ON THE APPLICABILITY OF STATE-OF-THE-ART FAULT DIAGNOSIS METHODOLOGIES TO SIMPLE AND COMPLEX SYSTEMS

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Abstract: This paper performs an analysis on the applicability of state-of-the-art fault diagnosis methodologies to both simple and complex systems. Here, a complex system represents a system whose global behavior, which emerges from the interactions between its usually large number of basic components, is difficult to accurately describe via a model. First, the basic notions used in fault detection and isolation, are introduced. Then, short reviews are given for the main quantitative methods, qualitative reasoning based methods, and soft computing approaches. The next section is dedicated to recent distributed approaches to fault diagnosis of complex systems. Finally, some conclusions are given.

Keywords: Fault Diagnosis, Complex Systems, Quantitative Methods, Qualitative Reasoning, Soft Computing.

1. INTRODUCTION

The goal of fault diagnosis research is improving the security, efficiency, maintainability and reliability of industrial plants. There are two main types of systems that are addressed: safety-critical systems such as nuclear plants and aircrafts, and lower safety-critical systems such as process and manufacturing plants. A fault diagnosis system is a monitoring system that is used to detect faults and diagnose their location and significance in a system (Chen and Patton, 1999). The diagnosis system performs mainly the following tasks: fault detection – to indicate if a fault occurred or not in the system, and fault isolation – to determine the location of the fault.

There are two main directions for developing fault diagnosis systems: using *hardware redundancy* or using *analytical redundancy* (Chen and Patton, 1999). Hardware redundancy uses multiplication of physical devices and, usually, a voting system to detect the occurrence of a fault and its location in the system. The main problem in this approach is the significant cost for the necessary extra equipment. Analytical redundancy uses instead redundant functional relationships between variables of the system. The main advantage of this approach

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compared to hardware redundancy is that no extra equipment is necessary. This paper reviews fault diagnosis schemes based on analytical redundancy.

When designing a fault diagnosis system the most common approach is to build first an analytical model of the monitored system able to describe reasonably accurate the behavior of the system during normal operation. Then, this model of the system is compared against the observed behavior of the system. The differences obtained, which are called *residuals*, are used to decide if there is or not a fault in the system and, eventually, which fault actually occurred. This scheme has been implemented by the major quantitative approaches on fault diagnosis, i.e. observer-based approach, parity relation method, parameter estimation method, etc. These methodologies are intended for linear systems or systems that may be linearized around a set of working points, and are well-established theoretically. The major approaches on quantitative fault diagnosis were developed during the 1980’s and early 1990’s. Some important tutorial papers from this period are Frank (1987), Isermann (1991), Basseville and Nikiforov (1993). The research community grouped around this general approach is known as the Fault Detection and Isolation (FDI) community.

During the last decade the research focused on qualitative models for non-linear systems. Soft-computing techniques: neural networks, fuzzy logic, and combinations of them are extensively and successfully applied. One important tutorial work is (Patton *et. al.*, 2000).

In the late 1980’s a group of researchers from the Artificial Intelligence community independently proposed a fault diagnosis theory based on First-Order Logic. The system is modeled using a oriented graph whose vertices are the components of the system and whose edges are the connections between them. The diagnosis consists in identifying the possible faulty components via an inference process. The papers laying the foundations of this theory are (de Kleer and Williams, 1984) and (Reiter, 1987). A more recent survey on this approach may be found in (Hamscher *et. al.*, 1992). The research community that follows this approach is known as the Model-Based Diagnosis (MBD) community. The relationship between the FDI approach and the MBD approach is studied in (Cordier *et. al.*, 2000) and (de Kleer and Kurien, 2003).

However, the state-of-the-art fault diagnosis methodologies are able to perform satisfactory well only on systems composed of a reasonable small number of interacting components. The weakness they all share is their inability to cope with complex systems. Isermann and Ballé (1997) underline the fact that a single diagnosis method is inadequate for matching all challenges posed by a complex system. Therefore, during last years, the fault diagnosis community concentrated their research efforts on distributed fault diagnosis methodologies. The main idea is to partition the monitored system in sufficiently small subparts and then to successfully apply state-of-the-art methodologies on these subparts. The global diagnosis of the system is going to be based on all these local diagnosis. A noteworthy research effort in this direction is the recent European Commission’s FP5 MAGIC Project (http://magic.uni-duisburg.de).

From the previous analysis, it may be concluded that currently there are two main trends in the fault diagnosis research field: (*i*) the earlier trend of finding methodologies suitable for fault diagnosis of systems composed of a reasonably small number of components, and (*ii*) the later trend of finding distributed methodologies able to partition a complex system into small enough subparts so that the local diagnosis may be successfully performed with state-of-the-art methodologies, and so that the global diagnosis may be obtained in a coherent manner from local diagnosis.

