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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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Abstract

The increasing complexity of large-scale industrial processes and the struggle for cost reduction and higher profitability means 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 digesting and screening process. The process is modeled using generic object-oriented Bayesian networks (OOBNs). The system performs reasoning under uncertainty and presents to users corrective actions, with explanations of the root causes. The system records users' actions with associated cases and the BN models are prepared to perform sequential learning to increase its performance in diagnostics and advice.
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1. Introduction

In large-scale and complex industrial processes, a failure of the equipment or abnormality in process operation is usually detected by means of hardware sensors. The process operator has to isolate the cause of a failure 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, as well as advice to the human operator on corrective actions.

In general, a fault diagnosis system for industrial process operation should satisfy the following requirements listed in (Vedam, Dash, & Venkatasubramanian, 1999 and Dash & Venkatasubramanian, 2000): early detection and diagnosis; isolability; robustness; novelty identifiably; multiple fault identifiability; explanation facility; adaptability; reasonable storage and computational requirements.

In this paper, we focus on key aspects of process monitoring and root cause analysis. In this context, Box and Kramer (1990) have discussed the roles of statistical/automatic process control for process monitoring/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, 1988; Cowell, Dawid, Lauritzen, & Spiegelhalter, 1999; Jensen, 2001), and BNs have the ability to adapt to changes (Spiegelhalter & Lauritzen, 1990; Olesen, Lauritzen, & Jensen, 1992). In a pre-study, we have also considered alternative approaches for diagnosis of industrial processes, e.g. the neuro-fuzzy approach (Nauck, Klawonn, & Kruse, 1997) would not provide causal interpretation of diagnostic conclusions. Supplying explanations to the user of a system, performing probabilistic reasoning in BNs, has been considered by (Suermondt & Cooper, 1993) and (Henrion & Druzdzel, 1999), who use approaches incorporating respectively entropy-based or scenario-based explanations. A probabilistic approach to fault diagnostics in combination with multivariate data analysis was suggested in (Leung & Romagnoli, 2000, 2002). (Arroyo-Figueroa & Sucar, 1999) have been using temporal (dynamic) BNs for diagnosis and prediction of failures in industrial plants. (Heger & Aradhye, 2002) have also applied BNs to diagnose sensor and/or process faults utilizing redundancies. For DS, (Weidl, Madsen, & Dahlquist, 2002) have combined the algorithm for decision theoretic trouble-shooting (DTTS) with time critical decision support (Kalagnanam & Henrion, 1990; Heckerman, Breese, & Rommelse, 1995). (Weidl et al., 2002) have applied an influence diagram for advice on the urgency of competitive actions for the same root cause.

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 & Pfeffer, 1997).

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.

The main contributions of the methodology include:

- The system design for RCA and DS in process operation.
- The BN combination with physical models of the process behavior (e.g. pressure-flow network), providing soft sensor information for BN reasoning.
- The use of OOBNs for causal modeling of events and explanations at different levels of plant hierarchy.
- OOBN for adaptive signal classification by mixture models and prediction of the level-trend development.
- OOBN for early risk assessment of disturbances, their probable root causes and cost estimations anticipating the potential production losses to ensure predictive maintenance on demand.
- The RCA system integration in the industrial IT platform for efficient data exchange with distributed control system (DCS) and various IT packages.
- The algorithm for decision support including corrective actions, cost issues and adaptation.

