PREDICTION BASED DIAGNOSIS USING ARTIFICIAL INTELLIGENCE METHODS

Theses of PhD dissertation

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1 Motivation and aim

Equipment failures of large and complex safety-critical plants are unavoidable. The forthcoming fault, failure changes the properties of the system and therefore its operation. In case of faulty operation, the fastest and most accurate fault localization is necessary, and with the help of this information the adverse consequences have to be determined. If there is enough information it is possible for the fault to be be identified in time and corrections can be made.

Fault Detection and Diagnosis (FDD) is important and lately it has become more and more conspicuous in the area of process engineering as well as in other engineering areas. Abnormal Event Management (AEM) [1] has also gained a lot of attention nowadays. The aim of AEM is detection, diagnosis and correction of errors occurring in a system. Fault Detection and Diagnosis is one of the main parts of Abnormal Event Management. The early identification and diagnosis of errors helps to prevent the spread of abnormal events and decreases productivity loss while the plant operates in a controllable range.

Industrial statistics show that big catastrophes are caused by faults in chemical plants. Small faults are very frequent in such plants (they occur nearly every day), causing injuries, diseases, and loss of billions of dollars [2]. This is why discovering faults in the early stage is very important. This way grave consequences can be avoided.

Operators of plants usually do not have professional skills concerning the system supervised and operated by them. However it can be of crucial importance in an abnormal or dangerous case to make a correct decision in the appropriate time and intervene so that the system gets back to normal and safe operating mode. To this end high level systematic theoretical and practical knowledge is necessary. Heuristic operating information can be obtained during the identification, or diagnosis of the danger as well as estimation and reduction of the damages using the method of Process Hazard Analysis (PHA) [3]. In PHA studies various methods are used such as Fault Tree Analysis (FTA), Hazard and Operability Analysis (HAZOP) [4], or Fault Mode Effect Analysis (FMEA) [5].

To fill the gaps in the operator's knowledge support of *intelligent systems* is required which ensure the safe operation of the plant or system. These intelligent systems operate using a framework consisting of some heterogenous expert knowledge (HAZOP, FMEA), some dynamical model of the system and the industrial experience. Since the plants are different, it is difficult and impractical to implement a unified and independent diagnostic system.

According to the above, I have chosen the research, development and analysis of intelligent diagnostic methods applicable in large scale and complex chemical plants (process systems) as the subject of my doctoral study.

1.1 Methods and Tools

Tools and methods originating from various fields: systems and control theory, artificial intelligence and process systems were applied because of the interdisciplinary nature of the work.

Prediction based diagnostics Process fault diagnosis [6, 7] has an enormous literature: analytic methods (eg. [8]), artificial intelligence based techniques (eg. [9]), statistical approaches (eg. [10]).

Fault detection and analysis methods can be separated into three main groups [11]: model free-, model based-, and knowledge based methods.

Model free methods do not use the system model. For example if the system operates in the neighborhood of an approximately steady state then limit checking usually works fine. The great advantages of these methods are simplicity, speed and reliability. Drawbacks may occur if the system has no operability region or if it changes frequently since the input dependent and situation dependent setting of the limit checking is a difficult problem.

The point of model based methods is the analysis of the analytic redundance based on signal- and process analysis. For the analysis of measurable signals correlation functions, frequency domain or statistical decision theoretical methods are used most frequently. In the case of model based systems parameter- and state estimators and fault detection filters are used together with the mathematical models of the processes and the failures for process analysis [7].

Prediction based diagnostics - a system theoretical approach In system theory input-output models and state-space models are used to describe dynamical systems [12]. Systems are influenced by disturbances from the environment. Disturbances can be modeled as unknown (uncontrollable) inputs. Process faults, therefore, can be regarded as disturbances acting on the system and causing changes on its output independently of the measured inputs. A nonlinear discrete time time-invariant state-space model extended with disturbances can be given in the following form:

$$x(k+1) = \overline{f}(x(k), u(k), z(k)) , \quad x(0) = x_0$$

$$y(k) = \overline{h}(x(k), u(k), z(k))$$

where $x(k)$ is the vector of state variables, $u(k)$ is the vector of input variables, $y(k)$ is the vector of output variables, $z(k)$ is the disturbance vector, $\overline{f}$, and $\overline{h}$ are smooth nonlinear functions.

