Introducing Default Models to Diagnose and Monitoring Dynamic Processes

Hatem AHRIZ
Laboratoire d'Intelligence Artificielle, Universite de Savoie,
2 route de Chambery, 73376 Le Bourget du Lac. FRANCE
phone: (33) 79 75 85 85 (7803), fax: (33) 79 75 87 85
email: ahriz@lia.univ-savoie.fr

Abstract: In this paper we describe an approach for introducing default models in the task of diagnosis. We are interested in diagnosis systems using a model of correct behavior of dynamic processes, and based on a causal representation. The objective is to allow these systems to continue monitoring after localizing faulty parts.

1 Introduction

Diagnosis Systems operating with only a model of correct behavior of processes, are unable to continue their task after default components localisation. However, Large-scale mechanisms such as chemical plants, space vehicles, and the human body have many self-regulatory systems, and are expected to continue functioning even in the presence of numerous faults.

Diagnosis thus, must blends smoothly into monitoring, where the task is to maintain an accurate model of a mechanism and its state, even while faults occur and are repaired [Kuipers 93].

A number of systems have been developed that deal with diagnosing and monitoring continuous dynamic processes: MIMIC [Dvorak 89], DOC [Kapadia & al.94].

Unlike these systems, our approach addresses the issue of introducing default models as an extension of some existing diagnosis systems that make use of only a model of correct behavior. Our contribution consists of an explanation[1] module, which is coupled with a diagnosis engine. An overview of the resulting system is provided in Figure 1.

To perform the monitoring task, the explanation module has to :

1. associate a faulty mode to the anomalous component ;
2. give an information about the (quantitative) importance of the fault ;
3. allow to continue a safe operation of the process by simulating the faulty behavior.

[1] in the sense of giving more details about the fault

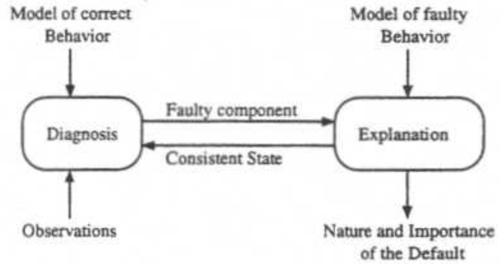

Figure 1: From Diagnosis to Monitoring

In this paper, we apply the above approach to a model-based diagnosis system for dynamic processes: PRIMACAUSE [Tomasena & al. 93]. Section 2 describes briefly PRIMACAUSE and its main tasks, while section 3 introduces default models.

2 Diagnosis System

There are two steps during the diagnosis task :

- The detection of a malfunction, based on a comparison of measured and simulated evolutions to detect malfunctions as early as possible
- The search of the primary causes of the malfunction, represented by a set of faulty components.

To reduce the algorithm's complexity [Gallanti & al. 89], [Mozetic & Holzbaur 91] in the search for primary causes, PRIMACAUSE uses hierarchical diagnosis based on the integration of two levels of abstraction (quantitative and qualitative) .

2.1 Modeling and causal reasoning

Causal reasoning is a central concept in Diagnosis, since it is used in the backward search to indicate what could have caused the malfunction.

The physical system is represented by a set of interconnected components (variables), and a set of functions called propagation functions, representing the cause-effect relations between the variables.

The propagation functions associated with the causality links represent the way in which a change

- monitoring the process by maintaining an accurate model.

3 Introducing Behavioral Modes

Introducing behavioral modes in diagnosis system dealing with only a model of correct behavior is done through two phases :

3.1 Off-line Phase

This phase is performed with the contribution of the process engineer, when the process is still off-line. The goal is to give answers to two questions :

- How to represent faults ?
- and, How to establish a relation between the fault and the faulty component ?

The first question addresses the task of modeling, while the second tries to introduce causality to deal with the representation used by the target systems.
The process engineer use two kinds of knowledge:

- experience acquired from similar processes ;
- chemical, hydraulic ... laws.