The rest of this paper is structured as follows. Section 2 provides some preliminaries. The developed methodology is presented in Section 3. It is implemented on a prototype system and applied to real industrial processes as described in Section 4. Finally, its validation follows in Section 5.
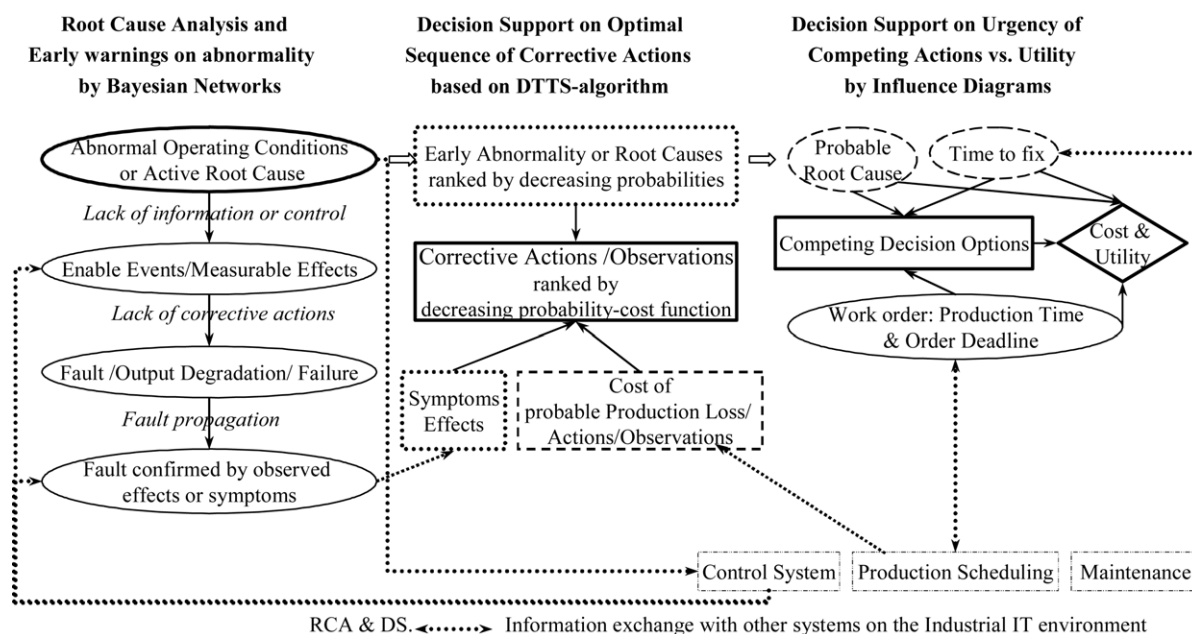

Fig. 1. The hybrid system for root cause analysis, decision support on efficient sequence of actions and observations, and DS on urgency of competing actions for the same root cause.

2. Bayesian networks and modeling

A Bayesian network $N = (G,P)$ (a.k.a. belief network, Bayesian belief network or causal probabilistic network) is a probabilistic graphical model for reasoning under uncertainty. It 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 (CPD): $P(X|$ pa$(X))$, see (Jensen, Kjærulff, Lang, & Madsen, 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 such that there is one CPD for each node given its parents in the DAG. The CPD expresses the strengths of the dependency relations of X given its parents.

An acyclic, directed graph $G = (V,L)$ induces a set of (conditional) (in)dependence relations between the nodes of V. The set of (in)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 (in)dependence relation between nodes given a (possibly empty) set of evidence can be read from the DAG G using linear complexity algorithms, utilized here for explanations.

2.1. 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.
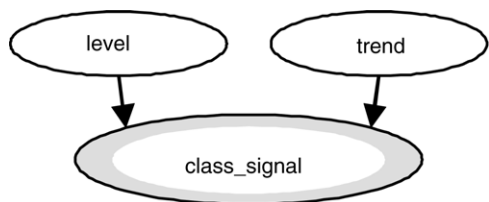

Fig. 2. Simplified BN class for signal classification, based on the signal level and its trend.
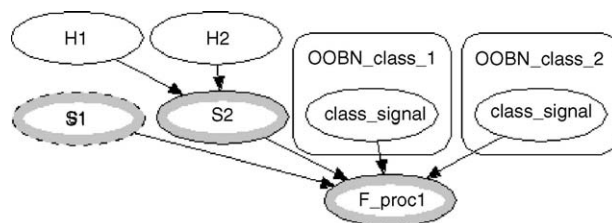

Fig. 3. Simplified OOBN for modeling of "subprocess failure" and containing "class signal" as instance, $S1$ as input interface node and $\{S2, F_{proc1}\}$ as output interface nodes.

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 Figs. 3 and 4.

A comparison with other non-causal object-oriented languages for modeling of physical and chemical systems and processes is given in (Weidl, Madsen, & Dahlquist, 2003b, Weidl, Madsen, & Israelsson, 2005).

2.2. Causal domain modeling using BNs

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. 5.

