Object Oriented Bayesian Networks for Industrial Process Operation

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Abstract

We present an application, where extensions of existing methods for decision-theoretic troubleshooting are used for industrial process operation and asset management. The extension includes expected average cost of asset management actions, prediction of signals' level-trend development, risk assessment for disturbance analysis and predictive maintenance on demand. By the use of a distributed control system (DCS), it incorporates requirements from the user and the industrial process operation. First level diagnostic packages serve as agents in the system architecture and provide evidence for automated reasoning on abnormality in process operation. The system collects user- and DCS-feedback for sequential learning to reflect changing process characteristics. The methodology has been applied on a screening process in a Pulp Mil.

1 Introduction[1]

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 found and eliminated means unplanned production interruption, which is the main source of cost increase due to lost production profit. 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. This should help avoid unplanned production interruption or at least ensure that the lost production is minimal. A disturbance analysis system for industrial process operation should include a combination of adaptive Root Cause Analysis (RCA) and Decision Support (DS).

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 (BN) for probabilistic reasoning in intelligent systems (Pearl 1988; Cowell *et al.* 1999; Jensen 2001) can be used to calculate the posterior probabilities and have the ability to adapt to changes (Spiegelhalter and Lauritzen 1990). Troubleshooting based on decision theory was first proposed in (Kalagnanam J. 1990), and further analyzed in (Heckerman *et al.* 1995). In a pre-study, we have also considered neuro-fuzzy hybrid systems as an alternative approach. 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. Scenario-based explanation of probabilistic inference has been discussed in (Suermondt and Cooper 1993) and entropy-based explanation in (Henrion and Druzdzel 1999). Models reusability, simple construction and modification of generic BN-fragments were other selection criteria in favor of object oriented BN (OOBN) (Koller and Pfeffer 1997).

We have previously developed a number of generic sub-OOBNs for diagnosis and process performance monitoring (Weidl *et al.* 2002, 2003). Here, we present an application of a combined methodology for root cause analysis and decision support. The most efficient sequence of corrective actions is obtained from a probability-cost function. The most probable root causes are estimated from the predicted signals' level-trend development in risk assessment for disturbance analysis and predictive maintenance on demand. The cost is represented by the expected average cost of process and asset management (corrective) actions. We demonstrate the application on a pulp screening process.

[1] This work was performed while Galia Weidl was associated with ABB Corporate Research and Erik Dahlquist with ABB Process Industries both Västerås, Sweden.

2 Statement of the Problem

Disturbance analysis (RCA and DS) in industrial process control could be a time-consuming task leading to big production losses. The overall goal of RCA and 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 this paper. 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 allow 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 conclusions and suggestions, 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 Interaction Condition Monitoring, RCA and DS

RCA is a structured procedure, which guides the failure analyst from the disturbance/failure event to its cause(s). 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 chosen 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 Methodology

The task of failure identification during production breakdown, its isolation and elimination is a troubleshooting task. While the task of detecting early abnormality is a task for adaptive operation with predictive RCA and maintenance on demand. Hence, these two tasks have different probability-cost functions as discussed in (Weidl *et al.* 2002). We combine both tasks under the notion of asset management aiming at predicting both process disturbances and unplanned production stops, and to minimize production losses. 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 and maintenance on demand, an extended methodology is suggested, able to:

1. detect a failure at an early abnormality stage with a reduced number of hardware sensors
2. find the most likely causes of abnormality
3. propose an efficient sequence of corrective actions and observations

For any abnormal case, once identified, the system is searching to find the root cause of observed or predicted disturbance. The basic algorithm of RCA as implemented in this application, is a modification of the decision-theoretic troubleshooting algorithm, where costs are assumed to be order independent to ensure an optimal sequence of actions (Heckerman *et al.* 1995). We extend this methodology to early treatment of abnormality in order to avoid potential losses of production. It incorporates the following steps (see Fig. 1), which are looped until the problem is solved:

1. Continuous on-line acquisition of evidence: DCS-signals, trends and effects, measured or computed by statistical and/or physical models, or status reports provided by agents. It also includes Signals Preprocessing and Classification of evidence into states
2. Continuous assessment of the risk of abnormality
    (a) Instantiate the risk (abnormality) assessment node, DCS-measurements, thereof computed statistical and physical variables, and observation nodes

(b) Automated propagation of evidence by the inference engine (Andersen *et al.* 1989; Jensen *et al.* 2002) and probability update

3. Optimal sequence of corrective actions, ranked after efficiency, involves computation of the probability-cost function $f(p_i, C_i)$ for the possible root causes of a disturbance

4. System-user interaction

   (a) Presentation and explanations to process engineers, operators or maintenance crew to provide guidance and decision support on control or maintenance activities

   (b) Choice of the actions based on the probability-cost function and own educated judgment

   (c) Collection of DCS- and user feedback on the actual root cause (and additional input on evidence)

5. Update the inference conclusions after performing actions. The update on the actual root is based on current evidence including also DCS-feedback, user observation (e.g. maintenance reports)

The troubleshooting algorithm with adaptive learning of BN parameters in an on-line operating RCA system is shown in Fig. 1. The RCA and DS are exchanging information with the Operator Station, Maintenance, and Control Systems. More details on the troubleshooting steps are given in the following sections.

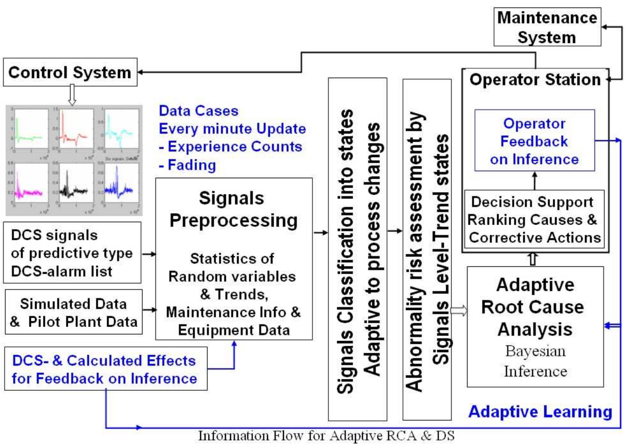

Figure 1: Information Flow for RCA on Observed or Predicted Disturbance and Adaptive Learning.

3.1 Handling 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. 2).

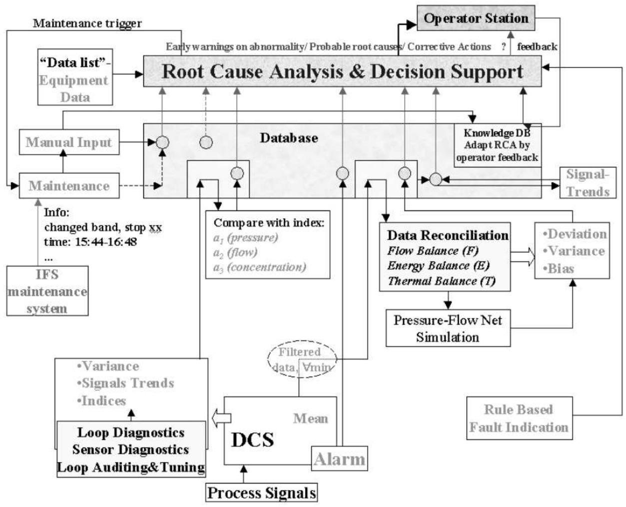

Figure 2: Evidence for Root Cause Analysis during Reasoning under Uncertainties.

3.1.1 Agents for Handling Uncertainties

First level asset diagnostic packages serve as agents in the system architecture. These include diagnostics of small asset units, e.g. sensors, actuators, control loops, soft sensors, see Fig. 2. 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. This reduces the degree of uncertainty in the acquired evidence. 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).

3.1.2 Discretization of Continuous Distributions

The system is receiving as evidence both discrete and continuous signals. The event lists contain only Boolean variables. The variation range of continuous signals (DCS-measured or thereof computed signals (e.g. from physical models)) are also discretized into a number of soft numeric intervals, represented as states of a BN node. We use discretization and not continuous nodes 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 (McLachlan and Basford 1988; Holst 1997).

