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Prediction-based diagnosis and loss prevention using qualitative multi-scale models

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Abstract

A prototype prediction based intelligent diagnostic system that is capable of integrating qualitative and quantitative process models and operation experience in the form of HAZOP result tables is proposed in this paper. The knowledge base of the system is organized in a hierarchical way following the hierarchy levels of the multi-scale model of the process system. This supports the focusing of the fault detection and loss prevention and thus decomposes the otherwise computationally hard problem. The system is illustrated on the example of a commercial fertilizer granulator drum.

Keywords: process systems, multi-scale modelling, HAZOP analysis, diagnosis

1. Introduction

Fault detection and diagnosis in large-scale process systems is a challenging area from a theoretical point of view as well as being of great practical importance. The information available for this task is typically of mixed origin and nature. This includes detailed dynamic models for parts of the system or for certain operating modes, and heuristic operational experience. The results of a systematic hazard and operability analysis (HAZOP) that are often available in practice are also of use here. Therefore the possibilities for using only conventional model-based fault detection and diagnosis approaches based on either dynamic state-space (Blanke et al., 2003) or qualitative models (Venkatasubramanian et al., 2003) can be limited.

In addition, process plants can often be regarded as large scale systems, where both analytical and symbolical/qualitative techniques may fail to be practically feasible. In such cases, a multi-scale approach (Ingram et al., 2004) is needed both in decomposing and handling the available information and in performing the on-line fault detection, diagnosis and loss prevention in these large complex systems. The multi-scale approach provides us with a natural mechanism-driven hierarchical decomposition of the underlying process model with any related information and an integration framework to organize the information exchange between the partial models.

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Due to the above characteristics our aim is to develop a model-based fault detection, diagnosis and loss prevention method for large-scale process systems that is able to

- handle uncertain and/or heuristic knowledge together with partial dynamical information,
- automatically focus on the faulty part of the system,
- handle multiple fault hypotheses and improve the diagnosis.

2. Multi-scale view of fault detection and diagnosis

Fault detection requires a dynamic model of a plant to determine the time of occurrence. In addition, fault diagnosis needs the model of the particular faulty modes to be isolated. One then needs to combine these features with the multi-scale modelling paradigm in the case of large-scale process systems.

2.1 Prediction-based diagnosis

If the fault detection and diagnosis is based on a comparison between real plant data and the predicted values generated by a dynamic model then we speak about prediction-based diagnosis. In the case of large scale complex process plants one often needs to cope with uncertain or heuristic information when performing the prediction. Therefore, one should cope with uncertain predictions and with growing uncertainty in time.

In addition, the computation of predictions with heuristic, logical and/or qualitative models is a computationally hard problem. It is necessary to decompose the system and then to execute only the relevant part of the dynamic model by automatic focusing to achieve a practically feasible solution for large scale systems.

Sometimes, it is not enough to detect and isolate the faulty mode of a system but advice needs to be given to the operating personal on how to avoid the unwanted consequences of the fault be suitably chosen preventive actions. In such cases an additional “what if” type conditional prediction is also needed to investigate the effect of a possible preventive action.

2.2. HAZOP result tables

HAZOP is a systematic procedure for determining the causes of process deviations from normal behaviour and their consequences in a process plant. The results of a HAZOP analysis are collected in a table. A row in the table corresponds to a process deviation from its normal operation condition that is characterized by using the following columns:

- *Deviation* describing a ***symptom*** of a fault or malfunction,
- ***Potential causes*** that can be traced to root causes of the deviation,
- ***Preventive actions*** that can be used to avoid any hazard or drive the process back to its normal state,
- Possible consequences of the unchecked deviation.

HAZOP provides a comprehensive analysis of the key elements that help constitute an effective diagnostic system. The incorporation of failure modes can greatly enhance the tool’s capabilities.

2.3 Multi-scale modelling for diagnosis

The basis of multi-scale modelling is to divide a complex problem into a family of sub-problems that exist at different scales. Multi-scale models of a system can be organized along various scales depending on the system and on the intended use of the model.

A multi-scale model is an ordered collection of partial models or sub-models that are connected by a so-called *integration framework*. Even in the simplest case, there is at least one partial model on each of the granularity levels. The way the integration framework integrates the partial models in a multi-scale model depends on the partial models and on their information exchange (see Ingram et al. (2004)).