The BN model for root cause analysis reflects the causal chain of dependency relations as shown in right part of Fig. 5. The dependency relations are between three (conceptual) layers of random variables in the problem domain: $\{H_i\}$, $\{S_j\}$, $\{F\}$, where $i = 1, \ldots, n, j = 1, \ldots, m$. Here, 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. 5) 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.
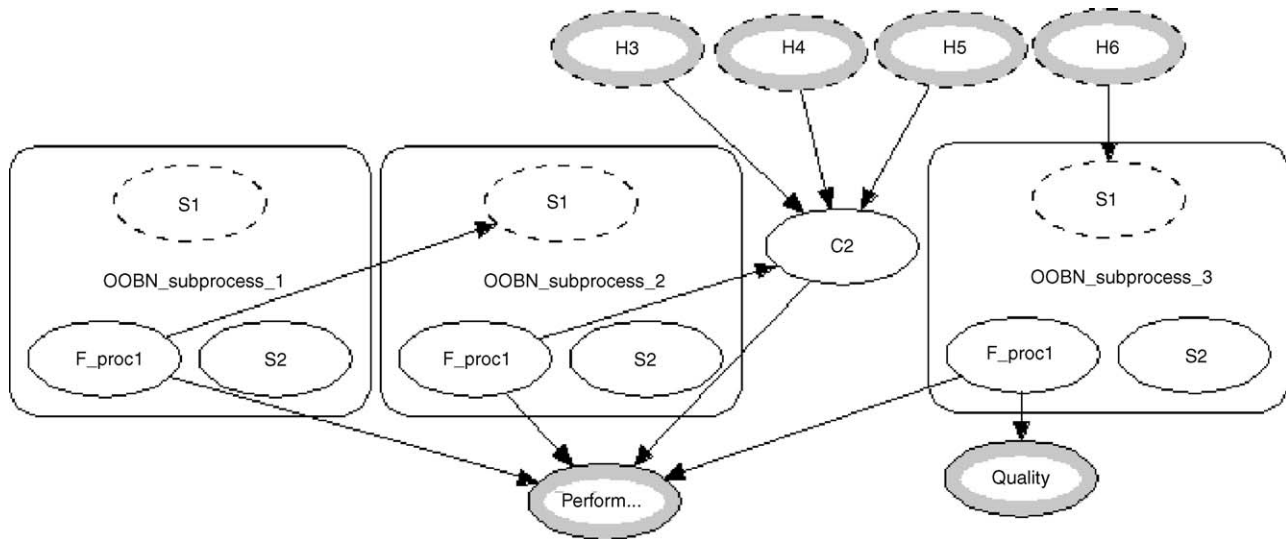
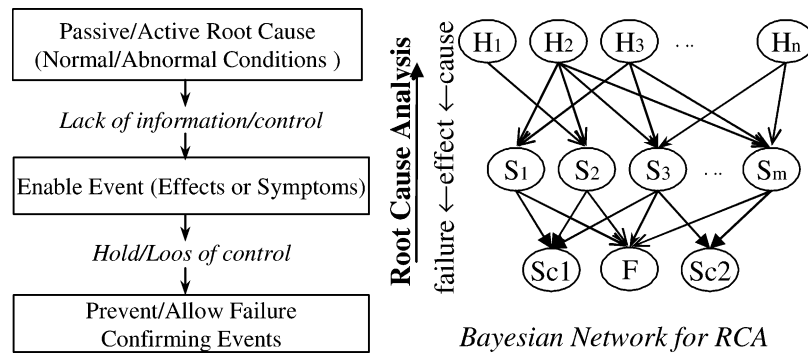Fig. 4. OOBN with node "subprocess failure" as an instance.

Fig. 5. The conceptual layers of the BN for RCA (column 1) and the corresponding variables in each layer of the BN.

3. Modeling 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.

3.1. 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 conceptually in Fig. 6. At the top are abnormalities in process operation and output quality, which
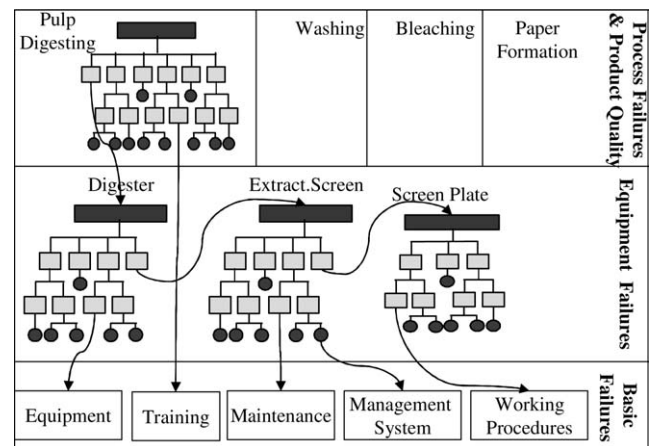

Fig. 6. Failure trees interconnections as a knowledge base for RCA and its process performance analysis.

can originate from abnormalities in equipment or in process conditions possibly due to basic failures.

3.2. 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. 7). Thus, the knowledge acquisition for the CPDs of the BN models is a mixture of different acquisition strategies for different fragments of the network (Olesen et al., 1992). Thus, it reduces the degree of uncertainty in the acquired evidence.

