-point in the next time-step, provided the real value of the signal should be changed to reach higher production rate or in cases, when it shows tendency of deviations due to non-measurable disturbances.

[1] *Definition [Markov process]*

A discrete or continuous random process x(t) is defined as (simple) Markov process, if for any finite set of points $t_1>t_2 \ldots >t_{n-1} >t_n$

$P(X_n,t_n|X_1,t_1; \ldots; X_{n-1},t_{n-1}) = p(X_n,t_n| X_{n-1},t_{n-1})$.

If $x(t_{n-1})= X_{n-1}$ is given, then evidence on $x(t_{n-2}), x(t_{n-3}), \ldots$ does not add any new information on the CPD of $x(t_n)$. The Markov random series is often called Markov chain. Any pure random process is a Markov process. Many physical processes can be described as Markov processes. This is a reasonable assumption for treatment of process variables, since the process conditions can be subject to non-measurable process disturbances of random character.

The time slices are connected through temporal links to construct the full BN model with one-step-ahead prediction. This is strictly repetitive temporal model, since the structure of the time slices is identical, the temporal links are the same and the CPDs in each time slice are identical. Therefore the model construction can be facilitated for large and complex industrial domains by use of Object Oriented Bayesian Networks (Weidl et al., 2002b, 2003b).

The temporal (dynamic) Bayesian network models are used to predict the development of the signals and evaluate their risk of abnormal deviation due to disturbances. This signals' prediction is used as evidence in the RCA model. Therefore, the RCA can provide early warnings on root cause activation. In that case, the control system can examine with short disturbance (e.g. opening or closing of valve) whether the suggested root cause is the real one and if confirmed (by the operator or directly by a DCS-signal, see Fig. 34) the needed corrective action is undertaken at an early stage of failure development.

The signal trend at any time step is directly influenced by random changes in the real_value at both previous t_0 and present t_1 time steps within the same operation mode. This is not the case at change of operation mode. Therefore, in order to keep the general character of the BN model, we assume causal independency between the trends in different time slices. And we calculate with an expression evaluator (Fig. 24) the trend of a process variable at each time step.

The predicted real_value of any DCS-variable at time step t_2 is directly influenced by random changes in two variables: the set-point of the DCS-operation mode and eventual problems with assets. To ensure model generality also at operation mode changes, it is reasonable to assume causal independence between the real_values in the consequent time slices. At operation mode changes, the assets problems are mainly due to malfunctioning actuators resulting in wrong process variables or wrong set-points for the new operation mode.

The probability distribution of the predicted real_value is given as mixture of Normal and Poisson distributions

(18) $$P(R_t(t_2)\big|c_p(t_2), A_s) = \begin{cases} Normal(c_p(t_2), x_{\pm} \cdot s), & \neg\, A_s \\ Poisson(m_{abn}), & o.w. \end{cases}$$

where $(x_{\pm}{}^{\chi} s)$ is different for the different set points.

Here one can see the advantage of using mixture models. They are helpful for calculating the probabilities of the signal states, their classification or of other discrete variables, like asset or process conditions. Evidence on the sensor reading and sensor status at the present time step allow retrieving the continuous real value of the signal from the probabilities of the different soft intervals states in the signal range. This on its turn allow to retrieve the continuous real value of the signal in the next time step, given evidence on the real value and trend of the signal at the present time step and its desired target set point for the next time step.

The signal predictions can be part of the problem domain model or performed outside in a separate module, which can share signal information with other problem domains. The predicted (expected) signal value can be used as input in the RCA to provide predictive diagnostics, which can be very useful for predictive maintenance and control before any actual failure has occurred.

The evidence for the BN models of Fig. 14 and Fig. 16 are automatically gathered by the RCA system and include DCS information on: Switch of process operation mode; new ensemble of set-points for controlled process variables; sensor readings; sensor status (from the simple statistical model on sensor diagnostics).

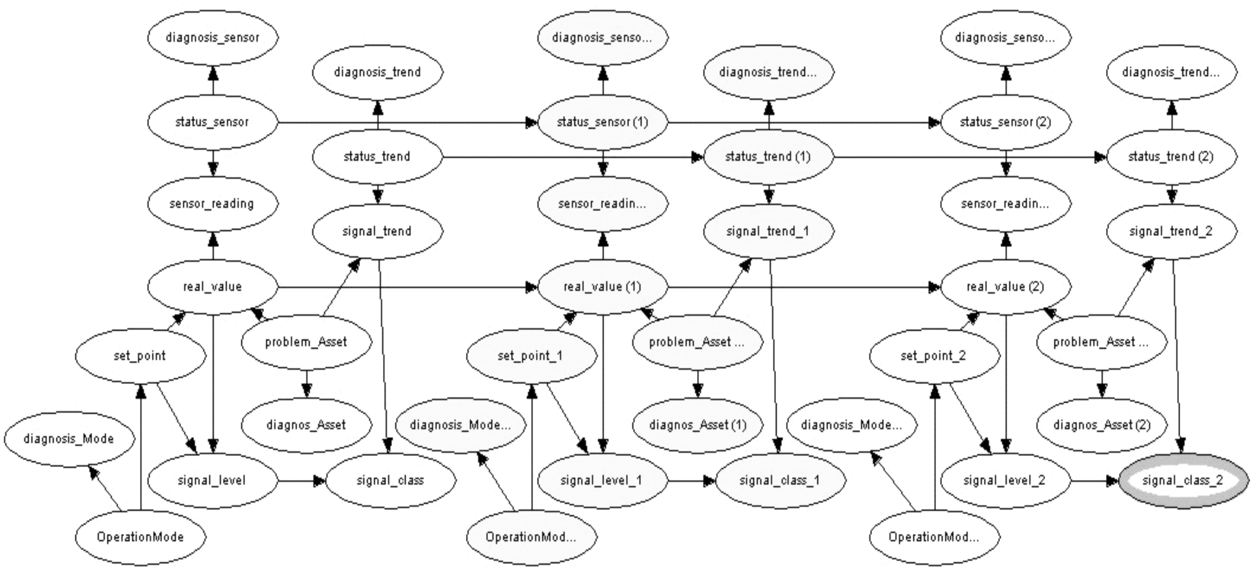

Fig. 16. Prediction of classified DCS-signals, based on present and past values of process variable

Remark: The switch of process operation mode can be handled in the same BN model for RCA only for continuous industrial processes, like pulp & paper production. For batch processes (e.g. metals, pharmaceuticals or petro-chemicals), the switch of operation mode would require also switch between the appropriate BN models representing the corresponding batch mode of operation.

4.3.3. Early Warning Based on Risk Assessment: A Case Story on Pulp Screening

The pulp is obtained as a result of cooking of wood-chips in a digester. The screening of pulp is a filtering process. In order to predict the condition of the screening process and to demonstrate the concept, we have selected a characteristic set of process random variables: S1 = dP is the differential pressure signal; S2 = F_{accept}, S3 = F_{reject} are the flows on accept and reject side, S4 = I (current) is the consumed power by the equipment during screening process operation, see Fig. 17. As noted for the signal classification model, the different production rates during normal screening operation are represented each by one specific combination of process variables. All deviations from operation mode-set combinations are symptoms of expected abnormality in the process or its equipment.

Instead of reactive troubleshooting, a long-term strategy requires a proactive system with early warnings and corrective (control or maintenance) actions, which prevent an abnormality to develop into a failure. For this purpose, we combine in the BN model (Fig. 18) the predicted *signal class* outputs as intermediate variables for risk assessment.

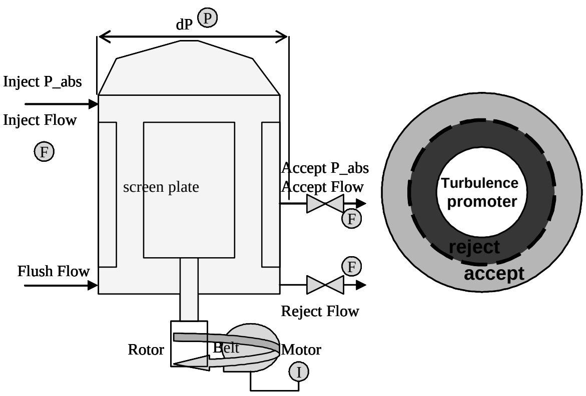

Fig. 17. Pulp screen – a pulp filtering equipment

Note, that in the OOBN model at Fig. 18, nodes S1-S4 are instance nodes representing network class shown in Fig. 16. This OOBN structure follows the generic mechanism of occurrence of disturbances or a failure built-up (Fig. 7).

This is based on certain combination of predicted events (e.g. signals S1-S4 in our screening application). The pressure-flow combinations of S1, S2, and S3 are responsible for a number of mutually exclusive states of the event node *enable Event*, while S4 can be the cause of Event2, which dependents on stochastic circumstances that might occur simultaneously, but not always independently of Event1. When an abnormality event is enabled, a corrective action from the operator/maintenance or DCS can prevent (or allow) an undesired event (failure), leading to abnormal or critical condition of the equipment or a sub-process (Fig. 18).

By analogy, we build the OOBN models at higher plant hierarchy levels (e.g. process diagnosis, control and performance management levels).