The aim of diagnosis is to discover, detect and isolate system faults and failures in different faulty modes using measured data and the system models describing the correct and the faulty operation. If the system theoretical model of the dynamical system to be diagnosed is available then two kinds of diagnoses can be performed [13]: diagnosis based on prediction error and identification based diagnosis.

Model reduction for diagnostic purposes In systems and control theory models of different fullness of details are necessary for different purposes. That's why a model prepared for a given purpose must have all important dynamical properties of the real system (such as stability properties, or the main time constants of the system), but this model should not produce behavior which can be neglected, or irrelevant from the actual viewpoint. There are various different methods available for model simplification and model reduction to achieve a model of appropriate complexity. They can be categorized based on the applied engineering knowledge used for model simplification.

Model reduction methods are of black box type: they use state transformations to determine the combinations of original state variables which don't have significant impact on the input-output behavior so they can be neglected.

Model simplification methods use engineering knowledge and operational experiences for omitting state variables. The selection of the state variables to be omitted is based on the dynamics and the physical meaning of the original state variable. For example, Leitold *et al.* (2000) [14] and Hangos and Cameron (2000) [12] proposed a graph-theoretic method for the structural simplification of dynamical process models with concentrated parameters. Németh *et al.* (2005) [15] gives a systematic method for the simplification of nonlinear state-space models with concentrated parameters which is based on physical insights and takes a previously defined performance criterion into account.

Unlike the above, the model simplification for prediction based diagnosis purposes is not analytic, but it is based on empirical knowledge, and its aim is to decrease the model size so that the model describes the faulty operation in the given faulty mode, this way it is suitable for diagnostic purposes.

Knowledge based diagnostic methods Knowledge based methods are based on the observed symptoms and the available heuristical knowledge about process systems, where symptoms are defined to be the deviations of the characteristic measurable variables of the process from the reference values in normal operation. If no information is available with respect to the causality of faults of symptoms then statistical- or geometrical classifying methods are used which are trained based on the experiences. If the causality of faults-symptoms can be described by “if-then” rules, then using reasoning methods is customary.

Knowledge based diagnostic techniques differ not only in the type of the used information but also in the diagnostic search strategies. Usually, the diagnostic searching strategy highly depends on the representation scheme of the knowledge which is determined by the characteristics of the a’priori knowledge. That is why the type of information (set of failures, connections describing the relation between observations (symptoms) and failures) is the most important distinctive characteristic in the knowledge based diagnostic system. The collecting and detailed description of methods using a’priori information is discussed by Venkatasubramanian *et al.* (2003) [1, 16, 17].

The following methodologies and tools are used most frequently in knowledge based diagnostic systems:

- Petri nets,
- expert systems,
- multi-agent systems.

Diagnostic application of Petri nets coloured Petri net models are suitable for modeling diagnostic problems using different modeling methods (e.g. model based reasoning using cause-effect rules). First Portinale (1993) [18] published a solution for the Petri net based modeling and solving of diagnostic problems in the case when the diagnostic problem is modeled in the form of datalog rules [12].

Another way of using Petri nets for fault diagnosis is the depicting and analysis of connected fault trees. The publication of Zouakia *et al.* (1999) [19] deals with this field.

Petri nets combined with other techniques applied in the field of artificial intelligence (e.g. fuzzy inferences [20], neural networks [21]) also provide an opportunity for fault diagnosis. In the above cases the Petri net is just a framework in which the applied techniques are used.

The signed directed graph (SDG), which is applicable for describing cause-effect relations is a widely used tool in the fault diagnostic field [16].

Some publications [22, 23, 24] deal with the application of Petri net models for automatic HAZOP analysis in which HAZOP digraph (HDG) models are used to accomplish the diagnosis problem.

Diagnostic expert systems Expert systems solving diagnostic problems [25] is one of the primary fields of application of expert systems, therefore it has great literature. In the literature diagnostic expert systems related to different process systems are available. Venkatasubramanian *et al.* (2003) [17] gives a survey on applying expert systems for fault detection and diagnostic purposes.

Venkatasubramanian *et al.* (e.g. [23, 26]) deal with the application of HAZOP knowledge in diagnostic expert systems.

