ADAPTIVE ROOT CAUSE ANALYSIS UNDER UNCERTAINTIES IN INDUSTRIAL PROCESS OPERATION

G.Weidl
ABB Group Services, Corporate Research
Trefasgatan 1, S-721 78 Västerås, Sweden

G.Vollmar
ABB Group Services, Corporate Research
Ladenburg, Germany

E.Dahlquist
ABB Process Industries & Mälardalen University
S-721 78 Västerås, Sweden

Abstract

We discuss a *Root Cause Analysis* (RCA) system implementing a probabilistic approach based on Bayesian inference for adaptive reasoning under uncertainties in industrial process operation. The proposed approach is model based and accumulates the process knowledge within the problem domain, which data is gathered and stored in *XML*-based information server. The Bayesian networks have been created automatically from the XML-structured data. The interconnection between XML-failure trees is handled as object oriented instances of Bayesian sub-networks within master-network covering the entire process and monitoring its overall condition, output quality and equipment effectiveness. We implement sequential on-line adaptivity of models' parameters to reflect changes in process operation. The system learning can be supervised by user feedback on the actual root cause. The general RCA methodology is applied to plate cutting in a hot rolling mill.

Keywords

Causal Probabilistic Networks, Bayesian Inference, Fault diagnostics

Introduction

With the growing complexity of industrial processes, the available information for inference on failures is often incomplete or the domain knowledge/data are uncertain. In addition, any modification in the facility due to aging, maintenance or replacement of components might change the initial data prepared for the analysis. Obviously, there is a need of non-forgetting and adaptive system, which is able to reason under uncertainties. This will provide the operators and maintenance staff with fast and flexible decision support on corrective actions. Early risk assessment of process abnormal deviations, predictive maintenance on demand and minimizing the search time of the root cause of a failure, while working under time pressure, allow to lead the process back to normal before any actual failure has occurred. This avoids inefficient treatment of cause's effects and has enormous potential for industry savings and higher overall plant efficiency.

Computerized analyzers are known to comprise hardware and software for processing data in accordance with a deterministic set of analyzing rules. A system for

RCA based on domain knowledge represented as library of failure tree models was proposed by Vollmar G. and R.Milanovi'c (2000). The library of hierarchically organized and interconnected failure tree models have been implemented in an XML-based information server by Hu Z. And Vollmar G. (2000) and was functioning as Intranet trouble-shooting manual in the operator search for the root cause of observed failure in a hot rolling mill.

Weidl G. and E.Dahlquist (2002) have been developing methodology for semi-automated RCA to allow fast inference and early warnings on abnormality in industrial process operation. The approach uses Bayesian Networks[1] (BN) and Inference. For more time efficient knowledge acquisition was preferable to target applications with database of structured process knowledge on the underlying failure classes. This will allow automated knowledge extraction for creation of BN.

In this article we propose an extension of the XML-based system for *RCA* by implementation of Bayesian probabilistic approach for modeling of cause-effect relations. This has been done by mapping the hierarchical XML-structured model library for RCA into BN and object-oriented BN (OOBN). The main advantage due to the Bayesian 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.

The contributions of this article are:

- the system design for Root Cause Analysis (RCA)
- The RCA algorithm, extended with automated collection of evidences, their adaptive classification for early warnings on abnormality; sequential adaptivity to process changes and supervised learning based on user feedback.
- automated creation of Bayesian Networks (BN) from XML-structured data;
- Application of object oriented BN for RCA in order to handle interconnection between failure trees, ease the construction and modification of BN and reduce the overall complexity of the industrial process network.

[1] A *Bayesian network* (BN) is a set of child and parents nodes representing random variables and a set of links connecting these nodes to build a directed acyclic graph (*DAG*). Each node has assigned a conditional probability table (*CPT*) which describes how the state of the child node depends on its parent's configurations of states. An *Object-Oriented Bayesian Network* (OOBN) is a network that, in addition to the usual nodes, contains *instance nodes*. An instance node is a node representing an instance of another sub-BN, which can itself contain instance nodes, whereby an object-oriented network can be viewed as a hierarchical description (or model) of a problem domain. To provide fast inference for RCA, we find it is natural to parser the XML hierarchical description into OOBN.

System Design

The BN creator is using *XML* parsers in order to map the *XML* model structure into a causal BN structure. The created *DAG*-structure is automatically oriented from cause to effect (encoded in the XML hierarchy) and is completed with *CPT*s. High probabilities (near 1) are assigned to BN parent-child configurations mapped from explicit XML-dependency relations. All created *BN* models are saved in a Database ready for on-line use. Interconnections between XML failure trees (e.g. Fig. 3) are mapped into OOBN (Fig. 4), which speeds up the RCA since the inference is performed locally in each sub-BN.

Automated Creation of Bayesian Networks Structure (DAG) and parameters (CPT)

The creation of *BN*-graph (DAG), see Fig. 1, from *XML*-failure tree (structured data) includes several steps:
- The failure (from XML) is mapped into observed *failure* node (in BN).
- The checkpoints for all hypotheses for the same XML-failure tree are mapped into effect nodes in the BN graph.
The effects can also represent *early symptoms of abnormality* in the process, which allows performing a corrective action before the actual failure has occurred.