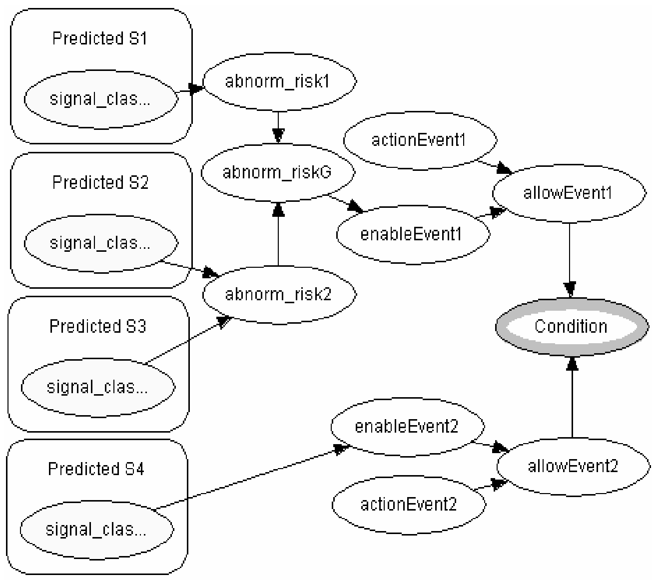

Fig. 18. Assessment of Abnormality Risk and Equipment/Sub-process Condition

4.3.4. OOBN for repetitive patterns

We also use the model of Fig. 14 as *OOBN for RCA of control loops*, where the associated asset is the loop actuator. It models control loops of general interest to process industry, e.g. pressure, flow, tank level and temperature control. The model output "class_signal" shows whether the control loop is providing the target value for a process variable or its "set_points" are wrong for the operation mode, alternatively its assets (sensors, actuators) are malfunctioning. The corresponding CPDs of this OOBN model have been given in section 4.3.1.

A malfunctioning actuator (i.e. valve or pump) is a root cause from the set of basic assets. The *OOBN for basic process assets* can be obtained from the model in Fig. 14 by a simple extension incorporating root causes due to related equipment (e.g. screen status) and other basic components (e.g. pumps and tanks). Adding all possible root causes, including “normal status” as extra states in the node “problem_Asset” and renaming it as “status_Asset” incorporates this. The findings on the status of sensors, actuators and the operation mode settings are provided by other diagnostic agents, see Fig. 8. On the other hand, this model allows under present evidence to reason on the performance of a selected diagnostic agent by pointing that agent as a root cause that needs treatment.

4.3.5. OOBN for RCA of Process Operation

A case study on digester process operation (details in section 6) has been the source of typical repetitive structures incorporated in the following OOBN models. The general applicability of this methodology has been proven by its easy migration to a case study of pump operation problems in evaporation process.

The *OOBNs for risk assessment of process abnormality* is given in Fig. 19. It will indicate improper operation conditions, recognized in changed level-trend pattern. A combination of several such OOBN models allow us to perform RCA of abnormalities observed in process conditions. Here, like in Fig. 13, we use as RCA-variables: the signal trend dp_i/dt and typical physical relations of the process variables, e.g. pressure/flow relations (p_i/F^2), obtained from simple physical models or following (5).

In Fig. 19, there can be findings on all nodes in the network, except for the mediating modeling nodes (statusP1F, statusP2F). The modeling nodes are used to simplify the construction of the network.

The effects nodes are used as feedback in the learning algorithm to confirm a possible root cause of abnormality. The learning algorithm will be discussed in section 4.4.1 and depicted in Fig. 22 and Fig. 34.

Note that Fig. 19*b)* is an extension of Fig. 19*a)* with a single node (diagnos_F) in order to cover for inheritance in OOBN. (Inheritance is currently not supported in Hugin). This simplifies the construction of an OOBN, see Fig. 20.

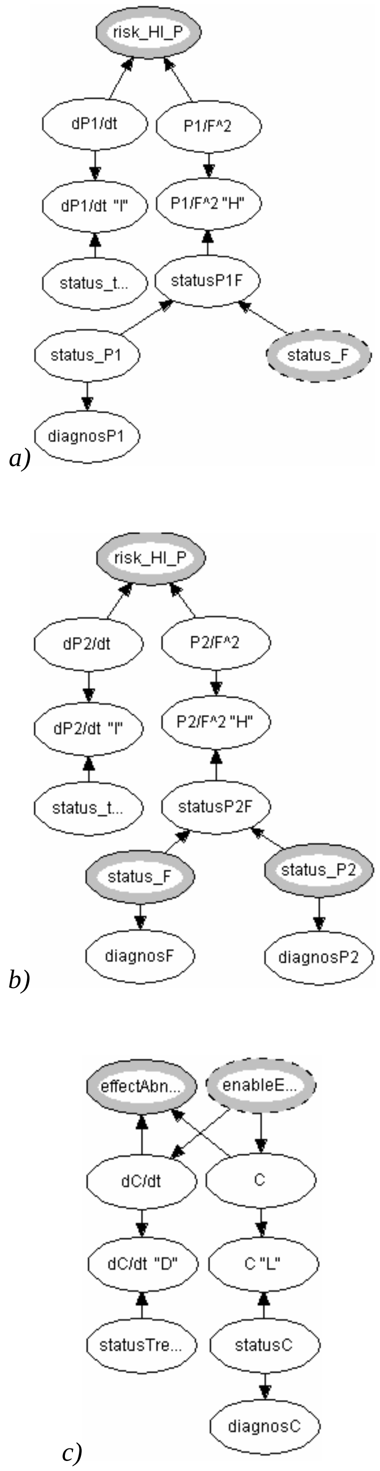

Fig. 19. OOBN models: *a) - b)* for risk assessment of abnormal process conditions, which can enable undesired events; *c)* for assessment of abnormality in effects from events.

Fig. 20 - Fig. 21 show how we use the above OOBN submodels as building blocks in order to represent the entire problem domain at different levels of RCA abstraction. The

OOBN models incorporate the consequent causality steps of the basic mechanism of a failure build up, as shown in Fig. 7. Fig. 20 shows an OOBN model of an event (e.g. pump plug), which is enabled by abnormal process conditions (e.g. high flow concentration) and is confirmed by another event (e.g. low pump capacity).

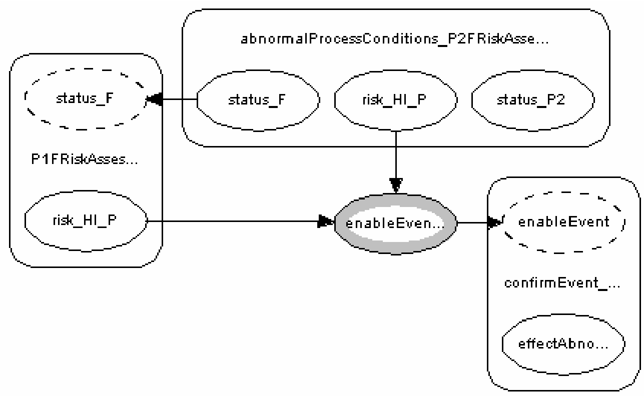

Fig. 20. OOBN model representing a configuration of different abnormality conditions in process operation, which can enable undesired events in basic assets, equipment or process operation. The effects of such events confirm or reject inference conclusions and serve as learning feedback.

Fig. 21 shows an OOBN modeling several events (e.g. various pump problems), which can cause process faults or failures (e.g. if a pump fails and it is indispensable for process operation, the plant should be shut down).

The model of Fig. 21 and its fragments represent the hierarchy of process operation.

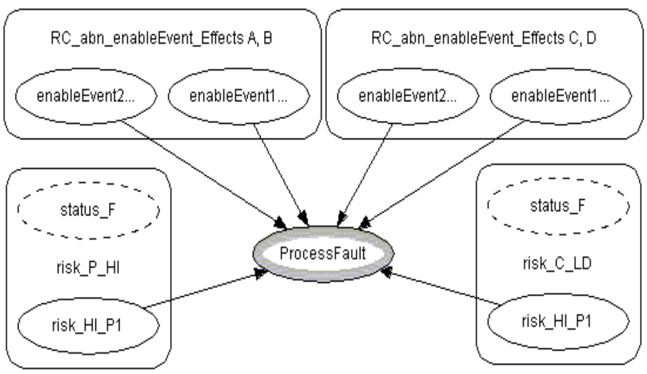

Fig. 21. OOBN model representing a configuration of different undesired events, which can cause a process fault, failure or undesired deviation in process output.

4.4. Decision Support on Process Operation

Additional functionality of the described system is planned to include decision support on process operation, which is taking into account technical root cause and their expected effects on the plant operation and economy. For this purpose, we utilize a probability-cost function in the decision support algorithm, where the cost is calculated according to the model for expected average cost.

4.4.1. Basic algorithm steps of the methodology

For any abnormal case, once identified, the system is searching to find the root cause of observed or predicted problem. The basic algorithm of RCA as implemented in this application, is a special modification of the decision-theoretic troubleshooting (DTTS) algorithm (Heckerman et al., 1995), which is further extended by (Weidl et al., 2003c) to early warning of abnormality to prevent the highest potential losses of production.

The algorithm presented in Fig. 22 incorporates the following steps:

- Continuous on-line acquisition of evidence: DCS-signals, trends and effects computed by physical models
- Classification of evidence into states
- Continuous assessment of the risk of abnormality
- Instantiate the risk (abnormality) assessment node, DCS-measurements, thereof computed physical variables and observation nodes
- Automated propagation of evidence by the inference engine and probability update
- Computation of the probability-cost function $f(p_i, C_i)$ for all possible root causes of the problem
- Presentation to process engineers, operators or maintenance crew to provide guidance and decision support on control or maintenance activities
- Choose the expected most efficient action based on the optimal probability-cost function

- Probability adaptation: Update of inference conclusions based on observation after performing action.
- Collection of DCS- and operator feedback on the real root cause (and case acquisition with evidence)
- Sequential Learning: Association of data cases with new indicated situations and update of OOBN.

This procedure continues in loop until the problem is solved.

For early warning on abnormality and preventive corrective actions, the cost functions (given in 4.4.2) are extended with the related production losses.