Let *S* be a continuous variable. Assume that *S* can be partitioned into sets s_1 ... s_n such that the probability density function *P(S)* can be approximated by a finite sum over its

n soft interval states s_i

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

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 . Gaussian mixtures are used most commonly as sub-CPD, since they allow to approximate any other probability distribution.

3.2 Generic OOBN Models

3.2.1 Adaptive Signal Classification

The process is usually operated at several normal operation modes dependent on production rate, process load, etc. During standard 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 asset faults can be the root causes of abnormal process deviations. This can cause degradation of process output (e.g. quality, quantity) or failure in process assets, when exploited under improper conditions.

Dependent on operation mode and set-points c_p of parameters, the signal's level and trend have different normal and abnormal states, see the first slice of Fig. 3. Normal operation mode is characterized by a number of set-points and their typical signal variations under normal and abnormal process operation. 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 is necessary to use signal classification, which is adaptive to changes in normal process operation.

The node sensor reading s_r represents the continuously measured value of a process variable. The node sensor status s_s represents the condition of the sensor instrument used to perform the measurement of a process variable. The node real value R_t represents the actual development of the process variable at time t. The node sensor diagnosis s_d receives input on the sensor status from the sensor diagnostics agent. 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. 2).

Suppose a DCS-signal S is discretized over soft interval states as given in (1). In cases of faulty operation or root causes originating in 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 A_s. Then, the conditional probability distribution (CPD) of the real value becomes a mixture of two Gaussian distributions around the set point during normal and abnormal process operation

$$P(R_t|c_p, A_s) = \begin{cases} Normal(c_p, x\sigma) & A_s \\ Normal(\mu_{abn}, x_{abn}\sigma_{abn}) & o.w. \end{cases}$$

For variables, which are directly manipulated in process control loops, the set point serves as mean μ in the Gaussian distribution with the respective scaled variance $x\sigma$ around the set-point of the operation mode. The variance is scaled by a factor x in order to avoid too many *internal alarms* for RCA. 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. The dependence on the status of the asset is expressed with a Gaussian distribution, where μ_{abn} is the real alarm threshold and $x_{abn}\sigma_{abn}$ 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, we use a mixture of Gaussian distributions on normal operation behaviour and Poisson distribution during faulty operation.

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 of normal and uniform distributions for the real value when the sensor status is true or false respectively

$$P(s_r|R_t, s_s) = \begin{cases} Normal(R_t, x\sigma) & s_s \\ u(y_{min}, y_{max}) & o.w. \end{cases}$$

where the uniform distribution ($u()$) is defined on the entire interval of signal variation.

The signal trend at any time step is directly influenced by random changes in the real value at both previous and present time steps. For robustness, the trend is calculated as the derivative on the averaged time history of the signal between the time points t_{i-N} and $t_{i=0}$ (current time):

$$Trend_{signal} = \frac{\delta S}{\delta t} = \frac{\mu(R_t(t_0)) - \mu(R_t(t_{-1}))}{(t_0 - t_{-1})} \quad (2)$$

where $\mu(R_t(t_i)) = \sum_{j=(i-N),\ldots,i} R_t(t_j)/N$.

This provides a filter of the noise in the signal behaviour. 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. The considered pulp screening process has slow