First level asset diagnostic packages serve as autonomous agents in the RCA system architecture Fig. 7 (Weidl, Madsen, & Dahlquist, 2003a). 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, control loops (by loop diagnostics), soft sensors and other process assets conditions. "Asset" is used as a collective notion to include actuators (valves, pumps), process assets (e.g. digester screens; pipes, can be represented as fake valves) and even equipment failures as a root cause of signal deviations.

The handling of uncertainties in fluid dynamics modeling includes also the developed class of agents based on simulations provided by a fluid dynamic model (Weidl et al., 2003b). For example, we use a physical model of a pressure-flow network. It serves 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.

3.2.1. More sensitive internal thresholds

In the developed methodology, condition monitoring interacts with RCA and uses more sensitive thresholds of abnormalty. Then, the large number of triggered "warnings" is first analyzed internally by the RCA system.

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

$$S = \mu \pm x_{abnormal}\sigma$$

where μ is the mean and σ is the standard deviation. We define as $x^H_{abnormal} = (\theta_{High} - \mu)/\sigma$, where $s^H = \theta_{High}$ is the signal's high threshold obtained from data analysis. The low threshold is defined as $s^L = \theta_{Low}$, $x^L_{abnormal} = (\mu - \theta_{Low})/\sigma$. From data analysis, we have found that, the $(x_{abnormal}\sigma)$ variation of signals covering the different operation modes is in the interval $1\sigma - 5\sigma$. 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 $(x_{abnormal}\sigma)$ variation provides *robustness* in the signal classification. 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. 5) of several signals' alarms (internal for RCA) in order to trigger an operator alarm or warning, pointing at root cause(s).

Fig. 7. System architecture for RCA.

3.2.2. 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 are Boolean. The variation range of a continuous signal (DCS-measured or thereof computed (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, see (McLachlan & Basford, 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

$$P(S) = \sum_{i=1,\ldots,n} P(s_i) P(S|s_i) \qquad (1)$$

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. 8. The sub-distribution of each soft interval state is chosen most commonly as Gaussian mixtures, 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 Bayesian terminology.

We use mixture of 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. 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 (Weidl, 2002).

For cases with low frequency of abnormal events, we use 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 (Weidl et al., 2003a,b).

3.3. 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 (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 signal uncertainties and signal level-trend classifications as small standardized model classes (a.k.a. fragments) within the problem domain model (Weidl, 2002).

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 (Weidl et al., 2003a, 2005). 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.

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), (Weidl et al., 2003a). In particular, we use a special kind of strictly repetitive time stamped models, called hidden Markov models of first order. There exist adaptive control techniques using extended Kalman filter to estimate both the process state and unknown parameters of 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.

3.3.1. OOBN for RCA of process operation

A case study on digester process operation (Weidl et al., 2005) has been the source of typical repetitive structures incorporated in 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 has been given in (Weidl, 2002; Weidl et al., 2002). It indicates improper operation conditions, recognized in changed level-trend pattern. A combination of several such OOBNs allows to perform RCA of abnormalities observed in process
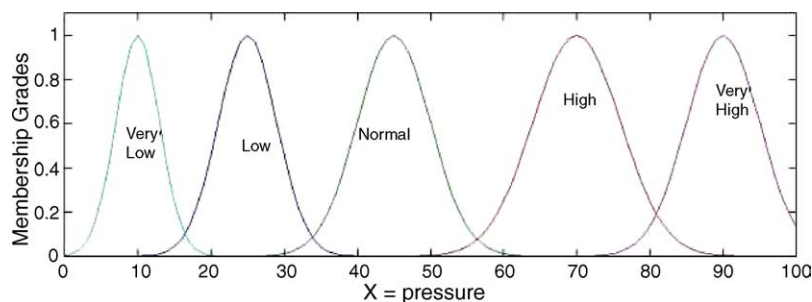

Fig. 8. Soft interval coding = discretization of continuous signals into soft range of states within the same process operation mode.

conditions. The OOBN models incorporate the consequent causality steps of the basic mechanism of a failure build up, as shown in Fig. 5. We have also developed OOBN models 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 (Weidl, 2002; Weidl et al., 2002).

3.3.2. Early warning based on risk assessment

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. 9.

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. 10) the predicted *signal class* outputs as intermediate variables for risk assessment.

Note, that in the OOBN model at Fig. 10, nodes $S1$–$S4$ are instance nodes representing network class for predicted development of process variables (Weidl et al., 2003a). This OOBN structure follows the generic mechanism of occurrence of disturbances or a failure built-up (Fig. 5).

3.4. Decision support on process operation

Another functionality of the described system is planned to include advice 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 (Wang and Sheu, 2003) model for expected average cost.

3.4.1. 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 DTTS algorithm (Heckerman et al., 1995), extended by (Weidl et al., 2003a) to early warning of abnormality to prevent the highest potential losses of production.