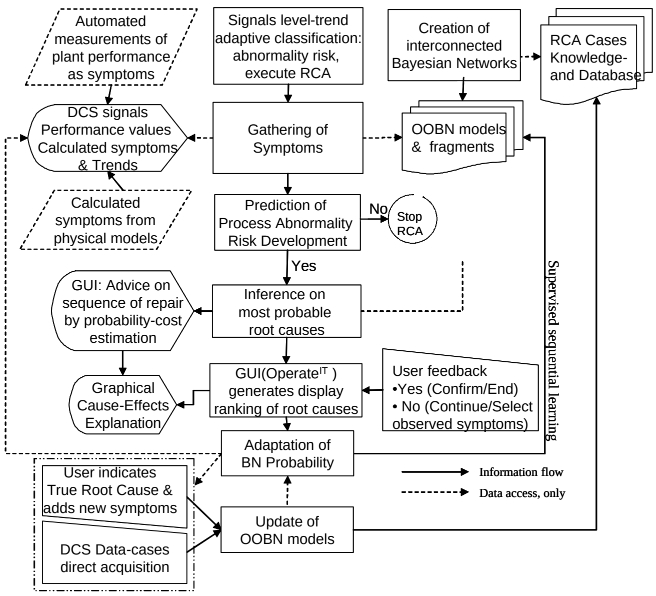

Fig. 22. The basic algorithm for Adaptive Root Cause Analysis with risk assessment

4.4.2. Expected Average Cost

Let X_n be the process state immediately after performing an inspection and possible adjustment of the process at time T_n. The inspection-adjustment time T_n is defined as $T_n = n \cdot j \cdot Dt$, where $j \cdot Dt$ is the maintenance inspections interval and n is the number of inspections during each production run. The expected average cost *C(I, j, w)* is assumed to be a function of the process transition step *I*, the frequency of inspections *j* and the repair level *w*, which reduces the virtual age of the process. It is obtained as the sum of expected average costs of inventory holding *h*, setup *K*, inspections *E(IC)*, repairs *E(RC)*, preventive maintenance *E(PC)*, and defective output $E(C_d)$ during a production cycle of a discrete batch process (or a continuous one at $\Delta t \to 0+$, i.e. inspection can be performed at any time) as follows:

$$(19)\quad C(I, j, w) = h(P-D)\frac{E(T)}{2} + \frac{K + E(IC) + E(RC) + E(PC) + E(C_d)}{T'}$$

where P is a deterministic, constant production rate (units/time); D is a deterministic, constant demand rate; *E(T)* is the mean length of time of a production cycle and the actual length of a production cycle is $T' = P\,E(T)/D$.

The expression in eqn. (19) was derived and solved numerically by (Wang et al., 2003) in order to minimize the maintenance cost. For derivation they have used a Markov chain in the production-inspection-maintenance model, under the following assumptions: (1) the “in-control” periods are generally distributed and process deteriorations are random; (2) the preventive inspection intervals are equal with uncertainties due to 2 types of errors: false alarms and missed alarms; (3) the defective items cost includes the reworked cost both before and after sale; (4) the general repair policy and general cost structure are incorporated. Thus, the assumptions of the traditional EMQ (economic manufacturing quality) model are relaxed to confirm closely to real-world situations.

We have added into the cost (19) - the production losses due to unplanned process stops *E(PL)* and we call it in total *expected average cost of asset management*. We have relaxed the EMQ assumptions further by lifting the assumption of negligible time for repair and introducing it as one of the random variables, while reasoning on the urgency of actions for time critical decision support on competing actions for the same root cause. This allows maintenance on demand at an early stage of a process failure development.

Following the DTTS algorithm, we utilize a probability-cost function, where the expected cost of repair is extended into the expected average cost of asset management, i.e. eqn. (19)+{*E(PL) / T´*}.

4.4.3. Advice Sequence

For an optimal (efficient) sequence of corrective actions involving several possible root causes, the RCA probabilities should be combined with the associated cost. Then, the recommended decision sequence will incorporate actions, which are sorted in decreasing order of efficiency. This is expressed by the probability-cost estimation (Heckerman et al., 1995):

$$P_i / C_i \geq P_{i+1} / C_{i+1}.$$

Here P_i is the probability that component i is faulty and C_i is the repair cost associated with component i and the ratio P_i / C_i is the efficiency of a corrective action A_i. The ordered efficiency represents the optimal sequence of *process management* actions, when the failure is a fact. This sequence is optimal under certain conditions including the single cause assumption and order independent costs. Note that not all conditions for optimal behavior are met during process operation. The assumptions of single cause and the independency of order of corrective actions may be violated in some cases. This is though not a limitation of the approach since multiple root causes can be treated one at a time.

For predicted events, it would be more appropriate to order the recommended sequence of corrective actions after decreasing risk of potential process breakdowns:

$$P_i C_i \geq P_{i+1} C_{i+1}.$$

The last relation is expressing the sequence of *preventive* actions, reducing the potential production losses according to the performed risk assessment on active root causes. In this case: the cost includes also the expected cost of "production stop to fix component *i* if it breaks" as well as the cost of expected production loses, as discussed in section 4.4.2. This preventive troubleshooting stops, when the estimated risk of abnormality is below a pre-set threshold value. The risk is assessed by models of the type given in Fig. 18.

This preventive approach is not theoretically proven yet. It reflects the industrial FMEA (failure mode and effect analysis) praxis, defining the risk of a failure as the product of the probability of failure and its cost.

In addition, for time critical Decision Support on competitive actions for the same root cause, one can use with advantage Influence diagram (ID), as shown in (Weidl et al., 2002b).

4.4.4. Explanation

Based on the causal character of the OOBN models, the operator can feed his own educated observations into the inference system, which then evaluates alternative actions with respect to their technical and economical impact.

A user explanation interface should include a ranked list of most probable root causes (see Fig. 23), a list of evidence (symptoms) for inference, as well as conclusions on possible effects.

Most Probable Root Causes: Rotor drive malfunction: 0.55 Slipping rotor shaft: 0.35 Too high concentration: 0.1	**Operator Feedback:** True / False True / False True / False
Explanation Symptoms (Measurable): Pressure Difference: High Power consumption: Normal Concentration in accept: Normal Concentration in reject: High Accept flow: Low Reject flow: Normal	**Sensor Status (from Diagnosis Agent)** True / False True / False True / False True / False True / False True / False
Failure Effects: Screen plate clogged	**RCA Update on Effects:** True / False

Fig. 23. GUI-functionality for presentation of RCA-results and collection of user feedback

Moreover, one can examine the dependency on evidence through the sensor status and update the RCA conclusions. The independence relations induced by evidence on a set of nodes in DAG are determined using the d-separation criterion (Pearl, 1988). In case there is more than one path between the root cause and the failure, the entropy is calculated for each of the connecting paths and compared before the propagation of evidence and after it. Then, the path with the largest reduction in entropy is presented to the operator in order to explain the conclusions. For large BNs, additional properties, as coloring of the most probable scenario of causes and effects allow visualization of the explanations.

5. Application of the methodology and System integration in the industrial IT environment

The application development has been closely related with its integration on the Industrial IT platform and has required the development of special modeling conventions, such as conventions on BN-nodes' names, as well as conventional node classes for measured, computed, observed, diagnosed or status variables. All BN models have been developed in the Hugin Graphical User Interface. The Hugin Decision Engine has been integrated as a Bayesian inference engine in the industrial IT environment (Weidl, 2004).

In addition, history handler (for the filtered computation of signal trends) and state handler (for classification of raw data into states of evidence) have been developed as small software packages and linked with the BN-models through the Hugin API. The history and state handler have also been essential for the tests of the BN-models on historical data and to simulate and evaluate the performance of the RCA system in an Industrial IT environment.

Thus, the infrastructure for applying this methodology in different domains is ready for immediate use, i.e. any new application of Bayesian networks is automatically integrated on the ABB Industrial IT platform. The modules of the RCA system integration architecture are given in Fig. 24.

Here, the OPC (Object linking and Embedding for Process Communication) is a standardized interface technology layer on the communication of process control data in the automation platform. OPC is intended as worldwide industry-standard for communicating real-time production information across all levels of the manufacturing enterprise.

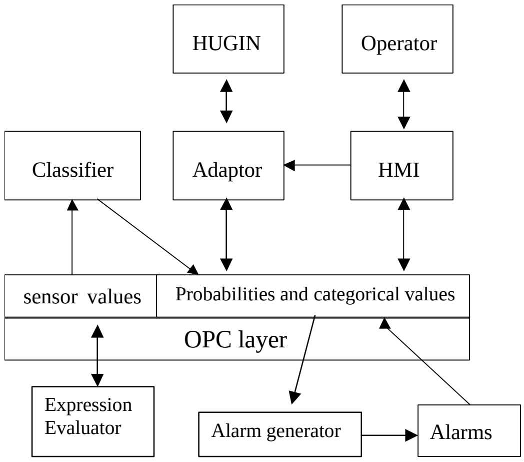

Fig. 24. The Integration Architecture of the RCA System

Hugin™ is the BN-software, which effectively calculates the probabilities from classified measurement signals and human input that are associated with the different root causes of certain abnormal event (e.g. hang-up). The *Adaptor* is the link between *Hugin* and the Automation platform. Its main purpose is to feed information from the OPC-layer into *Hugin* and to communicate the resulting probabilities back to the OPC-layer. It also publishes a function that when activated executes the inference in *Hugin* (updating the probability calculations).

Most measurements are real continuous data. Often the RCA reasoning does not require this level of detail. Hence the continuous signals are classified into discrete states. The *Classifier* reads OPC real continuous data and writes OPC discrete data. *Hugin* reads these discrete data (in the BN models). The classification level (e.g. low, high) of the signals is customizable, i.e. they can be changed by the user, see Fig. 25. The extension of system functionality will include an automated classification of the signal limits as described for the BN in Fig. 14.

