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Model-based fault diagnosis and prognosis of dynamic systems: a review

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Abstract

In maintenance of engineering systems, condition monitoring, fault diagnosis and fault prognosis constitute some of the principal tasks. With the increase of the number of machines within processing plants and their operational complexities, many engineers and researchers have started looking for automated solutions for these tasks. In most of the proposed solutions, these dynamic systems are modelled using tools like automata, Petri nets, bond graphs and Bayesian networks to diagnose and predict faults in those systems. This paper reviews these graphical model-based techniques related to fault diagnosis and prognosis and give suggestions for future research directions identifying research gaps in the field.

Keywords: model-based systems; fault diagnosis; fault prognosis; automata; Petri nets; bond graphs; Bayesian networks

1. Introduction

When engineering systems are designed sensors are added for control and feedback purposes, but when a fault occurs or when there is an impending fault in a system, this set of sensors may not be adequate to diagnose it or

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predict it before it takes place. Examples of this kind of situations would be mechatronic failures of aircrafts, vehicles, power plants, rapid rail transport systems and other safety critical reactive systems.

If the system behaves outside the specified behaviour for it, then we say there is a fault in the system. Failure of a bolt is a permanent fault while a loose wire connection is a temporary fault [1]. These faults are also called parametric faults because they change the system parameters like voltages, speeds etc. When this change is rapid compared to the system sampling time we call it an abrupt fault and an incipient fault, if it is a small drift in system parameters over a longer period.

In fault diagnosis, there are three operations; detection of occurrence, isolation and fault accommodation. In fault prognosis, observations are used to predict likely fault occurrences, whence alarms are activated [1].

The model-based solutions proposed for these problems can be grouped into automata, Petri net, bond graph and Bayesian networks based approaches, each of which have been adapted to find solutions in discrete event dynamic systems, continuous variable dynamic systems and hybrid systems (which is a combination of both types).

Some researchers may also be interested in state space-based fault diagnosis techniques, which mainly consider continuous variable behaviour of signals from/to sensors and actuators. Model based systems of this type have been reviewed in publications [2-5] and interested readers may refer to them for more details. This paper covers graphical model-based systems. Due to page limitation we have included in our reference list only the smallest subset of more recent papers that collectively cover all the earlier publications used in doing this review in their respective reference lists: these earlier references were consulted.

2. Motivation

Model based diagnosis/prognosis systems are popular among researchers because these systems perceive the behaviour of the plant through sensors and analyse it online or offline in relation to a formal model of the plant to provide solutions for diagnosis and prognosis issues. Most importantly the model should represent the true behaviour of the plant for the conclusions to be valid.

The model-based systems we have chosen are applicable in situations where the plant model, system/supervisory controller and fault diagnosis/prognosis unit can be modelled separately with the aim of applying them for fault diagnosis/prognosis problems in reconfigurable and evolving safety critical reactive systems.

The authors were unable to find a comprehensive analysis of model-based fault diagnosis and prognosis systems applicable to this kind of systems. The aim of this paper is to fill this gap.

3. Fault diagnosis approaches

3.1. Automata Based Solutions

An Automaton is a directed graph where nodes represent states and edges represent events. In literature, there are many types of automata (occasionally the only difference being in the name used for basically the same state transition structure) used to represent system behaviour: Finite Deterministic Automata [6, 7] Finite State Machines (FSMs) [8-10], Mealy Automata [11], Moore Automata [1, 12], Finite Nondeterministic Automata [13], ω-Automata, Push-down Automata and Labelled Transition Systems [14, 15]. Generally, in these systems there is a system model based on automata and another automaton for fault diagnosis, which is called the ‘fault diagnoser’ or simply ‘diagnoser’.

Compared to the centralized architecture for systems, distributed and decentralized systems have the ability of being progressively built up by adding module by module to the system with little or no disturbance to the other companion modules. Codiagnosability is investigated in [16]: conceptually, it discusses how the system level diagnosability decisions can be made without missing any faults and at the same time without generating false alarms when several local diagnoses are in operation.

In some systems a fault in one unit can have severe effects on dependent (causally downstream) components. For instance, in an aircraft if the landing gear is faulty, even if all other parts are working in normal condition, it could be difficult to control landing properly, which can severely damage even the normally operating parts when landing.

As a solution to this type of faults the concept of safe diagnosability is proposed in [16]. Technique of safe diagnosability assures the detection of the fault before the system runs into a hazardous state.