The algorithm presented in Fig. 11 incorporates the following steps:

- 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 of "Advice Sequence" to process engineers, operators or maintenance crew to provide advice 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.
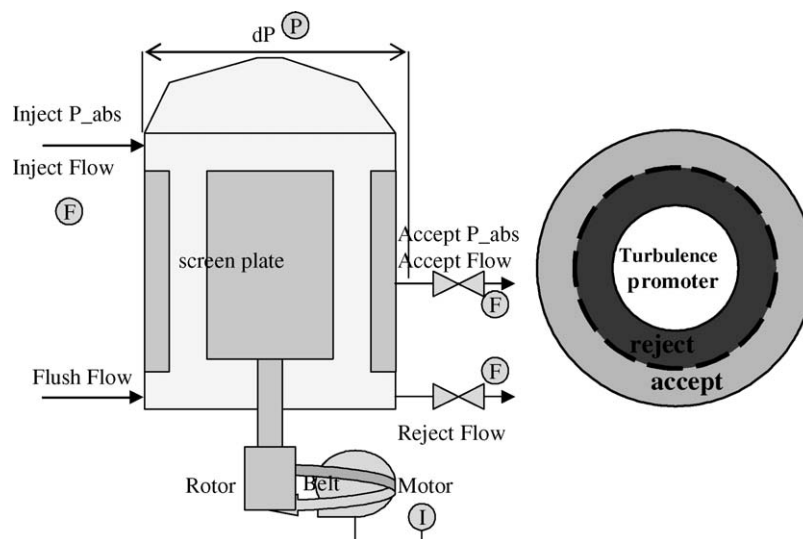

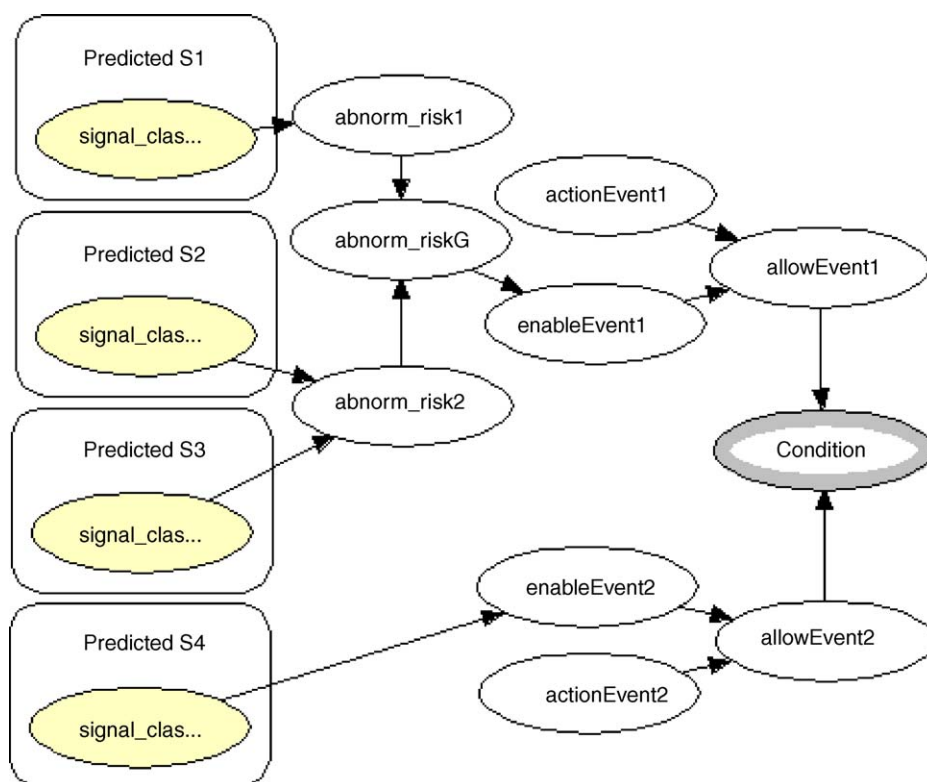Fig. 9. Pulp screen—a pulp filtering equipment.