The *Expressions Evaluator* reads OPC values and calculates new OPC values through mathematical and logical expressions.

Alarm generator: This component reads probabilities, which originate from *Hugin* as OPC values and generates an abnormal event (e.g. process fault) alarm, if high probability is encountered. These events are also stored in the historical database.

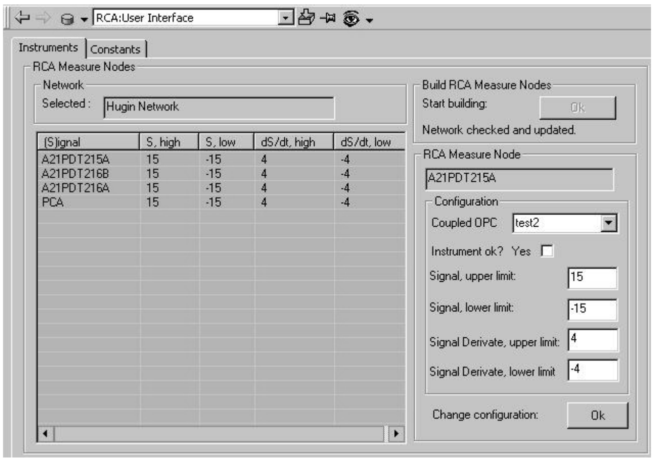

Fig. 25. Source: ABB RCA. GUI for configuration of the measurement instruments (sensors) and its status

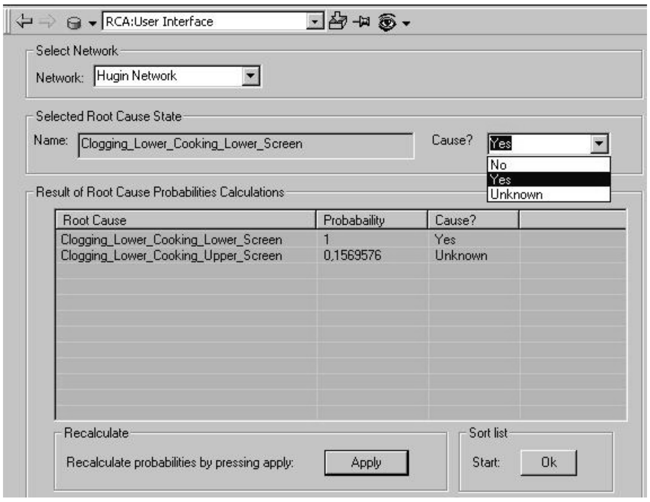

Fig. 26. Source: ABB RCA. HMI for presentation of the most probable root causes, acquisition of user feedback and following update of most probable root causes

The Human Machine Interface *(HMI)* presents the current probabilities for the different possible root causes to the operator or maintainer. The human may enter his knowledge of the current situation. The operator may give a feedback to the system on whether a certain root cause is present or not. HMI writes human input to the OPC-layer, it executes the command "recalculate" through the adaptor. The HMI also sorts the root causes ranked in decreasing probabilities.

A RCA System incorporated in the ABB Automation platform was verified to work at a real plant. An artificial problem was there modeled using measurements from a chosen problem domain during this verification. The methodology was integrated for data analysis as off-line functionality; and for data preprocessing, classification and RCA as functionalities on-line.

6. Evaluation of Application

For the proof of concept and to demonstrate the capabilities of the framework of Bayesian networks, a number of pulp and paper applications examples have been developed. Next, to demonstrate a real world application the monitoring and root cause analysis of the digester operating conditions in a pulp plant has been chosen, see Fig. 27. This application has been used for testing the system performance in a simulated scenario with historical data from a real pulp plant.

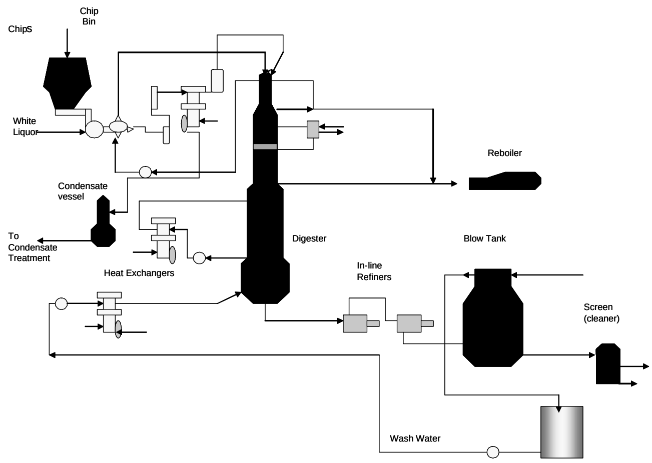

Fig. 27. Digester Fiber-line. Case-study: Monitoring of the digester operating conditions

The structure of one of the developed Bayesian networks is shown in Fig. 28. The repetitive structures of this network have been used as a source of typical patterns (model classes) for the development of OOBNs, as described in section 4.3.4. The BN model depicted in Fig. 28 has given rise to the development of an object oriented representations as shown in Fig. 19 - Fig. 21.

An OOBN version of Fig. 28 is shown in Fig. 29 for comparison of reduced structure complexity; some other of its model classes are given in Fig. 30 - Fig. 33.

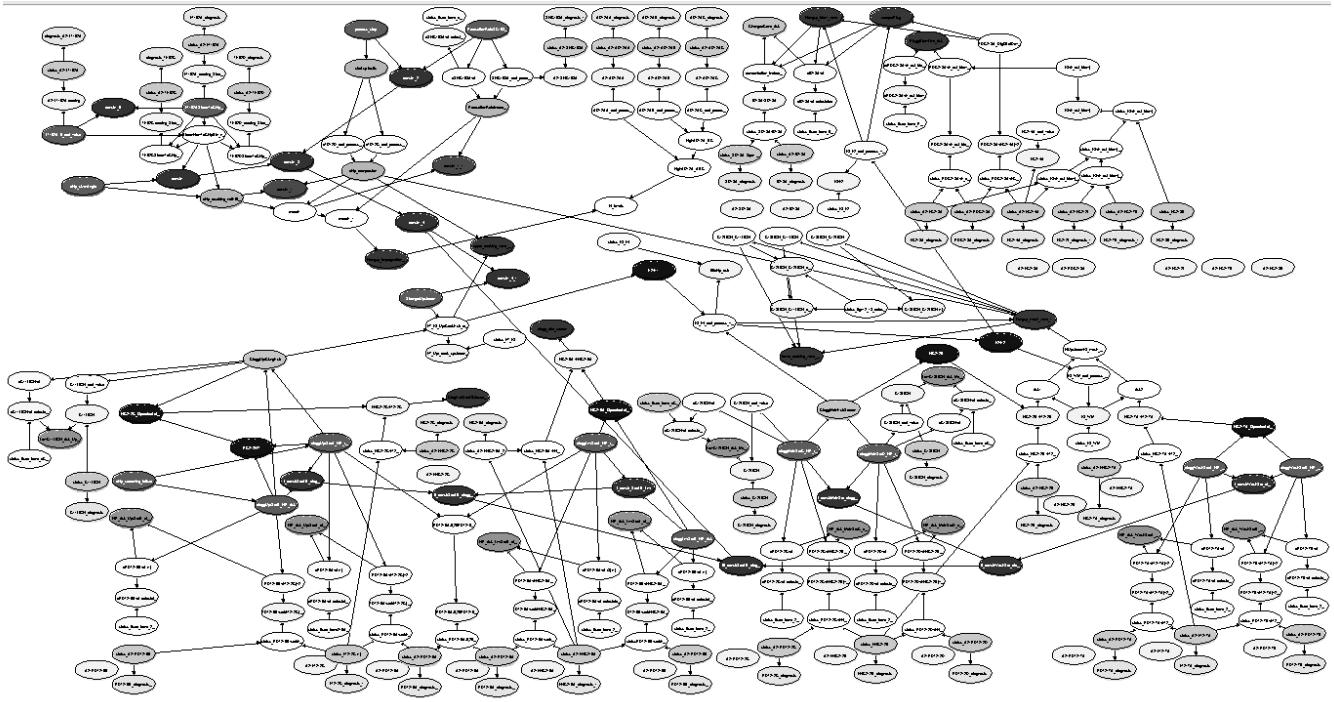

Fig. 28. An example of a Bayesian Network for root cause analysis of digester process operation.