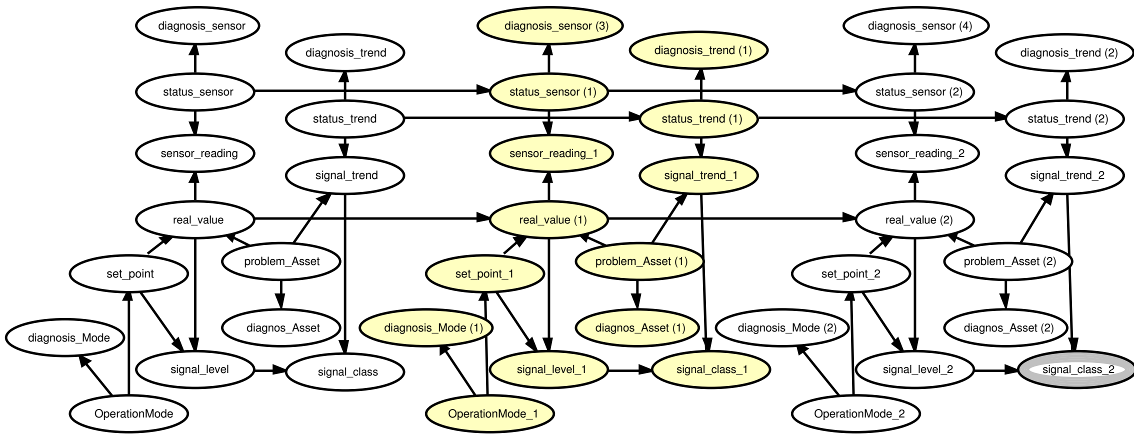

Figure 3: Prediction of classified DCS-signals, based on present and past values of process variable.

dynamics. Therefore, the trend is expressed by the derivative calculated over a floating interval window containing 20 points distributed uniformly on 10 minutes period.

The above is true for the static case. In the dynamic (predictive) case, it is preferable to consider the dependency on the asset state A_s (i.e. the condition of the screen plate, which can be normal, clogged, or cracked) and the sensor status s_s. For the example of pulp screening, the probability of the predicted development for the pressure trend T_p (Fig. 3) is dependent on A_s and s_s:

$$P(T\_p|A_s, s_s) = \begin{cases} steady & A_s = normal \wedge s_s \\ increased & A_s = clogged \wedge s_s \\ decreased & A_s = cracked \wedge s_s \\ u(y'_{min}, y'_{max}) & o.w. \end{cases}$$

where $[y'_{min}, y'_{max}]$ is the band of typical trend variations of the considered signal.

The signal class is conditionally dependent on random changes in two variables: signal level and signal trend. Its probability distribution is then defined to adapt the classification to changing operation mode.

The generic BN model for adaptive signal classification into levels and trends (see the first time-slice of Fig. 3) 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. Fig. 3 shows a past-present-future combination of such generic blocks for the purpose of risk assessment and early warnings on abnormality (e.g. screen plate clogging).

3.2.2 One Step Look Ahead Prediction of Signals

The temporal 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) the necessary corrective action is undertaken at an early stage of failure development.

In addition, temporal BNs can be used to express causality dependencies reflecting the dynamic character of the process. For example, alarm filtering deals mainly with time-delay effects. In Fig. 3 we use only three time steps to model an infinite step process. In the reality, such 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. 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. The forecasting of signal development and time-delays 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. Temporal Bayesian networks have also been used for failure diagnosis and prediction in thermal power plants (Arroyo-Figueroa and Sucar 1999).

3.2.3 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 group of process random variables: S1 is the differential pressure signal; S2, S3 are the flows on accept and reject side, S4 is the consumed power by the equipment during screening process operation. 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.

The generic mechanism of failure build up consists of root cause activation, which causes abnormal changes in the process conditions. The last represent effects or symptoms of abnormality. They are registered by sensors or 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

Passive/Active Root Cause → (Normal/Abnormal Conditions) → *Lack of information/control* → Event Enabling → (Effects or Symptoms) → *Hold/Loss of control* → Prevent/Allow failure

Instead of reactive troubleshooting, a long term strategy requires a proactive system with early warnings and corrective (control or maintenance) actions, which prevent abnormality to develop into a failure. For this purpose, we combine in the BN model (Fig. 4) the predicted *signal class* outputs as intermediate variables for risk assessment. This is based on certain combination of random variables (e.g. signals S1-S4 in our screening application). The pressure-flow combinations of S1, S2, 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 might occur simultaneously, but not always independently of Event1. When abnormality event is enabled, a corrective action from the operator/maintenance or DCS can prevent (or allow) undesired event (failure), leading to abnormal or critical condition of the equipment or a sub-process (Fig. 2).