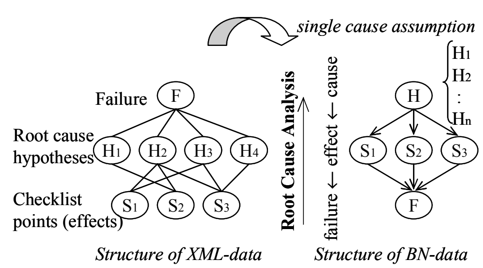

Fig. 1. Creating BN models for RCA from the hierarchical structure of XML-data models

- The XML-hypotheses are mapped into discrete root cause nodes in the BN graph. An extra root cause state can be added for the possibility of novel unknown fault hypothesis. *Single cause of a failure* is represented by one BN node, which states are *mutually exclusive and exhaustive hypotheses,* Fig. 1. The main assumption for applying single fault modeling approach is that everything was properly functioning before the failure was observed. It is also applicable to multiple causes, since they can be handled one at a time. The BN incorporates constraints when multiple causes have to be modeled explicitly, as shown in Fig. 2. Based on the evidence: "the plate is not cut through", the RCA algorithm ranks "damaged nozzle" as the most probable (62.9%) root cause of the problem. DCS measurement of the current and an automated vision system can provide evidence on the "plasma_cut" states and thus, confirm or reject this conclusion. User feedback on the actual root cause is used for supervised sequential learning.

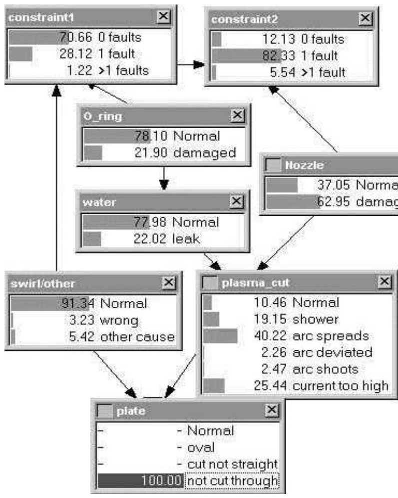

Fig. 2. Compact sub-BN for edge quality of cut.

Object Oriented BN (OOBN). Case study

The use of OOBN for facilitating the construction of large and complex domains, and simple modification of BN fragments was discussed in Koller D. And Pfeffer A. (1997). We use this idea to model all (DCS and computed) signals uncertainties and signals level-trend classifications as small standardized sub-OOBN or fragments within the OOBN of the problem domain. We also use OOBN for top-down RCA of industrial systems, which allows different levels of modeling abstraction.

We discuss RCA of the process operation cutting in a hot rolling mill.

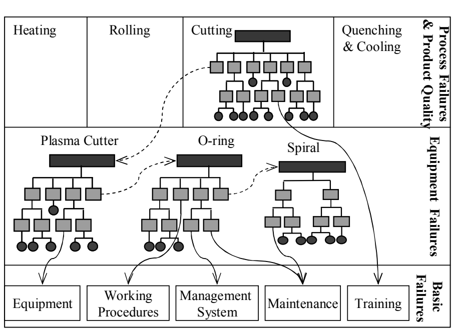

Fig. 3. RCA model library with interconnected failure trees (as XML-structured data)

The knowledge-based library of RCA models is in the form of XML-hierarchically structured and interconnected failure trees, Fig. 3. At the top are abnormalities in process operation and output quality,which can originate from abnormalities in equipment or process conditions, which could be due to basic failures. This structure is mapped into OOBN-instances, Fig. 4.

In the hot rolling mil, the slab is heated to become malleable. Rolling is flattening the heated slab into the desired thickness and dendrite orientation. The quality output variables from the rolling serve as BN input nodes of the consequent cutting process. Moreover, the interconnections between failure trees are mapped as BN nodes of input and output type in the master-BN or its OOBN-instances. RCA of the cutting process is modeled as OOBN-instance node "*process condition & output",* which requires an input (modeled as BN input node) from BN-instance node "*equipment condition"* of plasma cutter, requiring an input on *basic failures*, e.g. O-ring condition. Behind each instance node is a sub-BN, which is mapped from XML-structured failure-tree as discussed previously. For example, the sub-BN for RCA on cutting quality of the plate's edge is given in Fig. 2.

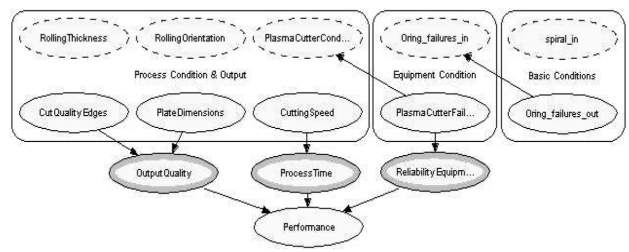

Fig. 4. Failure trees interconnections modeled as master-BN with OOBN-instances for RCA of cutting and its process performance monitoring

The performance monitoring can be applied to all four processes for monitoring of the overall plant efficiency.