The present work performs an analysis of the applicability of state-of-the-art methodologies, included in the earlier trend, to both simple and complex systems. Here, a complex system represents a system whose global behavior, which emerges from the interactions between its usually large number of basic components, is difficult to accurately describe via a model. Section 2 introduces the basic notions used in fault detection and isolation. Section 3 provides a short review of the main quantitative fault detection and isolation methods. Section 4 discusses applications of qualitative reasoning to fault diagnosis. Qualitative reasoning represents an important methodology contributed by the MBD community. Section 5 provides a short review of the latest soft computing approaches contributions to fault detection and isolation. Section 6 is dedicated to recent distributed approaches to fault diagnosis of complex systems. These approaches are included in the later trend mentioned in the previous paragraph, and, from the results obtained so far, it seems that such approaches are needed in the case of complex systems. The last section draws conclusions on the practical applicability of the surveyed methodologies on both simple and complex systems.

2. BASIC DEFINITIONS

The basic notions presented in this section follow the IFAC Technical Committee SAFEPROCESS terminology in the field (Isermann and Ballé, 1997).

A *fault* represents an unexpected change of system function, although it may not represent a physical failure. The term “*failure*” indicates a serious breakdown of a system component or function that leads to a significantly deviated behavior of the whole system. The term *“fault”* rather indicates a malfunction that does not affect significantly the normal behavior of the system.

A *fault diagnosis system* is a monitoring system that is used to detect faults and diagnose their location and significance in a system. The system performs the following tasks: *fault detection* to indicate if a fault occurred or not in the system, *fault isolation* to determine the location of the fault, and *fault identification* to estimate the size and the nature of the fault. The first two tasks of the system: fault detection and isolation are considered the most important. Fault diagnosis is then very often considered as fault detection and isolation (FDI).

“The *model based fault diagnosis* can be defined as the determination of the faults of a system from the comparison of available system measurements with a priori information represented by the system’s analytical/mathematical model, through generation of residuals quantities and their analyses. A *residual* is a fault indicator that reflects the faulty condition of the monitored system.” (Chen and Patton, 1999).

3. QUANTITATIVE METHODS

The central issue in model-based fault diagnosis is residual generation. Each residual generation method has associated a specific technique of computing the residual vector. The goal of an *observer-based* approach is to estimate system output using Luenberger observers in a deterministic setting (Frank, 1987; Patton and Kangethe, 1989), or Kalman filter in the stochastic case (Tzafestas and Watanabe, 1990). Then the output estimation error is used as a residual. The *parity relation* method consists in checking the consistency of the measurements of the monitored system (Chen and Patton, 1999). The *factorization* method synthesizes the residual generator in frequency domain by matrix factorization using the input-output model of the monitored system. The method was initiated by Viswanadham, Taylor and Luce (1987) and extended by Ding and Frank (1990). Also, system identification techniques like *parameter estimation* could be also used in model-based FDI (Isermann, 1991; Isermann, 1997). The premise in parameter estimation methods is that the faults are reflected in the physical system parameters. The system parameters are estimated using parameter estimation methods and afterwards compared to the parameters offered by the reference model obtained in faulty-free condition. Any substantial difference between the two sets of parameters indicates a fault.

The practice shows that the quantitative methodologies as those mentioned before perform well on reasonably small systems. The modeling errors in the case of small systems do not consistently affect the diagnosis process. Unfortunately, trying to model accurately enough a complex system proves to be a difficult task. There is a high probability to obtain large modeling errors that will affect significantly the diagnosis process.

4. QUALITATIVE REASONING BASED METHODS

The main deficiency of the analytical methods is that an accurate mathematical model of the system cannot be obtained. Qualitative reasoning methods have the property that can handle incomplete knowledge about a system through a *quantisation* of the variables, i.e. partitioning the space into a finite number of disjoint sets (Lunze, 2000). Qualitative reasoning manipulates these subsets instead of single values. The relationships between these subsets are called *constraints* and are expressed usually by differential equations. This methodology proposed initially by Forbus (1984), de Kleer and Brown (1984), and Kuipers (1984), describes the structure of the system and simulates it in order to determine its behavior given an initial state. Kuipers (1986) introduced the well-known qualitative simulation algorithm called *QSIM*, the Qualitative Simulation.

Shen and Leitch (1993) propose an extension of *QSIM* algorithm called *FuSim* (Fuzzy Qualitative Simulation) that brings together qualitative reasoning and fuzzy reasoning. The main contribution of the *FuSim* algorithm is that unlike *QSIM* it allows to estimate temporal information on how long a system variable remains in a certain state and how long it takes to transit to the next state. This feature allows fuzzy qualitative simulation to be applied for FDI purposes (Leitch *et al.*, 1994) as FDI makes use of a description of system behavior along with temporal information on the changes occurred in the system behavior. Zhuang and Frank (1997) propose a *qualitative observer* that is used for FDI purposes. When a fault occurs in the system, there are variables in the model for which the observed qualitative states do not match the measured states. Lunze (2000) develops theoretical results regarding the diagnosis of the *quantised systems*. The previous results are developed and applied to diagnosis of valve faults (Lunze and Supavatanakul, 2002; Lunze and Supavatanakul, 2003).