The addition of time to the discrete model of Automata can widen their application domain for diagnosability. Timed Automata can be constructed by replacing transitions which fire instantaneously, with transitions which take some time for firing [17, 18]. This opens up the scope of modelling to continuous variables and thereby hybrid systems using Automata.

To verify their theoretical development researchers have applied automata-based techniques to simple systems containing few active components with simple dynamics. For instance, in [9, 19] application was an HVAC system containing a pump, valve and a controller. These systems are modelled as centralized systems, decentralized systems, distributed systems or hierarchical systems. Finally, diagnoser construction procedure and diagnosability conditions are discussed in each case.

Safe diagnosability is also explained with a system containing a valve, pump and a controller [16, 20]. Timed Automata were applied to simple hypothetical systems in [17, 18]. Applications of stochastic systems are discussed in [21, 22]. Selecting an application to demonstrate a theoretical concept has to satisfy two conditions. First, it should be simple enough not to complicate the illustration because of the complexity of the system model. On the other end, the system should be rich enough to demonstrate the complex developments which derive from the particular theory.

In [9, 19] the main issue is that the system and the diagnoser have to be initialized together: the need to restart the whole system after each diagnosis, which may not be practicable in many applications; for instance, the discovery of a faulty landing gear in mid-flight. The method in [1] overcomes this problem but applications are similarly simplistic in nature. Also, these systems are only focused on fault diagnosis. Therefore, prognosis features need to be added for a complete solution. If the system is more diagnosable than the required level (with redundant levels of diagnosis which come at a cost), how can that be identified, and the number of observable events reduced resulting in reducing the total plant cost? Issue of optimal observability for diagnosis is addressed in [23, 24]. Commonly in automata-based development, researchers take action to model naturally distributed and decentralized systems as centralized models and use them to construct diagnosers, thus sacrificing dearly on scalability of their methods. This again requires rethinking.

Co-diagnosability concept is interesting, but proper applications are difficult to find in the literature for real-time physical systems. Safe diagnosability methods can be applied after the occurrence of a faulty event in a system if there are at least few observable events before the set of hazardous string of events occur. As indicated earlier, the real problems will arise when attempting to apply the concept to a real-scale physical system. Also, it is interesting to analyse whether safe diagnosability is only suitable for a newly designed system or if there are possibilities to apply it to an existing system. This is an open question.

Timed Automata can be applied to continuous systems with all transitions converted to timed-transitions or to hybrid systems by converting only a set of transitions to timed transitions. However, when compared with other modelling tools available for continuous systems like bond graphs the ability to model drifts of system parameters etc. is not so powerful or straight forward when using Timed Automata, because of the assumption of constant slopes for parameters. As a conclusion for Automata based systems, we can state that the development of Automata based techniques in discrete event system diagnosis is at a higher level compared with its development in the continuous domain.

3.2. Petri Net Based Solutions

Petri nets were first proposed by C.A. Petri in 1962 in his Doctoral thesis [25]. A Petri net is a bipartite directed graph. There are two types of nodes available, namely places and transitions. Places are associated with a kind of marking called tokens. By moving these tokens according to a set of specified rules the system state mobility is obtained [26]. At a snapshot of time the token distribution in all the places of the net is called its marking and this completely describes the state of the system being modelled.

Petri nets have the ability to easily model synchronization, sequential behaviour, conflict and concurrency [26], which need more attention and can lead to a state explosion when modelled using Automata. Therefore, they are used to model, centralized, decentralized, distributed and hierarchical systems within the framework of failure/fault diagnosis. Construction of decentralized and distributed systems [27] also has eventually become an easy task for Petri nets.

Even though Petri nets were initially proposed to model discrete (logical) behaviour of systems, later they have been extended to model time, converting the transition to a timed transition which takes some time to fire the transition (called as Timed Petri Nets) [28]. Their extension to the continuous domain [29] has resulted in continuous Petri nets and hybrid models. To analytically represent uncertainty in fault diagnosis knowledge fuzzy Petri nets were used in [30]. Straight-forward implementations of Petri net based fault diagnosers on PLCs, FPGA or parallel processor architectures can be envisaged.