Modeling

Let us see the example of leak (or blockage) occurred on Tank-1 . We can "intuitively" Consider it as an outlet, as shown in Figure 7.

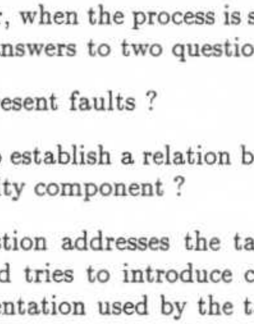

Figure 7: Representing leak and blockage

The new causal graph is obtained by associating a node to the fault (leak or blockage) and arcs between fault and component as shown in Figure 8.
In the case of leak (if L represents its outlet), we can establish that:
$\Delta L = f4(\Delta WL) = a.\Delta WL$; (Step function) with "a" a coefficient representing the valve open importance.
$\Delta WL_L = f5(\Delta L) = -b.\Delta L.time$; (Ramp function) with "b" a coefficient representing the influence of leak flow on the tank level.
The ΔWL_L influence is added to the other influences coming to WL.
The sign (-) means that the leak tend to lower the tank level.

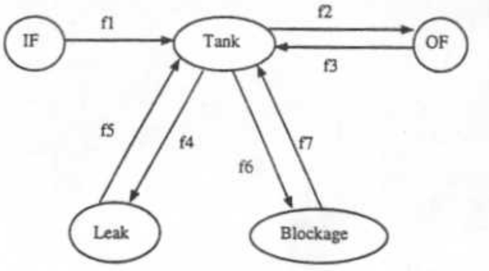

Figure 8: Faults on the causal graph

Coefficients "a" and "b", will be identified analytically later on the On-line phase. They will allow us to quantify the importance of the fault and to simulate the faulty model.

In the general case a default is characterised by :

- a variable (node) ;
- propagation functions (arcs) ;
- type of functions (step, ramp) ;
- general expression of functions (with unknown coefficient values).

Construction of decision trees

In order to reduce the algorithmic complexity of the candidate generation, all the possible faults which may occur on a given component (variable) are classified in a decision tree whose root represent the "qualitative" foreseeable discrepancy between simulated and measured values of the variable, and whose leaves represent faults. A given fault P_j is classified according to its effect on the component when it may occurs. Figure 9 shows the tree related to variable y.

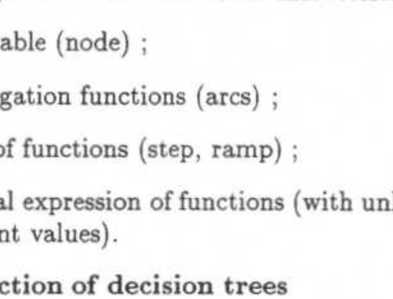

Figure 9: Construction of a decision tree

3.2 On-line Phase

The second phase of the module is the dynamic one, it consists in four main tasks :

1. Candidate generation;
2. Coefficient instantiation;

3. Candidate discrimination;

4. Simulation of the accurate model.

Their sequence in time is related to three events as shown in Figure 10:

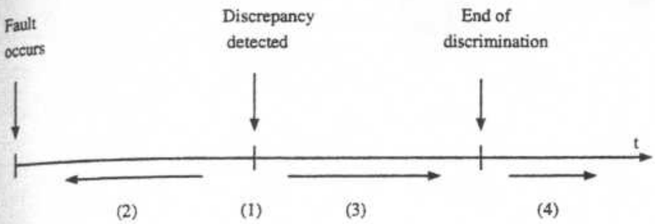

Figure 10: Sequence of On-line tasks

Candidate generation

The qualitative value (sign) of the discrepancy at the Primary-Cause variable is the key to prune the search space of candidate hypotheses. The result of using the decision tree is a set of hypotheses which may explain the discrepancy.

Coefficient instantiation

For each hypothesis generated by the decision tree, we try to instantiate its model scheme by computing (identifying) the coefficient values. This can be obtained by performing a counterbalance to the discrepancy between simulated and measured values. Thus, the leak variable evolution is, in fact, the evolution of the entity: $WL_{sim} - WL_{mes}$.