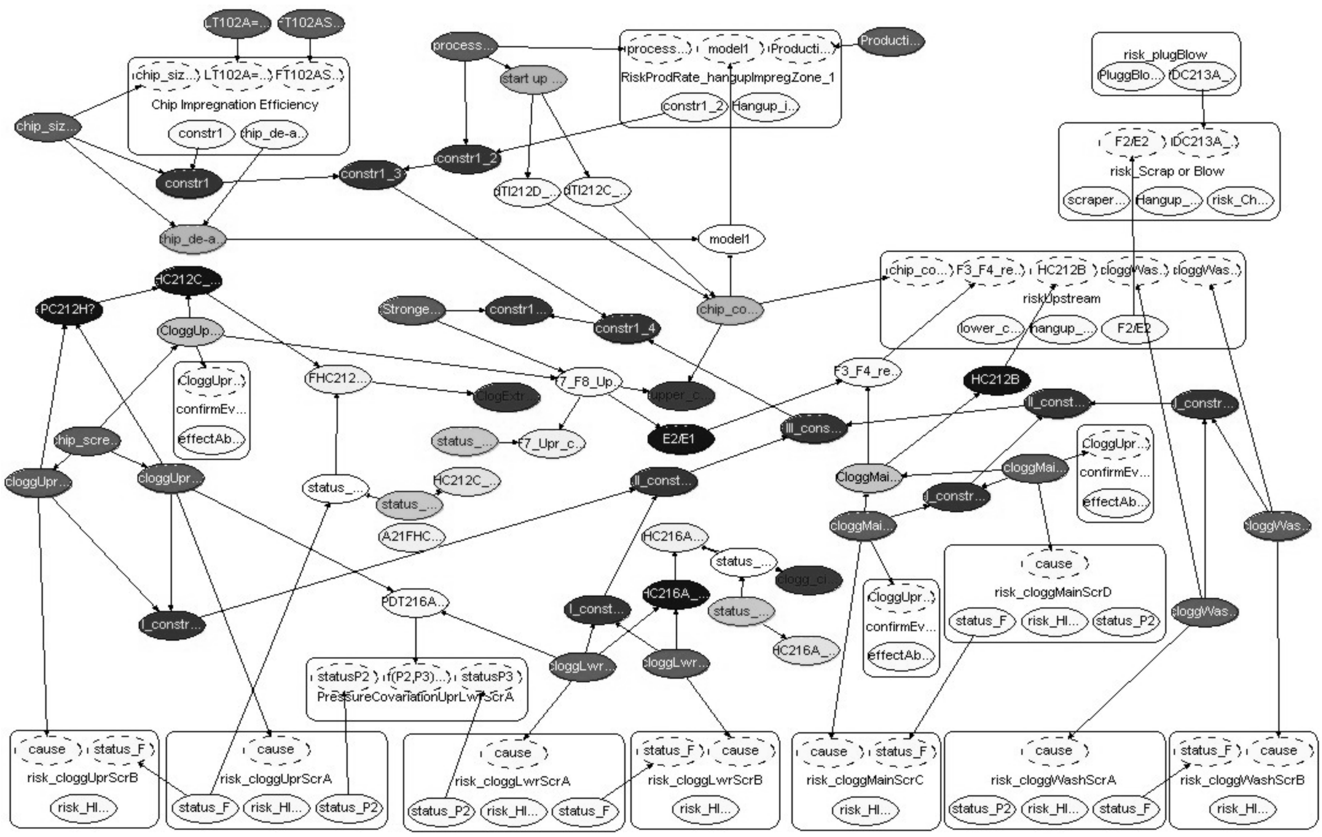

Fig. 29. An OOBN version of the RCA for digester hang-up.

The evaluation summary (Fig. 33) of possible hypotheses of a hang-up failure in the digesting process represents the „*process condition"*. This model requires as input OOBN-instance nodes (Fig. 31), which on their term are constructed from OOBN (Fig. 32), representing an abnormality enabling event (in the case of clogging in the extraction screens). The OOBN in Fig. 32 combines OOBN from Fig. 19a,b,c), Fig. 20 with the pressure covariation (Fig. 30) in different digester sections. The calculations for this pressure covariation are performed with principal component analysis.

Combination of the several OOBN of abnormality enabling type (Fig. 32) with certain process operation condition (or lack of control actions) can result in different failures during process operation (causing a digester hang-up) with certain probability. The corresponding model is shown in Fig. 31.

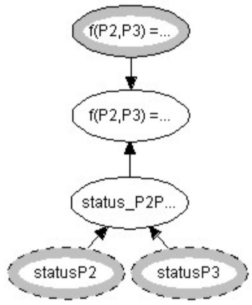

Fig. 30. OOBN for pressure covariation

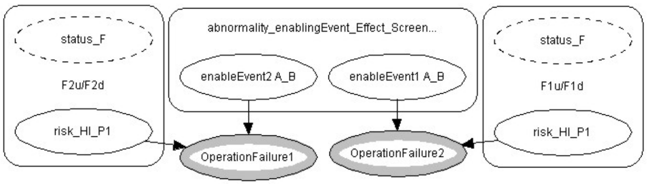

Fig. 31. OOBN for evaluation of hypotheses on process operation failures

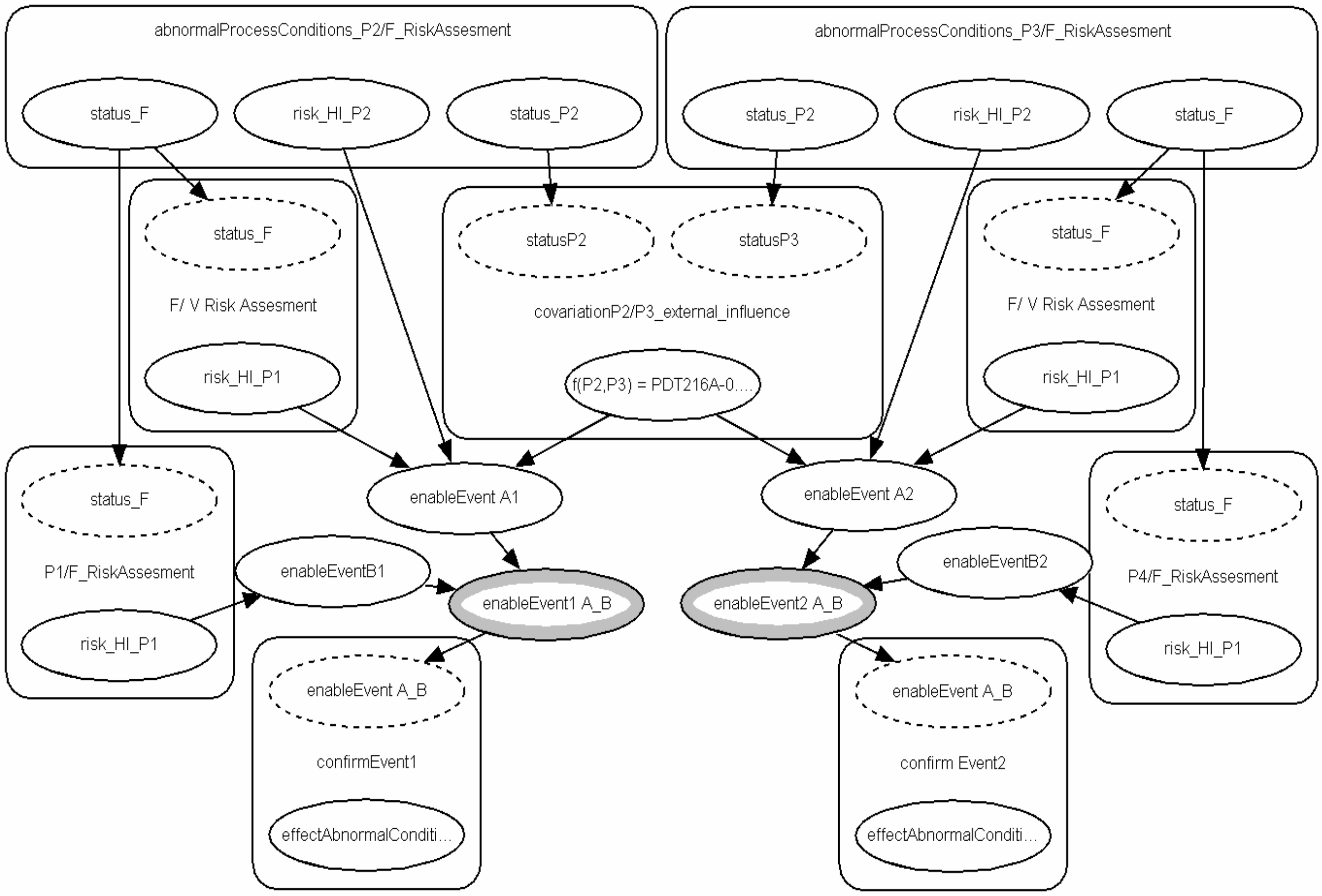

Fig. 32. OOBN for abnormality enabling events

While all possible hypotheses of failure/abnormality are evaluated simultaneously, the output is summarized in a logical node “Alarm_Warn” (for possible digester hang-up) and presented to the operator, see Fig. 33.

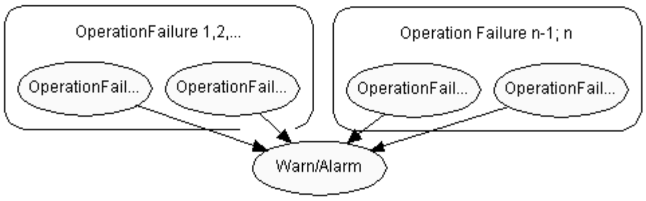

Fig. 33. OOBN for summary of hypotheses evaluation

6.1. Bayesian networks validation

Domain experts have validated the dependency and independence relations of the BN models while the performance of the models has been validated using historical and simulated data. Domain experts based on guidance from the knowledge engineers performed the validation of the qualitative part of the models.

For of purpose of validation, historical data analysis has been performed to set the allowed normal variations for measured signals, to examine expert opinions and adjust the Bayesian network structure. Design tests have been used to determine whether the BN is modeling correctly the expert and causal relations obtained from data analysis and to provide consequent revision of consistency in knowledge, expertise, experience and real plant data.

The BN models have been first tested qualitatively. This included testing the outcome of various root cause scenarios while providing evidence on the corresponding symptoms (measurements or observations) and vice versa. The main purpose of the qualitative testing has been to ensure the RCA-inference reproduces the intended outcome exactly as incorporated in the designed BN structure with combination of the corresponding states of the related variables. **Table 1** shows a representative example for testing the scenarios indicative of abnormality or fault (denoted as A with states true T and false F) in the problem domain. In the cases: the symptom variables are expressed as products of root causes (RC_i = H_i), i.e. S_i = ? $_i$ H_i, and take one of the possible states, e.g. low (L), normal (N) or high (H), $S_i=\{L,N,H\}$.