Diagnostic application of Multi-agent systems Because of the variegated interpretability of agents the applicability of multi-agent systems is multifold. Simulation applications play an important role among the possible applicability fields of agents and multi-agent systems. Agents are greatly useful in the implementation of diagnostic applications (e.g. [27, 28]), since the different subtasks are separated and only the needed ones are to be executed in a given diagnostic step. As the agents are not fixed to a place they can work in distant places, too.

Elements of prediction knowledge based diagnostic systems In the literature of knowledge based diagnostic systems working according to prediction principle the elements and concepts needed for such a system have already been crystallized.

Root cause In detection and diagnosis of the knowledge based fault a so called root cause can be assigned to every faulty model of the system. One occurrence combination of these root cases gives the cause of the fault. Root causes are frequently not measurable and have discrete values (indicator variables), thus from the system theoretical point of view a root cause can be regarded as a nonmeasurable disturbance in a process system for diagnostic purposes.

Symptoms A relation defined over measurable or computable quantities is called symptom if an optional failure or fault is connected to the root cause. From the operating point of view symptoms are known deviances which can be identified in a time dependent way because of the dynamical behavior of the system. Relations occurring in a symptom's definition appear most frequently as inequalities. The domain of symptoms is a set of logical values (true and false). In the case of dynamical systems the majority of the measurable quantities are time dependent variables, therefore the value (presence) of a symptom is also a time dependent quantity.

Hazard analysis, hazard identification Information needed for fault detection and diagnostic problems [1] can be obtained from different sources which can be described by different characteristics. These information sources contain conceptional design studies and hazard analysis, in addition to this the detailed dynamical models of subsystems and concrete operating modes, moreover heuristic operating experiences originating from operators and industrial workers.

HAZOP HAZard and OPerability analysis [4] applies a systematical approach for revealing hazards and operability problems originating from improper use and may have deleterious effects. The principle of HAZOP analysis is that deviations of the system's parameters or variables from their normal states is caused by already existing or emerging faults.

FMEA Fault Mode Effect Analysis [5] is a qualitative analysis of diagnostic aspect of systems, subsystems, equipments, functions, technological methods. Contrasted with HAZOP method which analyzes the succession and causality of processes taking place in the system it is mainly used for the fault analysis of mechanical and electrical equipments. FMEA charts the possible failures of the equipments and subsystems and the local and system level consequences of the failures.

HAZOP and FMEA results are given in a table with fixed structure, where the fault isolating elements are written in spoken language.

Multiscale modeling As technology develops more and more complex plants are designed, built, and operated. The celebrated multiscale modeling [29] is the best-fit for describing these complex systems, although this is a less applied, but changing and developing field.

A multiscale model [30] is a complex mathematical model, consisting of two or more partial models, which describe the features on different scale levels (size- and time scale).

Scale levels can be formed along the characteristic time, or size of the objects and they contain the features described by the model. The displacement of objects, processes, or symptoms can be represented according to the characteristic time or size, or both on a logarithmic axis using scalemaps.

1.2 Aim

The aim of my work was to work out prediction based diagnostic methods which can localize the fault if a failure occurs in complex process systems containing several equipments [12]. Afterwards, using the results of HAZOP and/or FMEA analyses determined by experts they determine the location of the fault and its consequences regarding the operability of the instrument and/or system and they advise possible interventions, preventing loss. I was to implement the algorithms using methods widely used in the field of artificial intelligence. I wanted to analyze the properties of the developed methods and tools using the carried out prototype diagnostic systems and case studies.

I defined the following tasks:

- Creating a diagnostic framework based on coloured Petri nets.
- Creating a prediction based diagnostic expert system.
- Implementing a prediction based diagnosis using multi-agent system.
- Creating a procedure that simplifies multiscale process models and can be used for diagnostic purposes, moreover, it uses the simplification steps widely used in engineering practice.

2 New scientific results

The main scientific contributions of the dissertation are summarized in the following theses.

Thesis 1 *Prediction based diagnosis using coloured Petri net* (Chapter 3) (**[P1], [P2], [P3], [P4], [P5]**)

A method has been developed for prediction based diagnosis realized by coloured hierarchical Petri nets, which define the structure and the knowledge elements of the Petri net based diagnostic system. Information used in the diagnostic system has been distinguished based on its type: the hierarchical (multi-scale), the symptom identification and the root causes determination layers. The elements of the layers are organized in a hierarchical way following the levels of a multi-scale model of the process system. Information extracted from the HAZOP result table has been realized in the form of "if-then" rules.