Figure 11 shows the evolution of variables related to the tank in presence of a leak that occurs at time t_2, and that is detected at time t_3.

Let us show how the explanation module computes the coefficients "a" and "b".

We have already established that : $\Delta L_{td} = a.\Delta WL_{td}$; so the coefficient "a" is given by the following expression:

$$a = \frac{\Delta L_{td}}{\Delta WL_{td}}$$

where

$$\Delta WL_{td} = (WL_{sim})_{td} - (WL_{sim})_{td-1}.$$

The expression of ΔL_{td} follows from:

$$\Delta L_1 = (WL_{sim} - WL_{mes})_{t1};$$

$$\Delta L_2 = (WL_{sim} - WL_{mes})_{t2} - (WL_{sim} - WL_{mes})_{t1}; ...etc.$$

$$\Delta L_{td} = (WL_{sim} - WL_{mes})_{td} - (WL_{sim} - WL_{mes})_{td-1}$$

where td is the fault detection time.

Likewise :

$$(\Delta WL_{td})_L = -b.\Delta L_{td-1};$$

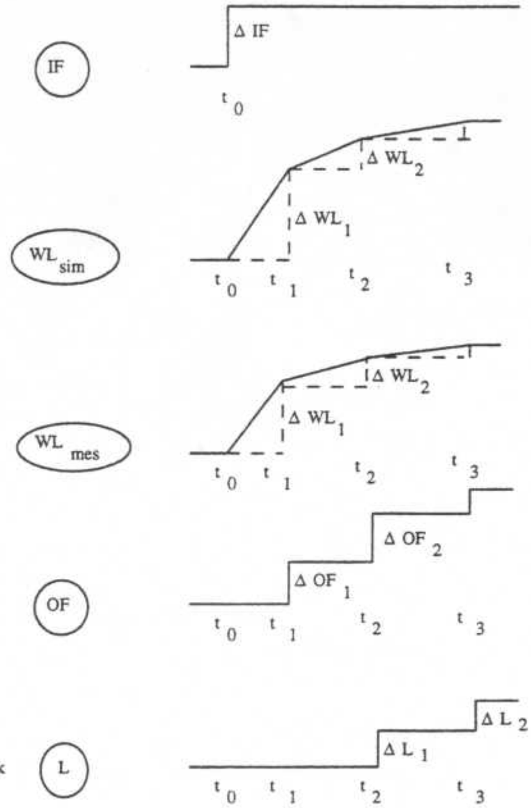

Figure 11: Evolution of some variables in presence of a Leak

so "b" is given by:

$$b = -\frac{\Delta(WL_{td})_L}{\Delta L_{td-1}}$$

with :

$$(\Delta WL_{td})_L = (\Delta WL_{sim})_{td} - (\Delta WL_{mes})_{td} = [(WL_{sim})_{td} - (WL_{\cdot}$$

and

$$\Delta L_{td-1} = (WL_{sim} - WL_{mes})_{td-1} - (WL_{sim} - WL_{mes})_{td-2}$$

Candidate discrimination

In this step, we obtain additional information in order to discriminate among multiple candidates (faults) ; so the result is the hypothesis that makes the best explanation on what happened in the process.

A local simulation is used to determine the new deviation index of each candidate $DI_{\{c\}}(WL)$, which represent the $DI(WL)$ after introducing the fault in the causal graph .

Three cases may arise :

- c explains $DI(WL)$ if $DI_{\{c\}}(WL) = 0$;
- c does not explain $DI(WL)$ if $|DI_{\{c\}}(WL)| \geq |DI(WL)|$;
- c explain more or less $DI(WL)$ if $0 < |DI_{\{c\}}(WL)| < |DI(WL)|$.

An explanation degree :

$$\mu_E(DI_{\{c\}}(WL), DI(WL)) = max(0, 1 - |\frac{DI_{\{c\}}(WL)}{DI(WL)}|)$$

is determined at each step until we obtain a significant[2] advantage of one candidate.