Variable	States: Low?/ Normal? / High?	States: True/False
S_1	*L/N/H*	
:	:	
S_n	*L/N/H*	
A		*T*
RC_1		*T/F*
:		:
RC_n		*T/F*

Table 1. Qualitative testing of BN. General representation of the combinations reflected by the various scenario in RCA.

In the case study, the frequency of about 75 events of digester screen's clogging during 97 days of operation (approximately 14x10^4 minutes or sampling cases) was recorded in the real process historical data. The corresponding pressure signal (Fig. 10) has been classified into states with CPTs as follows $P(X=low|A,B)=10^{-10}$; $P(X=normal|A,B) = 0.9995$; $P(X=high| A, B) = 0.0005$

This expresses the fact that process variables are behaving as expected for normal mode of operation in 99.95% of all sampled cases, and exhibit 0.05% of screening abnormalities distributed in high (0.05%) and low (0%, we use instead 10^{-10}) states of the signal values. It is not advisable to set a probability to zero, as in the case of “X=low”, which will cause a system “crash” (due to inconsistent evidence), if evidence on low signal state is encountered, e.g. due to a valve problem (valve open by mistake). Therefore, it is recommended to use small value instead of zero.

We could predict clogging (in the upper screen in the lower cooking circulation) in the mean 10-20 minutes before the time point when the differential pressure reached its critical value 0.05. The price for this was 10% of false alarms. In a few cases was possible to predict clogging of 1 to 4 hours ahead. We could also find mean effects that may influence the risk of clogging and updated the BN structure.

A direct prediction of a single clogging event has been difficult, since there were not enough historical data to validate hang-ups in its generality. Thus, only use of historical data is not satisfactory, especially for verification of RCA performance in the case of rare faults, as well as if the plant is in its design phase or in its start-up phase and the number of abnormality records is scarce or missing.

For a plant in a design or in a start-up phase, it is of advantage to perform statistical tests while exploiting the knowledge based BN structure and CPTs. The BN models are currently being evaluated based on simulated data. The goal of this phase of the model evaluation is to determine the success rate of Root Cause Analysis by experiment.

The experiments performed include both black box testing and unit testing. Black box testing is performed on the complete model whereas unit testing is performed on each individual OOBN class.

Network	Variables	RCs	Observations
liquor extraction	26	2	6
Digester hang-ups	297	11	84

Table 2. Statistics on the models used in the validation experiment.

The model-testing experiment proceeds in a sequence of steps. In first step we sample the data to be used in the subsequent steps of the experiment. The data sets to be used in the experiments are sampled from the models to be evaluated. Each data set will contain observations on the measurable variables of the model with some values missing at random to reflect real process operation (the amount of missing data is varied in order to test robustness with respect to missing observations). The second step of the testing phase is to process each of the sampled cases and determine the output from the model on the case. The third and last step is to determine the performance of the model based on the generated statistics.

We consider two different scenarios. The first scenario considers situations where no faults have occurred whereas the second scenario considers situations where a single fault has occurred. For each possible fault we randomly (according to the probabilities of the model) generate N cases. Each case will contain an instantiation of the observed variables only. This produces a database $D = \{c_1, \ldots, c_{nN}\}$ of $n * N$ cases with a single fault where n is the number of root causes in the model. The database D can be used to estimate the success rate of RCA. We determine the frequency of correctly diagnosed cased in D. Similarly, we generate a database of cases with no faults.

The above experiment is used to generate statistics on error detection and correct RCA of all possible faults. We describe the experimental results obtain on two different models. We consider the model for preventive root cause analysis on clogging in the extraction screens of the pulp digester and the model for root cause analysis on digester hang-ups. Some statistics on the two models are shown in Table 2. The BN model for RCA of screens' clogging in the liquor extraction consists of 26 variables with 2 root cause variables and 6 observation variables (e.g. sensor readings) while the *digester hang-up* model consists of 297 variables with 11 root cause variables and 84 observation variables.

We use a multiple step stratified sampling approach to generate the database of cases used in the experiment. We sample one strata where the root cause variables are forced to any non faulty state and one strata for each single fault configuration of the root cause variables. The none-fault configuration is enforced using likelihood evidence on the root cause variables. The likelihood evidence rules out all faulty states and thereby enforce the root cause variable to take on a value corresponding to a non-faulty state. Similarly, for each single fault case we force all non-fault root cause to a non-faulty state using likelihood evidence. This scheme ensures that probability of each non-faulty state is reflected in the evidence. On the other hand, we obtain an equal number of cases for each single fault combination of the root cause variables. For this reason we consider the probability of recognizing each single fault state separately.

Table 3 shows the names of the 2 root cause variables of the *liquor extraction* model while Table 5 shows the names of the 11 root cause variables of the *digester hang-ups* model. Table 4 and Table 6 show the validation results for the two models, respectively.

Id	Variable name
1	Clogging_Lower_Cooking_Lower_Screen
2	Clogging_Lower_Cooking_Upper_Screen

Table 3. Names of root cause variables in the model for preventive root cause analysis on clogging in the extraction screens of the pulp digester.

In Table 4 and Table 6 *FP* is the false positive rate while *All* is the overall performance of the model when considering the non-faulty as well as the faulty cases. The false positive rate is defined as the frequency by which a non-faulty case is identified as a faulty case.

Id	Correctly Identified % For different missing data rates			
	0%	0.01%	0.05%	0.1%
1	0.908	0.902	0.883	0.816
2	0.991	0.978	0.952	0.928
FP	0	0.001	0.002	0.004
All	0.9663	0.9597	0.9443	0.9133

Table 4. Validation results for the model for preventive root cause analysis on clogging in the extraction screens of the pulp digester.

For each root cause the tables show the frequency (in percentage) of correctly identifying the root cause in the case. We consider a faulty case correctly identified when the probability of the true fault state in the case is higher than the probability of all non-faulty states of the faulty root cause variable. Similarly, we consider a non-fault case correctly identified when the probability of no faulty state is above the probability of all non-faulty states for all root cause variables.

Id	Variable name
1	High_Steam_To_Chip_Bin_Flow
2	PreimRetime
3	StrongerUpstream
4	cloggMainScrD_hiP_risk
5	cloggMainScrC_hiP_risk
6	CloggMainScrB_hiP_risk
7	CloggMainScrA_hiP_risk
8	cloggLwrScrB_hiP_risk
9	cloggUprScrB_hiP_risk
10	cloggUprScrA_hiP_risk_PCA
11	cloggLwrScrA_hiP_risk_PCA

Table 5. Names of root cause variables in the model for root cause analysis on digester hang-ups.

For each strata we generate 1000 cases. In order to experiment on the robustness of the performance of the models, we consider missing data. For each observation in each case we randomly remove the value of the observed variables. We consider missing values percentages of 0, 0.01, 0.05, and 0.1.

Id	Correctly Identified % For different missing data rates			
	0%	0.01%	0.05%	0.1%
1	0.752	0.69	0.695	0.67
2	0.815	0.793	0.8	0.78
3	0.846	0.803	0.802	0.773
4	0.992	0.996	0.991	0.994
5	0.995	0.99	0.997	0.986
6	0.843	0.864	0.82	0.789
7	0.831	0.849	0.833	0.782
8	0.804	0.8	0.798	0.781
9	0.954	0.96	0.965	0.952
10	0.932	0.943	0.936	0.917
11	0.841	0.839	0.847	0.788
FP	0.122	0.115	0.11	0.108
All	0.8736	0.8677	0.8645	0.842

Table 6 Validation results for model for root cause analysis on digester hang-ups.

As shown in Table 4 and Table 6 the performance of the two models is generally quite high. It is clear from the tables that the performance of the model decreases slightly with the amount of missing data.

Further elaboration for better optimization criteria on acceptable alarm thresholds could consider the costs of a missed alarm and a false alarm, and could involve statistics of the dead time between alarm and event enabling.

In addition, we have also quantitatively tested the communication between computation of signals by simple physical models, classification of computed and measured signals into states or intervals, their propagation into BN and inference outcome.

The above described validation study indicates that the system actually works as designed, which has been a crucial ingredient in the proof of system concept and performance. Thus, this methodology represents an improvement (as automation technology) over existing techniques for manual root cause analysis of non-measurable process disturbances and can be considered as a powerful complement to industrial process control.

6.2. Compliance with system requirements

The used modeling techniques and the results of this work allow us to conclude that most listed requirements on RCA & DS are met as summarized in Table 7:

Table 7. System requirements and their realization

System Requirements	***Provided by***
Fast and flexible inference	inference in Bayesian networks. Inference takes < 1 sec. and provides a list of root causes ordered in decreasing probabilities for flexible actions, proposes a sequence of corrective actions ordered by efficiency
Handling of uncertainties	probabilistic reasoning in BN with missing data and discrete variables' states
Early detection and diagnosis	BN models for early assessment of risk in combination with built-in chain causality representing different scenario, Validation with data
Isolability	mixture models in BN for RCA in different operation modes, validation (Weidl G., 2002).
Decision support at higher automation level	causal BN structure with explanations and automated symptoms collection & inference; Higher automation by including automated DCS-feedback for root cause confirmation by immediate effects of root causes.
Explanation of conclusions	d-separation in causal BN, incorporating in their structure the underlying mechanism of a failure/abnormality build-up; calculation of the path with the highest entropy change (Weidl, G., Madsen, A.L. and Dahlquist, E. , 2002b)
Adaptivity to process changes	mixture models for CPD to handle change in operation mode and sequential learning of the BN-parameters for adaptation to on-line operation conditions
Robustness	Modeling tricks, mixture models, validation; (Weidl G. , 2002, 2004)

System-user interaction	operator feedback for “supervised” sequential learning allows interaction due to fast BN-inference (<1 sec.)
Novelty identifiability	additional state or node “other root cause”
Multiple faults identifiability	the single cause assumption – allow to treat multiple causes one at a time Alternative : constraints for explicit multiple cause modelling
Reasonable storage and computational requirements	distributed RCA and decision strategy (similar to DCS). The inference in static BN with several hundred variables takes <1 second
Reusable system- and model design for various process applications	object oriented Bayesian networks (Weidl, G., Madsen, A.L. and Dahlquist, E. , 2003c).