3. The components of a multi-scale diagnostic system

If one wants to develop a qualitative multi-scale, model-based diagnostic system, a real-time expert system is the best option to choose that supports hierarchical object-oriented model development, reasoning and has programmable automatic focusing features together with data acquisition and real-time capabilities.

3.1. Knowledge base (KB)

The knowledge elements that are needed to realize a multi-scale model-based diagnostic system are as follows:

- Symptoms
- Root causes and preventive actions
- Dynamic model segments capable of performing qualitative prediction.

The elements of the knowledge base are organized in a hierarchical way following the levels of a multi-scale model of the process system as Fig. 1 shows.

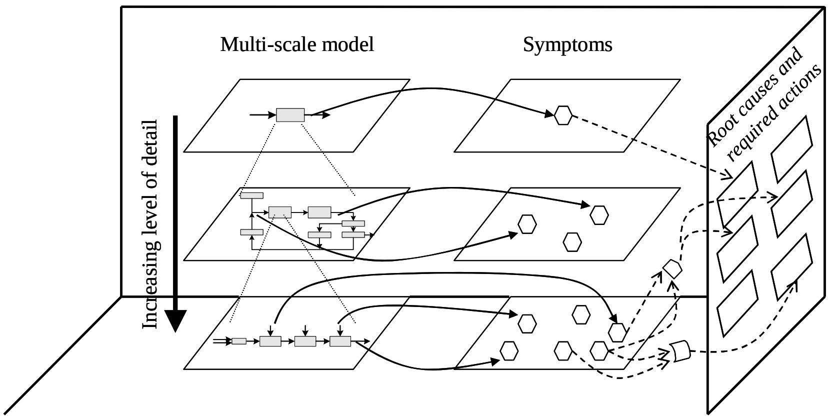

Figure 1. Hierarchical structure of the knowledge base

The symptoms, root causes and preventive actions together with their logical relationships in the KB can be algorithmically generated from the HAZOP result tables of the system. This part of the KB represents the heuristic operation experience provided by system experts.

The dynamic model segments stored in the KB describe the dynamic behaviour of the system in a given faulty mode associated to root causes. They can be algorithmically generated from the detailed simulation model of the plant by systematic model reduction. They are used for approximate (qualitative) prediction of the effects of possible preventive actions stored in the heuristic part of the KB.

For more details about the structure of multi-scale model for diagnosis we refer to (Németh et al., 2004).

3.2. Reasoning and prediction

The real-time operation of the system is cyclic, where the following steps are carried out in each discrete time interval.

1. Performing measurements and symptom detection:
   done by using the list of measured signals and the relationships between them and the symptoms.
2. Focusing and primary fault detection:
   starts by finding the hierarchy level and/or part of the model that is connected to the detected symptoms by using the symptom hierarchy connected to the given model hierarchy. By using the relevant entry or entries in the *HAZOP result table* the root causes and the preventive actions can be identified. Multiple symptoms connected to a common cause or multiple causes connected to common symptoms are also taken into account.
3. Fault isolation:
   Given the list of possible (cause, preventive action) pairs, the isolation, that is, the removal of the spurious pairs is performed by comparing measured data with predictions in the previous time interval.
4. Prediction:
   By using the dynamic model segments stored in the knowledge base, multiple one-step-ahead predictions are performed for each (cause, preventive action) pair with and without preventive action. If there is a unique solution and the suggested preventive action drives the system back to its normal operation mode then it is suggested to the Operator.
5. go to step 1.

4. Case Study: Diagnostic System for a Commercial Fertilizer Granulator Drum

The prototype of our qualitative multi-scale, model-based diagnosis system is realized in Gensym's G2 expert system (Gensym Corporation, 2004) development tool that supports hierarchical multi-scale model development, reasoning and has programmable automatic focusing features together with data acquisition and real-time capabilities. The proposed method and the prototype system are demonstrated on a commercial fertilizer granulation drum example (Ingram and Cameron, 2004). The system is for production of mono-ammonium and di-ammonium phosphate (MAP, DAP).

4.1. The granulator drum

The granulator circuit contains the granulator drum where fine feed or recycle granules are contacted with a binder or reaction slurry. The binder can be added at various points along the axial direction of the drum, thus controlling moisture content in the drum. Growth occurs depending on a number of operational and property factors. Drying, product separation and treatment of recycle material then occurs.