Unknown faults:

We are in presence of an unknown fault, if no candidate explains the abnormal behavior of the process.

Simulation of the accurate model

We have now to maintain an accurate model of the process behavior by simulating the kept candidate.

PRIMACAUSE is transformed to make simulation on a new causal graph obtained by adding the fault models (nodes, arcs and propagation functions).

3.3 General Structure of the module

To summarise our approach, Figure 12 gives the general structure scheme of the module: Off-line phase is a knowledge acquisition phase whereas the On-line phase treats data coming from the diagnosis module.

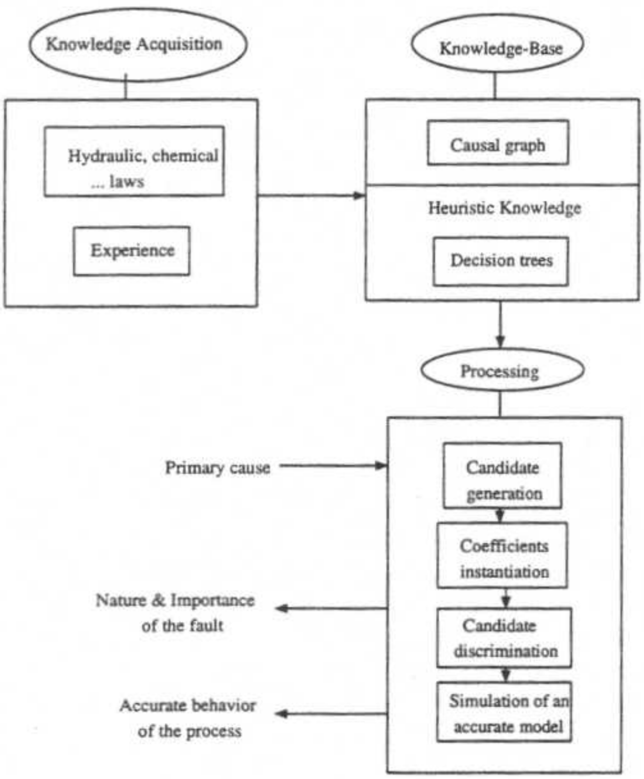

Figure 12: General structure of the Explanation Module

[2] We do not try to define the word "significant"

4 Related Work

Our work can be compared to MIMIC [Dvorak 89], as it uses fault models to continue monitoring and safe operation in the presence of faults. It tracks in parallel different behavioral modes, and thus the diagnosis approach relies completely on the anomalous modes. In our approach, we operate downstream the diagnosis module, which is able to isolate the anomalous component, even if modes of anomalous behavior are absent.

There are other works on operative diagnosis and monitoring: DRAPHYS [Abbott 90], PREMON [Doyle & al.], which are similar in objective with our work, but differ substantially in several aspects, especially the utilization of a single fault-free model.

More recent works are those on QHI [Catino & Ungar 95] and DOC [Kapadia & al. 94]. QHI (Qualitative Hazard Identification) matches a library of general faults such as leaks, brocken filters, blocked pipes and controller failures against the physical description of the plant. Faults may perturb variables in the original design model or may require building a new model. This is close to our approach of extending the original causal graph to fault models. However, in QHI, fault models are generated using QPC (Qualitative Process Compiler) [Farquhar 93] and simulated using QSIM [Kuipers 86]. We can also refer to DOC (Diagnoser Of Continuous valued systems) based on combined qualitative and quantitative analysis of an analytic constraint equation model of the process. It extends the parameter-based diagnosis techniques [Gallanti & al. 89], and apply them to component-based diagnosis. DOC performs a consistency-based dignosis and uses prior probabilities of component failures to generate a set of candidates that explains the observed deviations [Biswas & al. 94].

5 Conclusion

The aim of our work is to deal with default models in the context of diagnosing dynamic processes. We have described a general approach to extend diagnosis systems , based on a correct behavior of the process, and we have shown that it is possible to quantify parameters related to a default. This enable diagnosis systems to get more details about the process deviation, and track the default model.

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