Using qualitative reasoning based models for the monitoring systems fixes the problem of large modeling errors obtained when using analytical models. However, the model of a complex system may consist of too many constraints between the qualitative variables of the system. This fact makes the obtained model unusable for practical purposes. This problem is due to the usually large number of components of a complex system and to the even larger number of interactions between them, which may produce a global behavior difficult to describe.

5. SOFT COMPUTING METHODS

Another way to overcome the problem of modeling errors when using analytical models, especially when the monitored system is non-linear, is the use of soft computing techniques.

Neural networks may be applied in FDI systems for both detection and isolation (Patton *et. al.*, 1999). For detection phase, the normal behavior of the monitored system is *modeled* using a neural network. Residual signals are generated comparing the output of the neural network with the output of the system. For isolation phase, a neural network is used to perform the *classification* of the residuals into the corresponding classes of faults.

Fuzzy logic is also used to perform fault detection via modeling the normal state of the monitored system. Takagi and Sugeno (1985) model non-linear systems by using a set of linear models built around a set of operating points. The transition between different operating regions is performed using fuzzy logic. Lopez-Toribio *et. al.* (2000) design a fuzzy observer that uses a Takagi-Sugeno model. However, fuzzy logic is most commonly used to perform fault isolation tasks. Frank (1996) and Koscielny *et. al.* (1999) use fuzzy classifiers for residual evaluation purposes. The advantage of using this type of fuzzy classifiers is that the fuzzy rules provide details on the mapping of residuals to a faulty state via the use of linguistic terms.

Neuro-fuzzy systems represents a set of fuzzy rules put under the form of a neural network in order to make use of the learning, adaptation and parallelism capabilities provided by neural networks. The neuro-fuzzy systems may be used either for modeling or for classification purposes. In (Palade *et. al.*, 2002; Uppal *et. al.*, 2002) neuro-fuzzy systems are used for identifying the parameters of Takagi-Sugeno models. Two neuro-fuzzy systems used for fault isolation are the neuro-fuzzy hierarchical structures proposed in (Calado *et. al.*, 2001), and the B-Spline neural networks (Chen and Patton, 1999; Patton *et. al.*, 1999).

The main advantage of using soft computing approaches is that they accurately model the behavior of non-linear system. Their main disadvantage is that they all face the so-called "*curse of dimensionality*" when applied to modeling complex systems. In these cases, the structure and dimensions required for a neural network, respectively the number of fuzzy rules required by a fuzzy system, make the models too large for practical application.

6. RECENT DISTRIBUTED APPROACHES

There are two main approaches in performing distributed fault diagnosis of complex systems. One possible approach is to define a partition on the system structure and to assign one agent to each region of the partition. Each agent performs local diagnosis inside the region it is assigned to. Global diagnosis is obtained by defining a proper communication scheme among agents (Fabre *et. al.*, 2001; Letia *et. al.*, 2000; the DIAMOND project – Albert *et. al.*, 2001). Notice that this implementation focuses on the structural partitioning aspect.

The other possible approach to distributed fault diagnosis is to bring together the diagnosis expertise of different methodologies (the MAGIC project: Köpen-Seliger *et. al.*, 2003; Lesecq *et. al.*, 2003). That is, the agents represent in this case different diagnosis methodologies. The main task of the diagnosis system is to decide, for each region of the partition, the available diagnosis methodologies (agents) that provide best diagnosis results. Notice that, in this case, the implementation focuses on optimising the local diagnosis results.

The implementations mentioned above lack a coherent partitioning methodology of the structure of the monitored system into a set of regions such that the independence level of local diagnosis process for each region is *maximal* and such that the communication between different regions, required for formulating global diagnosis, is *minimal*.

The partitioning methodology proposed in (Bocaniala and Sa da Costa, 2004; 2005) partitions the monitored system into *fully* independent regions, i.e. *maximum* independence level of local diagnosis processes. The agents used within this framework are fully causally independent due to the causal independence of the corresponding regions in the partition. The fact that each region is causally independent by all other regions allows performing the diagnosis of that region locally, without needing to communicate with the rest of the partition. This property allows maintaining the diagnosis focus exclusively on those regions that are affected by faults. Hence, monitoring a complex system becomes a tractable problem. The partitioning also insures minimal borders between different regions, i.e. *minimal* computational complexity for communication. Communication between different regions is needed if and only if the causal independence between the regions in the partition does not hold anymore due to some fault occurrence.

7. CONCLUSIONS

As stated in Introduction, the authors consider that one of the main challenges that face the current Fault Diagnosis research is finding FDI methodologies capable to globally monitor complex industrial systems. The methodologies surveyed in this paper perform satisfactory well on systems composed of a reasonable small number of interacting components. However, the weakness they all share is their inability to cope with complex systems. Therefore, the survey in this paper strengthens the idea that a distributed approach is needed in the case of complex systems. The paper also reviewed the results obtained by recent distributed approaches to fault diagnosis of complex systems.

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