4.2. The structure of the diagnostic system in G2

The structure of the diagnostic system can be seen in Fig. 2. The system consists of three parts. The fault detection and isolation part is implemented in G2. We have used G2 for the model-based prediction part where we implemented the dynamic model segments in the form of Petri nets. The input measured data for the diagnosis is provided from the granulation circuit or a detailed model of the granulator drum (Balliu, 2004) implemented in the Daesim Dynamic simulator (Newell and Cameron, 2004). In our prototype system this detailed model serves as the "real plant".

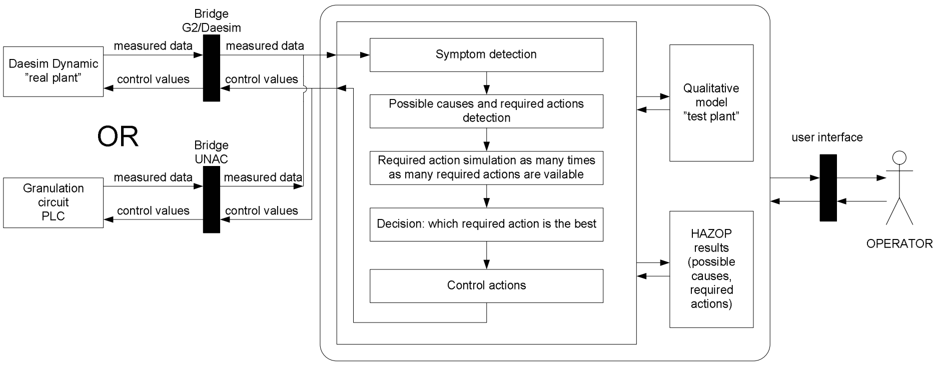

Figure 2. The structure of the diagnostic system

When a symptom is detected using the procedure *Symptom detection*, then the possible causes and required actions are identified by the procedure *Possible causes and required actions detection*. The operator is alerted to the symptom and given advice in order to rectify the problem.

The diagnostic system uses the possible preventive actions to predict their effects using the procedure *Required action simulation*. Sometimes the symptoms do not unambiguously define the possible causes, so the required actions are also indefinite. That is why the prediction for every identified required action is tested before any particular action is chosen. To find the best control action the procedure *Decision* makes a decision based on the prediction result. The procedure *Control actions* changes the value of the control variables in the "real plant".

4.3. Focusing and qualitative prediction

Having determined the possible causes and required actions by the procedure *Possible causes and required actions detection,* we need to focus on that part of the system where the possible causes are occurred. The focusing is directed by the identified symptoms that are connected to the relevant level and dynamic model segment thereon related to the fault. These partial models are implemented in the form of hierarchical Colored Petri Nets (CPNs) in G2 (see Németh et al. (2004) for details).

The result of the Procedure *Required action simulation* is the computed qualitative response of the system for the required action(s) by using the CPN model.

4.4. Simulation Results

To test the effectiveness of the knowledge base the disturbances in model input parameters (e.g. binder flowrates, feed flowrates) were used to evaluate the effects on the important controlled variables such as the recycle ratio and the particle size distribution. Fig. 3 shows the operator interface when the binder flowrates are changed causing some faults.

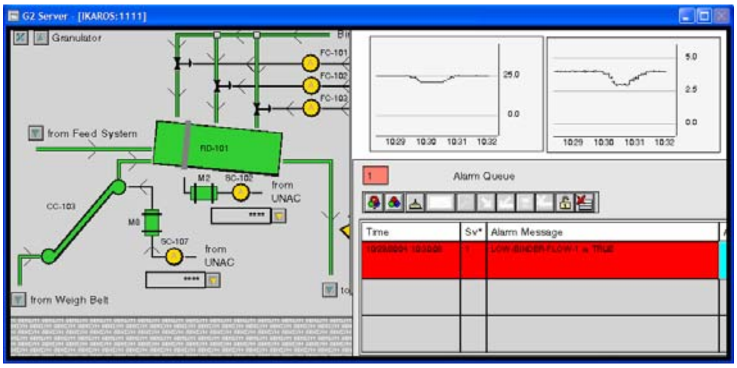

Figure 3. The operator interface of the faults of binder flowrate

4. Conclusion

A prototype prediction based intelligent diagnostic system that is capable of integrating qualitative and quantitative process models and operation experience in the form of HAZOP result tables is described in this paper that is implemented in G2. The critical part of the system is the CPN model based focusing and prediction to test the validity of the possible preventive actions.
Further work is needed to investigate the effect of the hierarchical model decomposition and of the uncertainties on the diagnostic resolution and possible action determination.

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