A future improvement could take advantage of a preprocessing algorithm (originating e.g. from Information theory), that filters all available signals to the amount sufficient for RCA. Then, the BN model structure would be completed with relations extracted from data in a systematic and automated way.

With the growing size of domain applications, it might be preferable to have a simpler classifier (e.g. based on PCA or NN) for binary decision on whether fault is present or not. Once abnormality is detected, the RCA system will find the root cause and explain its underlying mechanism.

Some requirements related to efficient system development still need some improvements e.g. methodology for systematic (and automated) system testing. The later becomes more and more important as applications grow in size.

7. Future Work

7.1. Adaptation

In any real process application, RCA needs adaptation to incorporate the ongoing changes in process behavior. A suitable adaptation algorithm is the sequential learning with fading due to (Spiegelhalter et al., 1990) and (Olesen et al., 1992). The fading is a convenient feature after maintenance activity on the plant. The sequential learning is performed on the actual root cause nodes and corresponding evidence for that particularly observed case, see Fig. 34. This is based on feedback from DCS and on operator/maintenance reports, as shown in Fig. 23.

The combination of several OOBN (e.g. Fig. 19 - Fig. 21) allows also a confirmation on effects of failure events, which are used for sequential adaptive learning from data. We perform adaptation with the Hugin tool, see (Olesen et al., 1992). In the OOBN, adaptation is performed in the run-time domain, where any OOBN has an equivalent “run-time” BN. By using supervised sequential learning in OOBN, each node in the run-time BN is adapted independently of its source (i.e. network class node). This behavior is preferable in order to take into account individual node conditional probability distributions, but placed in different context or position in the industrial process.

We do not use adaptation in the time-sliced models, since this will violate the assumption of the process being stationary. The sequential adaptation in an OOBN or DBN has not been considered in the literature until now and it will be a subject of future research and development of the system functionality.

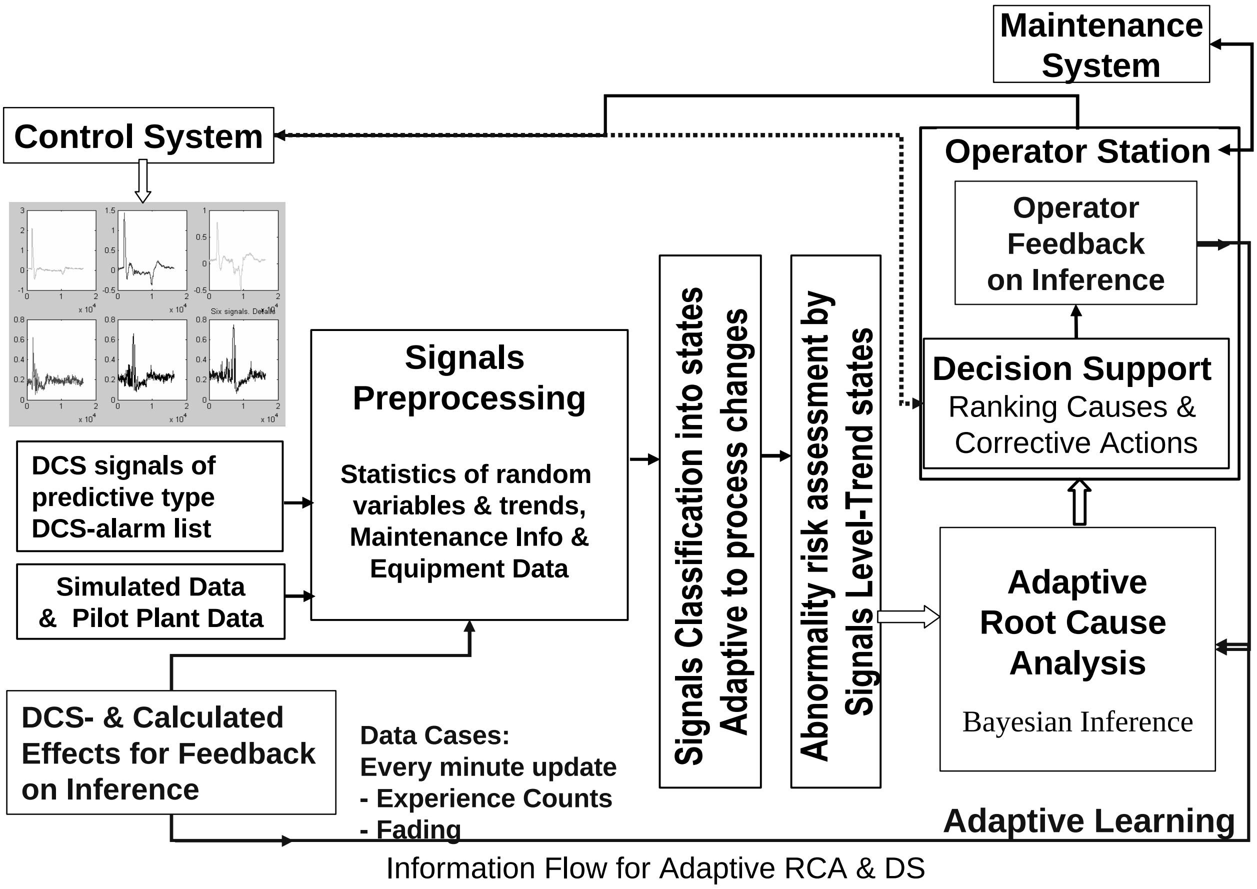

Fig. 34. Information flow for RCA and Adaptive Learning. RCA & DS Communication with Operator Station, Maintenance and Control Systems

7.2. Discussion. Prediction of Process Dynamics

For the purpose of risk assessment and early warnings on abnormality in the signal development we have constructed a past-present-future combination of generic BN-fragments as shown in Fig. 16.

Some corrective actions, if carried out by users, will result in changes of operation modes of the process as implicated by the model in Fig. 16. This can be reflected in the temporal (dynamic) OOBN, where the time-delays in process variables are incorporated in d_t time slices later, where d_t corresponds to the typical time delay for the corresponding process variable. This will introduce causal dependency between the past and the future. Therefore, in order to preserve the first order Markov property of the temporal model (i.e. in order to maintain the property that the future is independent of the past given the present); it may be necessary to create a hierarchical temporal model where each time-slice contains a temporal model on its own. This hierarchical approach will make the top-most temporal model obey the first order Markov property and it fits well with the object-oriented framework.

Temporal BNs can also be used to express causality dependencies reflecting the dynamic character of the process. For example, alarm filtering deals mainly with time-delay effects and has been addressed in (Leung et al., 2000).

In Fig. 16 we use only three time steps to model an infinite step process. In the reality, such a temporal network is a static network, since it represents a finite and fixed number of time slices and it can reason only with a finite series of observations coming from a dynamic process or system. For real time applications, it is desired to include in the model as many time slices as possible to account for time delayed effects. The last can cause an inefficient and time consuming inference, since evidence propagation would involve all time slices although probability update is desired only for a limited number of time slices.

A computation scheme, which can handle infinite series of observations in dynamic BN has been described in (Kjærulff , 1992). It changes dynamically the width of the time slice window, as well as the number of backward smoothing and forecasting time slices. Thus, it can provide flexible and selective inference. It also supports inclusion and modification of time-delayed observations. This approach will often produce a complete separator containing all variables representing the belief state of the system. It does not introduce too much complexity as the belief state of the system (according to Fig. 16) includes only a few variables (status_sensor, status_trend and real_value). Forecasting of signal development and time-delays (based on (Kjærulff , 1992)) will be incorporated in the proposed RCA system in the near future.

Another issue is concerned with suitable approximations for handling of large number of temporal relations between the different time slices, as discussed in (Boyen et al., 1998 a,b). This will be a subject of further study.

8. Conclusions

Our intention has been to develop a methodology, which is generally applicable for root cause analysis and decision support in industrial process operation.

The outlined application has been a subject for feasibility study of our methodology in pulp process operation.

In the validation with simulated data, the performance of the models is generally quite high. It is clear from the tables that the performance of the model decreases slightly with the amount of missing data.

In the application tests of the digester hang-up prediction, we accepted 10% false alarms. This limit was implied by tha fact that a tendency of hang-up development is very difficult to forecast, but in case it occurs it might have sever consequences, if handled at a late stage of a hang-up development. Due to economical reasons, the digester operators prefer rather a few false alarms, than missed alarms.

The sequence of repair actions can be considered as an improvement over existing policies, since it can provide an on-line assistance to the operators and thus, it can save process operation time. Therefore, we can presume that the system can reach the goal of reducing "substantially production losses". Based on this results and indications, we can conclude that this application does demonstrate real improvement in the state of the art. Because of the wide applicability of this methodology, we expect the results of this paper will be the interest to other system designers who are considering similar problems.

A methodology for systematic (and automated) system testing still needs to be developed, in order to ensure efficient system development, especially when applications grow in size.

The experience shows, that simple updates of typical repetitive structures (e.g. sensors) in a BN may turn into annoying and time-consuming task. Instead, we have used OOBNs with advantage for RCA & DS in process operation, i.e. OOBNs ensure causal modeling of interdependency of events, simplifies modification and reusability of BN.