On-line use and Algorithm for Adaptive RCA

The risk of abnormality in process operation is detected by an adaptive classification of level-trend patterns of signals. Then, the *BN* Inference Engine accesses the BN models. The *BN* Inference Engine is updating the posterior probabilities (under uncertain, changing and/or incomplete data) of possible root causes (H_i) of a failure, based on evidence (ε) entered as early abnormality symptoms. The inference uses the Bayesian theorem $P(X|Y) = P(Y|X)\,P(Y)/P(X)$, which becomes:

$$P(H_i|\varepsilon) = P(\varepsilon|H_i)\,P(H_i) \,/\, \left(\Sigma_{n=1..N} P(\varepsilon|H_n)\,P(H_n) \right)$$

The use of Bayesian inference engine allows fast simultaneous evaluation of several root causes under uncertainties related to changes or deviations of normal operating conditions in the industrial process or system. This is feasible, since the observed symptoms are entered automatically as one evidence set in the *BN* model, where all hypothesis for a certain failure are built in (see Fig. 1).

Fig. 5 shows the scheme for automated simultaneous verification of several root cause hypotheses by use of Bayesian inference and supervised sequential adaptation.

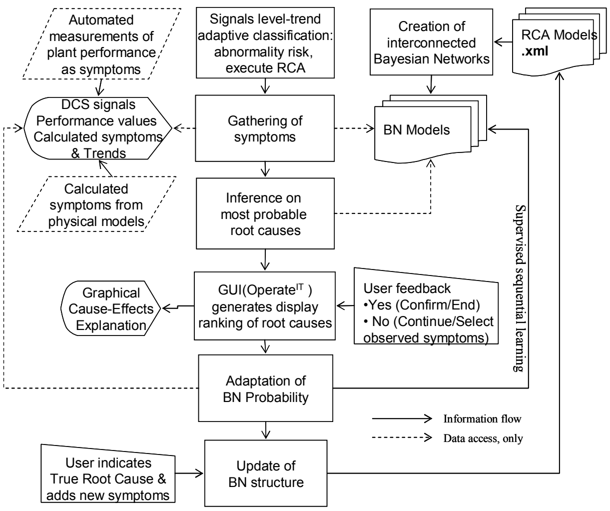

Fig. 5. The basic algorithm for Adaptive Root Cause Analysis by Bayesian Inference.

The basic algorithm for RCA is modification of the troubleshooting algorithm of Heckerman D. et.al (1995). Here, we extend it to monitoring of process condition, risk assessment for early warnings of abnormalities and predictive maintenance. This is reached by the use of adaptive level-trend classification of signals, which are chosen to be of predictive character for the process operation. Higher automation and precision is provided with combined evidences from DCS signals, computed symptoms by physical models, plant performance measurements and observed symptoms by user. The evidence data is classified into discrete states: low-normal-high for each signal and decreased-steady-increased for its trends. The classification is adaptive to process variations in different operating regions.

The *RCA* system collects on-line the operator feedback to system advice, i.e. user final indication on actual root cause, which is used for adaptation. It also collects new operator experiences within the problem domain for structure update, e.g. adding new observed symptoms of a failure/abnormality and their weighting in relation to existing ones for probability update, etc. The obtained system deduction on possible root causes can be represented together with graphical cause-effect explanations of conclusions and recommendations on suitable actions or safety procedure for correction of the failure or abnormality in process behavior.

Sequential learning of probability is based on the algoritm by Olesen K.G. et.al (1992). It is extended to supervised adaptivity due to user feedback on actual root cause, which the system combines with process conditions in their corresponding states configurations. Structure update is based on user indications of true root cause and may include new symptoms into the XML-data, from which the BN models are completed with "Noisy-AND/OR" CPTs for all new nodes. Sequential probability learning helps to adjust on-line the CPTs of existing or new added symptoms, effects and root causes in order to reflect the observed dependency relations.

Conclusions

The proposed generic solution for RCA is applicable to different Process Industries. For development time efficiency is preferable to use hierarchically structured knowledge library or database, which allows to automate the creation of BN. When extensive database on faulty operation is built, the structured knowledge on abnormal scenarios can be used as constraints on BN learning.

The use of object oriented BN allows more efficient model construction by completing the sub-BN of the problem domain with standardized sub-BN fragments for abnormality risk assesment, as well as efficient handling of interconnections between failure trees for fast reasoning on root causes under process uncertainties.

The object oriented BN framework fits very naturally into the ABB industrial IT environment, which utilizes aspect objects as containers of different applications communicating via the aspect integration platform in order to allow overall process optimization. When deployed in the industrial plant, the implementation of sequential adaptivity allows learning the local BN model with its domain specific probability data.

The accumulated knowledge is processed by a computerized system utilizing Bayesian Inference to provide decision support with explanation facility and has the advantage of being non-forgetting, independent of circumstances perceived as critical by a human.

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