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

3.3 Expected Average Cost

Let X_n be the process state immediately after performing an inspection and possible adjustment of the process

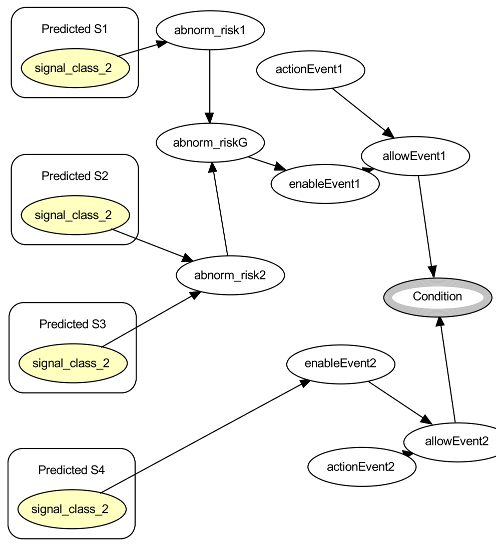

Figure 4: Assessment of Abnormality Risk and Equipment/Sub-process Condition.

at time t_n. The inspection-adjustment time is defined as $t_n = nj\delta t$, where $j\delta t$ 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 $\mathbb{E}(IC)$, repairs $\mathbb{E}(RC)$, preventive maintenance $\mathbb{E}(PC)$, and defective output $\mathbb{E}(Cd)$ 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:

$$C(I, j, w) = \frac{h(P-D)\mathbb{E}(t_p)}{2} + \\ + \frac{K + \mathbb{E}(IC) + \mathbb{E}(RC) + \mathbb{E}(PC) + \mathbb{E}(Cd)}{t_p}, \quad (3)$$

where P is a deterministic, constant production rate (units/time); D is a deterministic, constant demand rate; $\mathbb{E}(T)$ is the mean length of time of a production cycle and the actual length of a production cycle is $t_p = P\mathbb{E}(t_p)/D$.

Equation (3) was derived and solved numerically by (Wang and Sheu 2003) in order to minimize the maintenance cost. They 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 two 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 — equation (3) — the production losses due to unplanned process stops $\mathbb{E}(PL)$ 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 (Weidl *et al.* 2002). This allows maintenance on demand at an early stage of a process failure development.

Following the troubleshooting algorithm of (Heckerman *et al.* 1995), we utilize a probability-cost function, where the expected cost of repair is extended into the expected average cost of asset management, i.e. $(3) + \mathbb{E}(PL)/t_p$. For optimal (efficient) sequences of corrective actions involving several possible root causes, their 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 (Heckerman *et al.* 1995): $P_i/C_i \geq P_{i+1}/C_{i+1}$, for the optimal sequence of process management actions, when the failure is a fact. Note that not all conditions for optimal behavior are met during process operation. The assumptions of a single fault and order independence of corrective actions may be violated in some cases. This is not a serious limitation of the approach as root causes can be treated myopically.

While for predicted events, it would be more appropriate to order the recommended sequence of corrective actions after decreasing risk of potential process breakdowns: $P_iC_i \geq P_{i+1}C_{i+1}$, for sequence of preventive actions, reducing the potential production losses according to the performed risk assessment on active root causes. This preventive troubleshooting stops, when the estimated risk of abnormality is below a pre-set threshold value. The last approach has not yet been proved theoretically. 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.

3.4 Explanation and Adaptation

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 includes, besides the sequence of actions, a ranked list of root causes (see Fig. 5) and their dependency on evidence, on which the conclusions were reached. 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 highest entropy is presented to the operator in order to explain the conclusions. For large BNs, additional properties, such as coloring of the most probable scenario of causes and effects allow the user to visualize the explanations.

The industrial process is changing its behavior over time. The adaptation is compensating the classification of those states of the system, which the models do not fully capture. It reflects slowly changes in the process due to aging, wear, maintenance, as well as natural changes in the process operation and its environment. In the considered screening application the sequential learning algorithm (Fig. 1) is taking into account uncertainty in the knowledge acquisition from: training-data, on-line measurements and initial expert estimates; the initial guess of an iteration procedures of the first level diagnostics agents; estimated variables from physical models assumption (Weidl 2002).