The use of OOBNs has simplified the development of the model for adaptive signal classification and prediction of the development of signals' level-trend. Moreover, the overall RCA-model complexity has been reduced at different levels of industrial plant hierarchy. This can be used to provide an overview for explanations of RCA-conclusions at different levels of abstraction (plant hierarchy). In addition, these OOBNs are used in a next level OOBN for risk assessment of disturbances and estimation of their most probable root causes for predictive maintenance on demand.

In case only one large OOBN of the problem domain is used, one can expect limitation of the scale of models, due to the computational demands of evidential reasoning in temporal OOBN. Therefore, we have used as agents a number of OOBNs for prediction of the signal development.

The object-oriented BN framework fits very naturally into any industrial IT environment, which utilizes object-oriented integration of applications as containers of different applications communicating via the aspect integration platform in order to allow overall process optimization.

The scalability and modification of an existing system is feasible due to the OOBN-approach deployed in our tools. It will require the development of new overall BN model only for a new process. This overall process model will use OOBN for all standard components with default probabilities, which can adapt either with historical process data or by in-situ cases during operation to the new process environment and its typical operation. This scalability is feasible as long as the qualitative structure of the process remains similar to the previously developed application.

For practical use we expect that six man months is a reasonable estimate on the effort required for an industrial group to develop a new application by using the proposed framework and tools described in this work. The estimated work effort includes the development and verification of a BN model for a problem domain described by 200-500 relevant process variables, provided data and knowledge on the problem domain are available or acquirable.

The proposed system design for Root Cause Analysis (RCA) & Decision Support (DS) is incorporating agents for handling of uncertainties. We have developed one particular agent, based on fluid dynamics modeling. This is solving an equation system for the pressure-flow network. It provides soft sensor (non-measurable) information for evidence in the reasoning under uncertainties.

This allows us to estimate the risk of abnormality at an early stage and to propose early treatment by an efficient sequence of actions. The last is utilizing cost estimations anticipating also potential production losses. This allows efficient troubleshooting and predictive maintenance on demand (Weidl et al., 2003c).

This application demonstrates that fast and flexible disturbance analysis (RCA and DS) is feasible in industrial process control. It need not be a time-consuming task, if a computerized troubleshooting system is deployed. Thus, it has the potential of reducing substantially the production losses due to unplanned process breakdowns.

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References

Andersen, S.K., Olesen, K.G., Jensen, F.V. and Jensen, F. (1990). HUGIN - a shell for building belief universes for expert systems. In Readings in Uncertainty; Shafer, G., and Pearl, J. (eds.); Morgan Kaufmann; 332-337.

Arroyo-Figueroa, G. and Sucar, L. (1999). A temporal bayesian network for diagnosis and prediction. In Proceedings of the 15th Annual Conference on Uncertainty in Artificial Intelligence (UAI'99), Stockholm, Sweden, July 30-August 1, 1999, pp. 13-20.

Boyen X. and Koller D. (1998). Tractable inference for complex stochastic processes, in Proceedings of the 14th Annual Conference on Uncertainty in AI (UAI'98), Madison, Wisconsin, July 24-26, 1998, pp. 33-42.

Boyen X. and Koller D. (1998). Approximate learning of dynamic models, in Proceedings of the 12th Annual Conference on Neural Information Processing Systems, Denver, Colorado, December 1998, pp. 396-402.

Cowell R.G., Dawid A.P., Lauritzen S.L. and Spiegelhalter D.G. (1999), Probabilistic Networks and Expert Systems, Springer Verlag

Dash S. and Venkatasubramanian V. (2000). Challenges in the industrial applications of fault diagnostic systems, in the Proceedings of the 7th International Symposium on Process Systems Engineering (PSE 2000), Keystone, Colorado, USA, July 16-21, 2000, pp.785-791; Reprinted in: Computers and Chemical Engineering, 24, pp. 2-7,

Fritzson, P. and Engelson, V. (1998). Modelica - A Unified Object-Oriented Language for System Modeling and Simulation. In Proceedings of European Conference on Object-Oriented Programming ECOOP98, Brussels, Belgium, July 20-24, 1998

Heckerman D., Breese J. and Rommelse K (1995). Decision-theoretic Troubleshooting, Communications of the ACM, 38(3): 49-56

Heger A.S. and Aradhye H.B. (2002). U.S. Patent No: US 6.415.276 B1, Bayesian Belief Network for Industrial Processes

Henrion, M. and Druzdzel, M. (1990). Qualitative propagation and scenario-based approaches to explanation of probabilistic reasoning. In Proceedings of the 6th UAI, pp. 10-20; Reprinted in: Machine Intelligence and Pattern Recognition 12, (pp. 17-32), Elsevier, North Holland: Amsterdam, 1991

Holst A. (1997), The use of Bayesian Neural Network Model for Classification Tasks, PhD Thesis, dept of Numerical Analysis and Computer Science, Royal Institute of Technology, Stockholm, Sweden.

Jensen F.V. (2001). Bayesian Networks and Decision Graphs, Springer Verlag, New York

Jensen F.V., Kjærulff U., Lang and Madsen A. (2002). HUGIN - The Tool for Bayesian Networks and Influence Diagrams, in proceedings of the First European Workshop on Probabilistic Graphical Models,212-221

Kalagnanam J. and Henrion M. (1990). A Comparison of decision analysis and expert rules for sequential analysis. In Besnard P. and Hanks S., editors, Uncertainty in Artificial Intelligence 4: 271-281. North-Holland, New York

Kjærulff U. (1992). A computational scheme for reasoning in dynamic probabilistic networks, In Proceedings of the Eighth Conference on Uncertainty in Artificial Intelligence, 121-129, Morgan Kaufmann, San Francisco.

Koller D. and Pfeffer A. (1997). Object-oriented Bayesian networks, In Proc. UAI-97, pp. 302-313, Morgan Kaufmann

Box, G. E. and Kramer, T., Statistical Process Monitoring and Feedback Adjustment: A Discussion, Technical report, Center for Quality and Productivity Improvement, 1990; Technometrics, 1992, Vol. 34, No. 3, pp. 251-285.

Leung D. and Romagnoli J. (2000). Dynamic probabilistic model-based expert system for fault diagnosis, Computers and Chemical Engineering 24: 2473-2492

Leung D. and Romagnoli J. (2002). An integration mechanism for multivariate knowledge-based fault diagnosis, Journal of Process Control 12: 15-26

McLachlan G.J. and Basford K.E. (1988). Mixture Models: Inference and Applications to Clustering. Marcel Dekker, New York

Nauck D., Klawonn F. and Kruse R. (1997). Foundations of Neuro-Fuzzy Systems, John Wiley & Sons Ltd.

Olesen K.G., Lauritzen S.L. and Jensen F.V. (1992). aHugin: System creating adaptive causal probabilistic networks, UAI 92: 223-229

Pearl J. (1988). Probabilistic Reasoning in Intelligent Systems, Morgan Kaufmann Publishers

Sohlberg B. (1998), Supervision and Control for Industrial Processes. Using Grey Box Models, Predictive Control and Fault Detection Methods, Springer-Verlag London

Spiegelhalter D. and Lauritzen S. (1990). Sequential updating of conditional probabilities on directed graphical structures, Networks 20: 579-605

Suermondt, H. and Cooper, G. (1993). An evaluation of explanations of probabilistic inference. In *Proceedings of the* Sixteenth Annual Symposium on Computer Applications in Medical Care, Baltimore, MD, (pp. 579-585) 1992; Reprinted in: Computers and Biomedical Research, 26, 242.54.

H. Vedam, S. Dash and V. Venkatasubramanian (1999), An Intelligent Operator Decision Support System for Abnormal Situation Management", Comput Chem Eng, 23 (in the Proceedings of ESCAPE 9), pp.577-580.

Wang C.-H. and Sheu S.H. (2003). Determining the optimal production-maintenance policy with inspection errors: using Markov chain, Computers and Operations Research, vol. 30, pp. 1-17

Weidl G. (2002). Root Cause Analysis and Decision Support on Process Operation. Doctoral Dissertation, dept of Public Technology, Mälardalen University, Sweden

Weidl G. and Dahlquist E. (2002a). Patent Application WO02099550: Provision of Process Related Information

Weidl, G., Madsen, A.L. and Dahlquist, E. (2002b). "Condition Monitoring, Root Cause Analysis and Decision Support on Urgency of Actions". In Book Series FAIA, vol.87, “Soft Computing Systems - Design, Management and Applications”, pp. 221-230. IOS Press, Amsterdam, the Netherlands

Weidl G., Milanovich R., Vollmar G., Dahlquist E. (2003a). Patent Application WO03042770: Provision of Data for Analysis

Weidl G., Vollmar G. and Dahlquist E. (2003b). Adaptive Root Cause Analysis under uncertainties in industrial process operation, in conference proceedings of FOCAPO (Foundations Of Computer Aided Process Operations), Florida, January 12-15, 2003, USA

Weidl, G., Madsen, A.L. and Dahlquist, E. (2003c). Object Oriented Bayesian Networks for Industrial Process Operation, In proceedings of the Bayesian Modeling Applications Workshop associated with the 19th Conference on Uncertainties in Artificial Intelligence, August 7-10, 2003, Acapulco, Mexico; http://citeseer.ist.psu.edu/705216.html

Weidl G. (2004). Decision-Support System for Process Analysis and Supervision, invited paper for ERCIM News No.56, special theme “Analysis, Diagnosis, Planning and Simulation of Industrial Systems”, Jan. 2004: http://www.ercim.org/publication/Ercim_News/enw56/

Weidl G. (2004). Adaptive risk assessment in complex large scale processes with reduced computational complexity, In CD-proceedings of 9th International Conference on Industrial Engineering Theory, Applications & Practice, Auckland, New Zealand, November 27-30, 2004

Zadeh L.A. (1965). Fuzzy sets. Information and Control 8: p. 338-353.