The reported applications of Petri nets are much wider compared with Automata: manufacturing systems, thermal systems [31] and complex systems. The reason for this is its higher expressive power and the related theoretical support. Application of stochastic Petri nets is discussed in [32]. In decentralized and distributed systems, communication events can be easily modelled with transitions of Petri nets. Supervisory control and deadlock avoidance have been major applications of Petri nets in manufacturing plants.

Another issue is if we need to model the system as a distributed system, sometimes these modules may not be directly identifiable or separable from other units in the system. With Petri net models, methods like those proposed in [33] facilitate dividing the system into manageable local modules. Fuzzy Petri nets permit advanced Knowledge management techniques. Hence, compared to other systems, Petri net-based approaches are well developed in the area of fault diagnosis and prognosis, integrating other powerful technologies. The main challenge of using Petri nets is the judicious construction of the model, which demands a certain skill.

3.3. Bond Graph Based Solutions

Bond graphs are labelled directed graphs. Edges are of two types, namely bonds and signals. Bond graphs initially constructed to model continuous systems, were later extended to discrete variables. As they can model resistive, capacitive, inductive and inertia loads together with transformation units like transformer and gyrator units it has become a powerful tool among engineers and scientists for modelling multidomain physical systems.

Versatility of bond graphs has been a factor deciding their application in complex systems, especially in the area of Control Engineering [34]. One attempt to model discrete behaviour in bond graphs is by introducing a switch. This technique was illustrated in [35]. This switching behaviour is further improved in [36] including causality. Hybrid bond graphs were applied for robust systems in [37].

In the context of fault diagnosis, development of a Temporal Causal Graph (TCG) facilitates deriving a fault diagnoser from the bond graph model [38-40]. The fault diagnoser is implemented as a Bayesian network. By assigning suitable conditional probability values to the network it can be used as a fault diagnoser for the bond graph model [41]. Causal relationships in TCG can be used to determine the minimal overdetermined subset of equations in a bond graph. These equations can then be used to identify Possible Conflicts (PCs) in the bond graph and the related sections of the bond graph. This was used for fault diagnosis in [42]. This concept is also applicable in hybrid systems.

By integrating Hidden Markov models and Bayesian networks, a Dynamic Bayesian Network (DBN) can be constructed. This approach was applied in continuous variable systems and/or hybrid systems for fault diagnosis [43, 44]: discrete behaviour was realised as a switch, which enables and disables branches of the bond graph.

4. Fault prognosis approaches

4.1. Automata Based Solutions

Using Hybrid Automata for fault prognosis is common. The reason is the capacity to handle both discrete events and continuous variables [45]. In [46] degradation of the system model is represented by a Weibull probability distribution and used for fault prognosis. Another approach to model for prognosis is to model the system using Timed Automata [47]. The ability of modelling time in this type of systems has been used successfully for fault prediction. In [7] and [48] an automaton has been modified to generate a fault prognoser which can perform robust fault prognosis.

A Finite Nondeterministic Automaton was employed for fault prognosis of distributed systems in [49, 50]. This is a more complicated model because for one input event there can be several output states. Most of the work done in this area used hypothetical systems to illustrate the techniques developed. This may be because of the difficulty of finding a simple application, which fits exactly the situation. While designing the system as a hybrid system, an ageing technique is applied to model the time evolution of the system in reference [46]. In general, hybrid systems have separate fault diagnosis and fault prognosis units.

Most of the models assume the sensors and transducers used to be working perfectly all the time. But in real situations they also deteriorate. Handling sensor failures will also be a good area of research in the same line.

4.2. Petri Net Based Solutions

When designing the system, there is a possibility of building sensors into the Petri net to detect some of the events and markings. This kind of a Petri net is called a partially observed Petri net, used to detect failures and forecast future failures. This is the approach reported in [51-53]: in [52] and [53] a conveyor network was used as the example system and in [45], the application was a single water tank system.

If more accurate prediction is needed, the number of sensors being employed to detect states and important observations need to be increased. Main advantage in these methods is that they do not require to detect the system initialization to run the algorithm: they only need the present condition of the part of the system one is interested in. Therefore, one can use this method locally to a specific part of the system which one is more interested in, or somehow more critical. This can save on cost of sensors.

4.3. Bond Graph Based Solutions

Unlike in the general Bayesian networks, dynamic Bayesian networks model the evolution of the system with time. This technology allowed researchers to use bond graph generated Bayesian networks for fault prognosis tasks.