Fig. 10. Assessment of abnormality risk and equipment/sub-process condition.
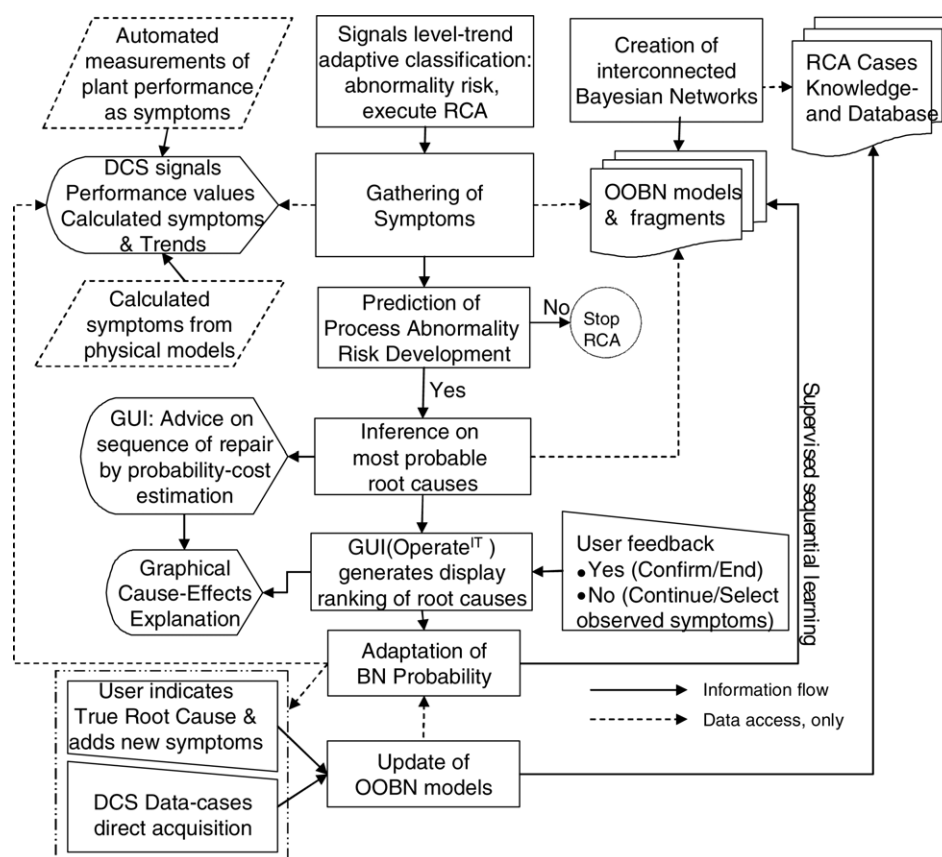

Fig. 11. The basic algorithm for adaptive root cause analysis with risk assessment.

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

Fig. 12. GUI-functionality for presentation of RCA-results and collection of user feedback.

This procedure continues in loop until the problem is solved.

3.4.2. *Explanations*

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. 12), a list of evidence (symptoms) for inference, as well as conclusions on possible effects.

Moreover, one can examine the dependency on evidence through the sensor status and update the RCA conclusions (Fig. 13). 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.

4. Application and system integration

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 BN-nodes' names, as well as conventional classes for measured/computed/observed, diagnosed or status variables.

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 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.

Most measurements are real continuous data. The classification level (e.g. low, high) of the signals is customizable, i.e. they can be changed by the user, see Fig. 14. The extension of

Fig. 13. Source: ABB, RCA. HMI for presentation of the most probable root causes, acquisition of user feedback and following update of most probable root causes.
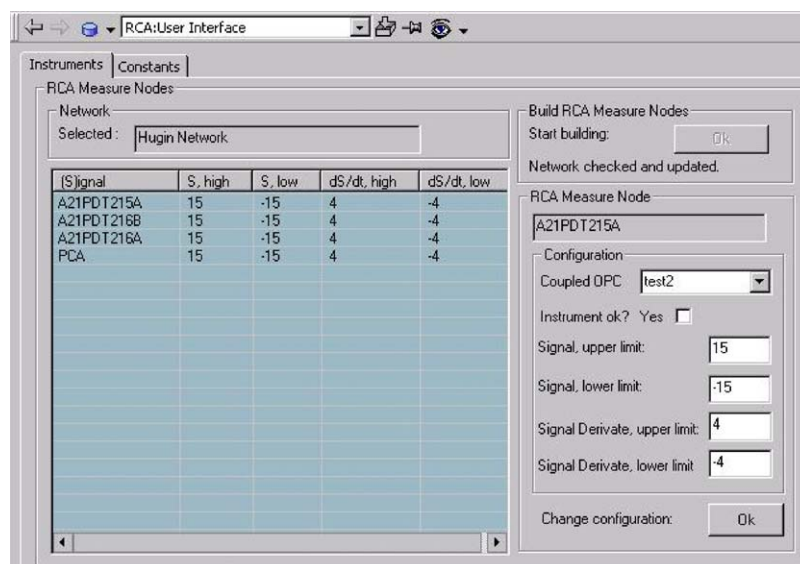
Fig. 14. Source: ABB, RCA. GUI for configuration of the measurement instruments (sensors) and its status.

system functionality will include an automated classification of the signal limits as described in (Weidl et al., 2005).