The Design/CPN computer tool for coloured Petri nets has been chosen for realization of the diagnostic system.

Thesis 2 *Prediction based diagnostic expert system* (Chapter 4) (**[P6], [P7], [P13]**)

A method has been proposed for the realization of prediction based diagnostic expert system. The diagnostic expert system has been built up as follows.

(a) The knowledge representation is needed for the realization of the multi-scale diagnostic expert system and it describes the knowledge coming from the experts. The heuristic knowledge elements (symptoms, root causes and preventive actions) originated from the HAZOP table and the logical relationships between them have been represented by rules. Every row of the HAZOP table is identified by *(cause, consequence, preventive action)* triplet.

(b) The diagnosis is based on rule-based reasoning method. The knowledge base consists of rules mapped from the HAZOP table, which has been divided into two parts: diagnostic rules and preventive action rules.

After the symptom detection for finding the hierarchy level and/or part of the model that is connected to the detected symptoms the *focusing* has been used by using the hierarchies of the model and the rules.

The prediction plays a part of the fault isolation so that the system compare variable value predicted in the previous diagnostic step with the corresponding measured values, thus eliminate the mistaken/false causes.

For the realization of the diagnostic system the G2 expert system shell has been chosen.

Thesis 3 *Prediction based diagnosis using multi-agent system* (Chapter 5) (**[P8], [P10], [P11]**)

A method has been developed for prediction based diagnosis realized by multi-agent system. The diagnostic expert system has been built up as follows.

(a) Considering the general and modular applicability of the diagnostic system, two sets of ontologies have been defined as a knowledge representation tool. The process-specific ontology describes the concepts, their semantical relationships and constraints regarded to the processes. The diagnostic ontology contains the diagnostic concepts and the semantic knowledge on diagnostic notions. A real-time database has been used to store the time-varying elements of the ontologies.

(b) The agents of the diagnostic system have been classified by the usage of ontologies, so there are process-related, diagnostic-related and real-time service related agents.

The diagnostic agents implicate in cooperation and/or perform numerical computations on behalf of the most accurate identification of the fault (Fault isolators), or the more complete diagnosis (Completeness coordinator agent), or the more consistent diagnosis (Contradiction, or conflict resolving agent).

For the agent based diagnostic method fault isolation was gained by the coordinated work of the HAZOP method that uses backward reasoning from the symptoms and FMEA method that implements forward reasoning from the root causes.

The multi-agent diagnostic system is implemented in JADE Java-based agent development environment, which is integrated with the JESS reasoning machine, with the Protégé ontology editor and with the MATLAB/SIMULINK simulation environment.

Thesis 4 *Simplification of multiscale models for diagnostic purposes* (Chapter 6)

([P9], [P12])

I proposed a method for the simplification of multiscale process models serving prediction diagnostic purposes.

As a starting point I described the problem statement of model simplification of multiscale process models using formal tools and I determined the necessary conditions of simplification: separating the levels of the time scale. I defined the steps of the multiscale models' model simplification: determining the time level corresponding to the given diagnostic scenario; the selection of the scalereduced nonlinear model; writing up the scalereduced linear model; determining the parameters of the scalereduced linear model. I proposed a method for the empirical determination of the time scale separation using the analysis of the step response functions that can be performed on the detailed multiscale model or on the real system.

3 Publications related to the theses

[P1] **E. Németh** and K. M. Hangos, "Prediction-based diagnosis using coloured Petri nets," in *Proceedings of the 4th International PhD Workshop on Information Technologies and Control - Young Generation Viewpoint, Libverda, Czech Republic*, 2003. on CD. (**1. thesis**)

[P2] **E. Németh**, R. Lakner, K. M. Hangos, and I. T. Cameron, "Hierarchical CPN model-based diagnosis using HAZOP knowledge," Technical report of the Systems and Control Laboratory SCL-009/2003, Computer and Automation Research Institute of HAS, 2003. `http://daedalus.scl.sztaki.hu`. (**1. thesis**)