In prognosis using dynamic Bayesian networks, probabilistic reasoning is used to estimate the possible future states of the system. If the last executed state of the system is known, the Remaining Useful Life of the component being considered can be estimated. Reference [54] uses a dynamic seal in a hydraulic actuator for illustrations. The fault prognosis of a high-speed railway traction device was done using bond graphs-based Bayesian network in [44]. In [55] the methodology for fault prognosis was extended using particle swarm optimization for multiple failure prognosis. When compared to other two methods, applications of bond graph-based techniques for fault prognosis are rare.

Many researchers use Dynamic Bayesian Networks together with Bond graphs for fault detection, diagnosis and prognosis. Even Hybrid-Bond graphs which can model both continuous parameters and discrete events using the method of possible conflicts can be applied in many situations. Bayesian estimation and Expectation Maximisation algorithm are adopted to generate conditional probability distributions required for Bayesian networks.

Learning in Bayesian networks and fault diagnosis and prognosis need a high degree of computational power. Also, applying these technologies for complex real systems will be a challenge not only because of the expected computational power, but also because of other issues like signal conditioning, noise filtering and related issues.

5. Conclusion

This paper summarizes graphical model-based systems widely used in the context of fault diagnosis and prognosis. We only looked for solutions with discrete events and timed events because comprehensive reviews of literature related to state space models of continuous variable systems are already available in [2-5]. In summary,

- Automata based solutions for discrete event systems related fault diagnosis and prognosis is developed to a high degree, but the situations where these solutions have been applied to complex real-world systems are rare.
- In automata-based methods, continuous variable parametric systems were approximated with timed automata. Events here only consider the start and the finish of firing of the event. The dynamics of the variables in between are neglected. Variables are considered to have fixed slopes.

Table 1 Summary of literature

Reference	Approach	Fault diagnosis	Fault prognosis	Type of System			System
				Centralized	Decentralized	Distributed	
[1], [8], [9], [12], [14], [23], [19], [21], [24]	Automata	✓		✓			Discrete
[7], [13], [22], [24]	Automata	✓			✓		Discrete
[6], [10], [15], [19], [21]	Automata	✓				✓	Discrete
[16]	Automata		✓	✓			Discrete
[56]	Automata		✓			✓	Discrete
[17]	Automata	✓		✓			Continuous
[18]	Automata, Bond Graph	✓		✓			Continuous
[25], [26], [27]	Petri net	✓		✓			Discrete
[25], [26], [33]	Petri net	✓			✓		Discrete
[25], [26], [32], [33], [27], [31]	Petri net	✓				✓	Discrete
[28], [29]	Petri net	✓		✓			Continuous
[30]	Fuzzy Petri nets	✓		✓	✓	✓	Discrete
[34], [38]	Bond Graph	✓		✓			Continuous
[44]	Bayesian Net	✓		✓			Continuous
[35], [37], [40], [41], [42]	Bond Graph	✓		✓			Hybrid
[36]	Automata	✓		✓			Hybrid
[39], [41], [43]	Bayesian Net	✓		✓			Cont. and Hybrid
[45], [47]	Automata		✓	✓			Hybrid
[46]	Automata	✓	✓	✓			Hybrid
[49]	Automata		✓			✓	Discrete
[48]	Automata		✓	✓			Discrete
[50]	Automata		✓		✓		Discrete
[51]	Petri Net		✓	✓			Discrete
[52]	Petri Net	✓	✓	✓			Discrete
[53]	Petri Net	✓	✓	✓			Continuous
[54]	Bayesian Net	✓	✓	✓			Hybrid
[55]	Bond Graph	✓	✓	✓			Hybrid

- Solutions for the same using Petri net-based approaches are successful, but again the transitions in Petri nets for continuous variable systems are similar to event firings of Timed Automata.
- Bond graphs which are generally used with continuous variable systems have been extended to include discrete event behaviour using techniques of possible conflicts and switching systems. Fault diagnosis and prognosis are done using Temporal Causal Graphs, Bayesian Networks and Dynamic Bayesian Networks.
- Generally, when the method behaves more promisingly with discrete event systems the continuous variable behaviour may not be properly represented and vice versa.

Finally, the objective of many research efforts has been to develop an effective framework for fault diagnosis and prognosis of the integrated type of systems containing discrete events and continuous parametric variables. To get an exact representation, models that perform well with discrete event systems need to be integrated with models which can accurately represent continuous variables.

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