5. 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. 15.

This application has been used for testing the system performance in a simulated scenario with historical data from a real pulp plant. The structure of one of the developed

Bayesian networks is shown in Fig. 16. More details are provided in (Weidl et al., 2005).

5.1. Bayesian networks validation

Domain experts have validated the (in)dependency 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.

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
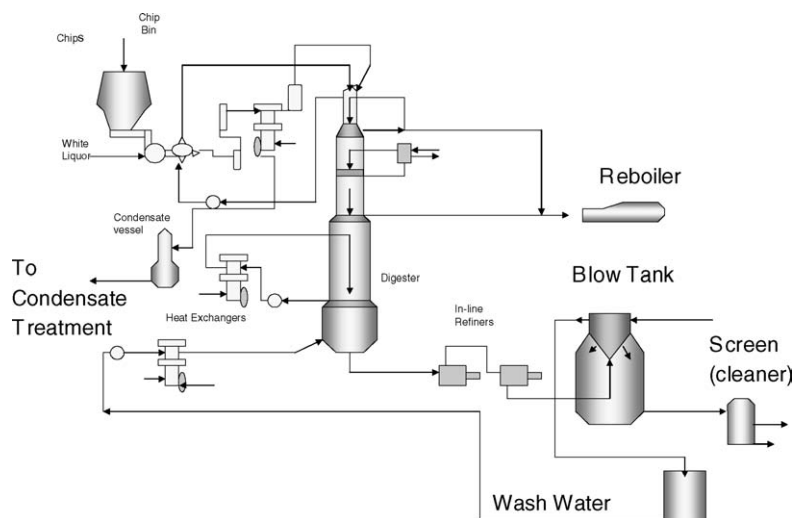

Fig. 15. Digester fiber-line. Case-study: monitoring of the digester operating conditions.
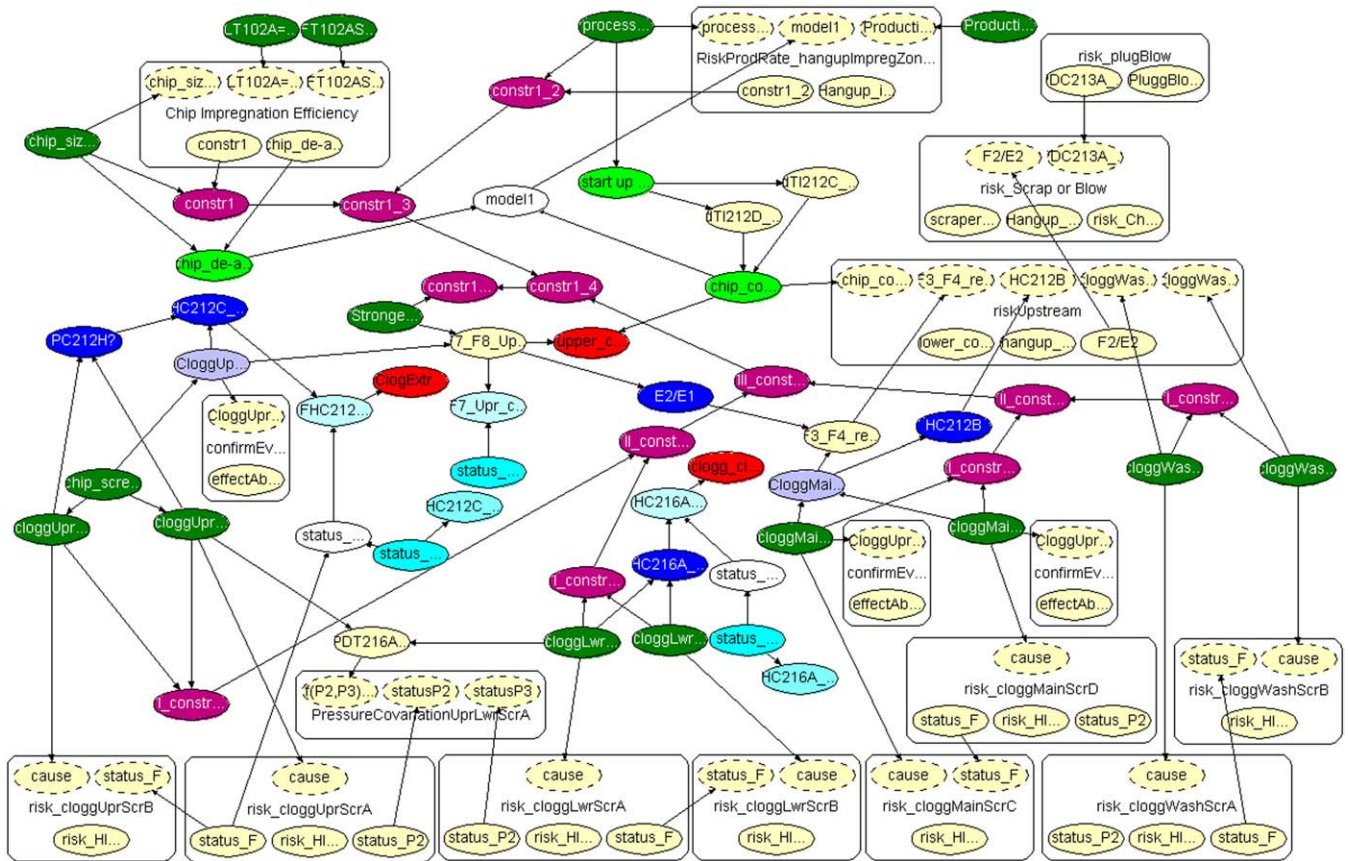
Fig. 16. An OOBN version of the RCA for digester hang-up.

