Villez, K, Spinner, T, Garcia, H, Rieger, C, Venkatasubramanian, V (2010). Bayesian belief networks (BBNs) for integration of parallel fault diagnosis modules into supervisory control systems. Proceedings of the 2010 AIChE Annual meeting, Salt Lake City, UT, USA, November 7-12, 2010, 260



# Bayesian Belief Networks (BBNs) for Integration of Parallel Fault Diagnosis Modules Into Supervisory Control Systems

**Wednesday, November 10, 2010: 8:30 AM**

250 D Room (Salt Palace Convention Center)

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### Introduction

The safeguarding of the integrity of large and complex systems is a long-standing problem in control engineering. The problem is relevant in the context of large-scale systems such as electricity, transportation and communication networks, hazardous processes like nuclear and certain chemical production systems, where resiliency of the designed systems is vital.

The problem has been attacked from many angles, using very different techniques, and by many researchers, applying different schools of thought, theories and assumptions. A particular niche in this research area is the one of fault detection and identification (FDI). An overview of techniques in this area is given in a series of review papers [1-3]. Despite the important progress in both the FDI and control engineering area, fully integrated control systems which enable the detection, identification and accommodation of abnormal conditions in a process have not been accomplished yet. We are investigating this opportunity in a project that has been set up to make critical advancements in the integration of available techniques for automated management of abnormal events. Our study is particularly focused on a pilot-scale plant, both established in real-life and in simulation, which mimics the hydraulic behavior of a secondary cooling loop in a nuclear plant. A crucial deliverable of the project is that several identified FDI methods can be implemented in parallel and used simultaneously. Simulation and real-life testing will be used to ensure that both theoretical and practical challenges for the project are tackled effectively. As a result, critical steps will be made toward automated fault diagnosis for complex systems, which will reduce the impact of fault and failures on the system and its performance, leading to increased resilience [4] of the automated system.

### Bayesian Belief Networks for FDI integration

When applying different fault diagnosis methods in parallel it is likely that the formulation of results may vary which makes the integration a challenge. To solve this challenge a Bayesian Belief Network (BBN) will be constructed. Such a BBN structure is an intuitive way to handle the diverse set of information flows. To apply BB's to FDI, consider that a set of FDI techniques is implemented in a modular fashion with each of them operating in parallel. These techniques are set up in such a fashion that their outcome is a vector of probabilities or beliefs associated with all or a subset of the considered faults in the system. The BBN takes these probabilities as inputs and integrates the overall probability of each of the faults based on the separate module outcomes.

To do this, Bayesian statistical theory is applied straightforwardly. This theory is based on two rules, namely the sum rule and Bayes' rule. The sum rule says that the overall likelihood of an outcome, L(y), is the sum of the products of conditional likelihoods, L(y|x), and corresponding prior likelihoods, L(x) :

$$L(y) = \Sigma_x L(y|x) . L(x)$$

Bayes' rule says that the conditional likelihood of a first condition to a second condition, L(x|y), is the same as the likelihood of the second condition conditional to the first multiplied by the prior likelihood of the first condition and the total likelihood of the first, or mathematically:

$$L(x|y) = L(y|x) . L(x) / L(y)$$

Consider that L(x,y) represents the likelihood of a certain fault, x, conditional to available information, y. Then L(y|x) is the likelihood of having obtained that information in this fault case. L(x) the prior likelihood of the considered fault and L(y) the overall likelihood for the obtained information. The above two equations allow to compute the likelihood for all faults. One can then select the fault with maximum value for this likelihood, called the Maximum A Posteriori (MAP) likelihood. However, one then ignores that other faults may also explain the observations to a similar extent, especially when obtained likelihoods are close to each other. Subsequent control actions may therefore not be optimal or may actually degrade performance further. To avoid this, the likelihoods for each fault, rather than the MAP selected fault will be communicated to the controller module in the supervisory control system. The controller can then evaluate the best control actions by integrating expected performance over the range of probable conditions. As such, the effects of uncertainty in fault identification are reduced, thereby increasing the resilience of the whole system to accidental or willful faults and failures.

Figure 1: Feedback and propagation of information through the supervisory Control system

Figure 1 displays the Bayesian strategy graphically. At the left one finds the system which delivers various sensor signals to the control system. This information is passed on to the FDI modules first. Several methods will individually inspect these data for anomalies and associate likelihoods with potential faults. Following this, the Bayesian Belief Network integrates the results of the different methods to obtain overall likelihoods of all considered faults. This information is passed on to the control module. Selected FDI techniques include:

- Process history methods such as Principal Component Analysis, e.g. [5]
- Qualitative Trends Analysis (QTA), e.g. [6-7]
- Model-based fault identification, e.g. [8]
- Signed Directed Graphs (SDGs), e.g. [9]

**Benchmark model and pilot-scale plant**

A pilot-scale Machine Condition Monitoring (MCM) plant has been constructed for real-life experimentation and testing within the context of automated process state awareness and resilient control. The setup mimics the hydraulics of a nuclear plant service water system at 1/400 scale. The setup includes a default PI controller and artificial introduction of faults in the sensors and actuators (bias, drift, stiction). In addition, ball valve positions can be adjusted so to emulate tube ruptures or to introduce pump cavitation. An model of the same system has been set in ASPEN 7.1 (open-loop model) and Matlab (controls). Several fault models are included in the model, including sensor bias and drift, valve stiction and tube ruptures.

**Perspectives**

Expected results will have important impacts on control engineering of complex and safety-critical systems. First, the real-life validation of existing FDI techniques coupled with automated control logic will enable to validate accepted scientific results that have so far been established in silico only.

Second, the Bayesian developments for integration of FDI methods and to account for uncertainty in the control decision logic will provide the necessary tools to enable supervisory control under uncertainty. In addition, the modular FDI structure achieved by means of the BBN allows to add and activate new modules for FDI in a straightforward fashion. This allows to incorporate several methods with different theoretical bases into the same framework.

Third, we expect the integrated system for condition awareness and resilient control will be one of the first real-life implementations of a closed-loop supervisory control system on this scale. Major barriers between simulation-based research and real-life control engineering are expected to be alleviated by the end of the project.

**Acknowledgement**

Work supported by the U.S. Department of Energy under DOE Idaho Operations Office Contract DE-AC07-05ID14517, performed as part of the Instrumentation, Control, and Intelligent Systems Distinctive Signature (ICIS) of Idaho National Laboratory.

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**Extended Abstract:** File Not Uploaded

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