In principle, the prior probabilities of the BN models can be learned from a (large) number of cases representing the problem domain behavior. It is though seldom praxis to maintain a large and detailed data base on industrial process operation. We use for adaptation sequential learning with fading (Spiegelhalter and Lauritzen 1990). 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. This is based on feedback from DCS and on user/maintenance reports (see Fig. 5).

4 Conclusions

The outlined methodology, which in a feasibility study has been applied on liquor screening during the pulp digesting process, could be generally applicable in process industries. In the tests (with historical data) we had about 15% false alarms. The possibility of reducing the number of false alarms seems to be a trade-off between the number of false and missed alarms, but it requires further study. Due to economical reasons, the operator prefers rather a few false alarms, than missed alarms.

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

The contributions of this paper are as follows. We use OOBN models to ensure models reusability, simpler modification and overview at different levels of plant hierarchy. Explanation of conclusions is based on the path with highest entropy and d-separation. Reasonable storage and computational requirements are guaranteed by a distributed RCA and decision strategy (similar to DCS). First level diagnostic agents allow to handle efficiently the uncertainties

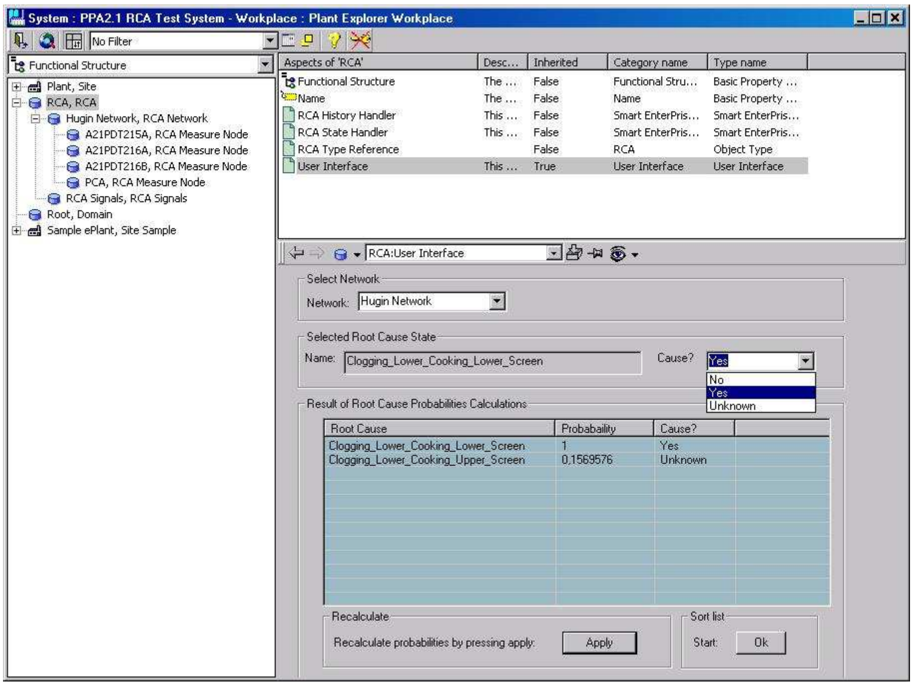

Figure 5: Screen-shot of GUI for user feedback (source: ABB Industrial IT platform. RCS Application Integration).

in acquisition of knowledge and data. We have developed an OOBN model for adaptive signal classification by mixture models. It incorporates standard changes in process operation mode and both normal and faulty operation conditions. We use it also as an OOBN-fragment in one step look ahead prediction of the level-trend development of the signal. 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. We have introduced feedback for on-line update of BN parameters. The feedback is based on DCS- and user/maintenance reports on the actual root cause of a problem. It is *supervising* the system in its sequential adaptation to the real process.

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 can reduce substantially the production losses due to unplanned process breakdowns.

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