modeling correctly the expert and causal relations obtained from data analysis and to provide consequent revision of consistency in knowledge, 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 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.

In the case study, the frequency of about 75 events of digester screen's clogging during 97 days of operation (approximately 1.4×10^5 min or sampling cases) was recorded in the real process historical data. We could predict clogging (in the upper screen in the lower cooking circulation) in the mean 10–20 min ahead. We could also find mean effects that may influence the risk of clogging and updated the BN structure.

The use of *historical data only* 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 this purpose, 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.

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

Table 1
Statistics on the models used in the validation experiment

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

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 nN 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 1. The BN model for RCA of screens' clogging in the liquor extraction consists of 26 variables with two root cause variables and six 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 non-fault configuration is enforced using likelihood evidence on the root cause variables. The likelihood evidence rules out all faulty states and thereby enforces 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.

Tables 2 and 3 show the validation results for the two models, respectively. The name of the root cause corresponding to each identifier can be found in (Weidl et al., 2005).

Table 2
Validation results for the model for preventive root cause analysis on extraction clogging in the pulp digester

Id	Correctly identified percentage 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 3
Validation results for model for root cause analysis on digester hang-ups

Id	Correctly identified percentage 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

In Tables 2 and 3, *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.

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.

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.

As shown in Tables 2 and 3, 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.

5.2. Compliance with system requirements

The used modeling techniques and the results of this work allow to conclude that most listed requirements on RCA and DS are met as summarized in (Weidl et al., 2005):

- Fast and flexible inference in BN with several hundred variables takes <1 s.
- Handling of uncertainties is provided by probabilistic reasoning in BN with missing data; agents.
- Early detection and diagnosis—by BN for early risk assessment with built-in causal scenarios, validation.
- Isolability—by mixture models, validation.
- Decision support at higher automation level—automated symptoms collection and inference explanations; automated cause confirmation by DCS-feedback.
- Explanation of conclusions—by d-separation in BN, and by calculation of the path with the highest entropy change.
- Adaptivity to process changes—by 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—by modeling techniques, mixture models, validation;
- System-user interaction operator—by feedback for "supervised" sequential learning; fast BN-inference.
- Novelty identifiability—by additional node state.
- Multiple faults identifiability—the single cause assumption allow to treat multiple causes one at a time; contraints for explicit multiple cause modelling.
- Reasonable storage and computational requirements: distributed RCA and decision strategy (similar to DCS).
- Reusable system and model design for various process applications—by use of OOBN (Weidl et al., 2003a).

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.

In any real process application, RCA needs adaptation to incorporate the ongoing changes in process behavior. The sequential learning is performed on the actual root cause nodes and evidence for that particularly observed case. This is based on feedback from DCS and on operator/maintenance reports. A detailed discussion on adaptation and on issues related to the prediction of process dynamics is given in (Weidl et al., 2005).

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.

Future functionalities to incorporate in the proposed RCA system include forecasting of signal development and time-delays, based on (Kjærulff, 1992). Another issue is concerned with suitable approximations for handling of large number of temporal relations between the different time slices, as discussed in (Boyen & Koller, 1998a,b).

6. 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 the 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.

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. Because of the wide applicability of this methodology, we expect that the results of this paper will be the interest to other system designers who are considering similar problems.

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

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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