[P3] **E. Németh**, "Diagnostic goal driven modelling and simulation of multiscale process systems," in *Proceedings of the 5th International PhD Workshop on Systems and Control - Young Generation Viewpoint, Balatonfüred, Hungary*, 2004. on CD. (**1. thesis**)

[P4] **E. Németh** and K. M. Hangos, "Multi-scale process model description by generalized coloured CPN models," Technical report of the Systems and Control Laboratory SCL-002/2004, Computer and Automation Research Institute of HAS, 2004. `http://daedalus.scl.sztaki.hu`. (**1. thesis**)

[P5] **E. Németh**, I. T. Cameron, and K. M. Hangos, "Diagnostic goal driven modelling and simulation of multiscale process systems," *Computers and Chemical Engineering*, vol. 29, pp. 783–796, 2005. (**1. thesis**)
Impact factor: 1.678 (2004)

[P6] **E. Németh**, R. Lakner, K. M. Hangos, and I. T. Cameron, "Prediction-based diagnosis and loss prevention using model-based reasoning," in *Lecture Notes in Artificial Intelligence*, vol. 3533, pp. 367–369, Springer-Verlag, 2005. (**2. thesis**)
Impact factor: 0.251 (2004)

[P7] **E. Németh**, R. Lakner, K. M. Hangos, and I. T. Cameron, "Prediction-based diagnosis and loss prevention using qualitative multi-scale models," in *European Symposium on Computer Aided Process Engineering - 15* (L. Puigjaner and A. Espuna, eds.), vol. 20A of *Computer-Aided*

Chemical Engineering 20 A/B, pp. 535–540, Elsevier Science, 2005. (**2. thesis**)

[P8] **E. Németh**, R. Lakner, and K. M. Hangos, "A multi-agent prediction-based diagnosis system," in *Proceedings of the 6th International PhD Workshop on Systems and Control - Young Generation Viewpoint, Izola, Slovenia*, 2005. on CD. (**3. thesis**)

[P9] **E. Németh**, R. Lakner, and K. M. Hangos, "Diagnostic goal-driven reduction of multiscale process models," Technical report of the Systems and Control Laboratory SCL-001/2005, Computer and Automation Research Institute of HAS, 2005. `http://daedalus.scl.sztaki.hu`. (**4. thesis**)

[P10] R. Lakner, **E. Németh**, K. M. Hangos, and I. T. Cameron, "Multiagent realization of prediction-based diagnosis and loss prevention," in *Lecture Notes in Artificial Intelligence*, vol. 4031, pp. 70–80, Springer-Verlag, 2006. (**3. thesis**)
Impakt faktor: 0.251 (2004)

[P11] R. Lakner, **E. Németh**, K. M. Hangos, and I. T. Cameron, "Agent-based diagnosis for granulation processes," 2006. Accepted to the ESCAPE-16 Conference. (**3. thesis**)

[P12] **E. Németh**, R. Lakner, and K. M. Hangos, "Diagnostic goal-driven reduction of multiscale process models," *Model Reduction and Coarse-Graining Approaches for Multiscale Phenomena*, ed. by A.N. Gorban, N. Kazantzis, Y.G. Kevrekidis, H.C. Ottinger, C. Theodoropoulos (Springer, Berlin–Heidelberg–New York 2006), 2006. In press.
(**4. thesis**)

[P13] **E. Németh**, R. Lakner, K. M. Hangos, and I. T. Cameron, "Prediction-based diagnosis and loss prevention using qualitative multi-scale models," *Submitted to Information Sciences*, 2006. (**2. thesis**)

4 Publications not related to the theses

[O1] **E. Németh** and K. M. Hangos. Deadlock analysis in hierarchical Petri nets. In *Proceedings of the 3rd International PhD Workshop on Advances in Supervision and Control Systems - Young Generation Viewpoint*, *Strunjan*, *Slovenia*, 2002. on CD.

[O2] Á. Kovács, **E. Németh**, and K. M. Hangos. Coloured Petri net model of a simple runway. Technical report of the Systems and Control Laboratory SCL-001/2004, Computer and Automation Research Institute of HAS, 2004.
`http://daedalus.scl.sztaki.hu`.

[O3] Á. Kovács, **E. Németh**, and K. M. Hangos. Modeling and optimization of runway traffic flow using coloured Petri nets. In *International Conference on Control and Automation - ICCA05*, pages 881–886, 2005. on CD.

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