Online Monitoring and Fault Diagnosis of Hybrid Systems Using Switched Dynamic Bayesian Networks

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ABSTRACT

Modern real-world engineering systems typically have hybrid dynamic behaviors that can be modeled by continuous behaviors with discrete mode transitions. These complex systems present many significant challenges for online monitoring and diagnosis, including tracking system behavior, dealing with noisy measurements and disturbances, and diagnosing different types of faults. In this paper, we propose an integrated model-based diagnosis approach that extends the traditional Dynamic Bayesian Network-based particle filter approach for tracking continuous system dynamics. A novel mode diagnoser is presented that discriminates between residuals generated by inaccurate system tracking, discrete faults, and parametric faults. An extended quantitative fault isolation and identification scheme is combined with a qualitative fault isolation scheme to identify the abrupt parametric faults. We demonstrate the effectiveness of our approach by applying it to Reverse Osmosis (RO) subsystem of the Water Recovery System (WRS) developed at the NASA Johnson Space Center for long duration human missions.

1. INTRODUCTION

With the increasing complexity of modern engineering systems, there is a pressing need to guarantee their safety, reliability and efficient operation. Although these systems undergo rigorous testing and validation before deployment, degradation and faults in system components are inevitable due to their long and sustained operations. Therefore, online monitoring and diagnosis for these systems becomes particularly significant to avoid the catastrophic consequences of failures in the system.

Most of these systems are hybrid in nature, so accurate online monitoring of dynamic system behavior becomes a primary challenge. For hybrid systems, the interactions between discrete mode changes and continuous behavior evolution make system state estimation more complicated. Moreover, the uncertainty from modeling errors and sensor noise may degrade the estimation accuracy.

For fault isolation and identification, multiple types of faults need to be considered. Hybrid system faults can be classified into: (1) parametric faults and (2) discrete faults. Parametric faults cover partial failures and degradations in system components, and can be further characterized by different fault profiles: abrupt, incipient, and intermittent (Mosterman & Biswas, 1999). On the other hand, a discrete fault is a discrepancy between the actual and estimated hybrid system modes, and this generally occurs for discrete actuators associated with valves in hydraulic systems and relays in electrical systems. In this paper, our focus is on abrupt parametric faults and discrete faults.

Over these years, many researchers have proposed different methods for diagnosis of hybrid systems. An important class of approaches employs observers or filters based on the estimation of unknown variables. Hofbaur and Williams (2004) and Wang and Dearden (2009) predefine hybrid system behaviors into discrete nominal and fault modes. Extend Kalman Filters (EKF) and Particle Filters (PF) can be employed to track the system state. When discrete faults occur, the approach will converge to the fault mode as the system evolves. The work in (Narasimhan & Biswas, 2007) extended TRANSCEND (Mosterman & Biswas, 1999) from continuous system diagnosis to hybrid systems diagnosis. Soon after, Daigle et al. (2010a) incorporated discrete faults into the diagnosis framework, and demonstrated its effectiveness by applying it to spacecraft power distribution systems (Daigle et al., 2010b). Another class of research approaches relies on analytical redundancy relations (ARRs), and the key idea is to eliminate unknown variables. Cocquempot et al. (2004) and Bayoudh et al. (2008) check the consistency of residuals to determine current system mode and detect and isolate faults. Arogeti et al. (2010) and Levy et al. (2014) introduce global ARRs (GARRs) into quantitative FDI to implement discrete mode tracking and identification.

In this paper, we propose an online monitoring and fault diagnosis framework for hybrid systems. We extend the observer based approach for continuous systems (Roychoudhury et al., 2008) to hybrid systems. For hybrid systems, a statistically significant non-zero residual can be the result of (1) inaccurate system behavior estimation, (2) discrete faults, and (3) parametric faults. It is well known that discrete faults can result in significant changes in system behavior. We propose a novel mode diagnoser algorithm to distinguish between these three situations when faults occur. Our approach first checks for inaccurate mode estimation and discrete faults, and once these are determined not to be presented, the fault isolation and identification (FII) module is invoked to analyze abrupt parametric faults. In this module, Qualitative fault isolation (Qual-FI) method by means of Hybrid TRANSCEND (Narasimhan & Biswas, 2007) and extended Dynamic Bayes Nets (DBN)-based PF method for Quantitative FII (Quant-FII) (Roychoudhury, et al., 2008) are combined together to generate and refine possible parametric fault hypothesis and compute the fault magnitude.

This paper is organized as follows: A description of the case study is given in Section 2. Different models used for our diagnosis framework are shown in Section 3. Section 4 provides an overview of our common diagnosis framework for hybrid systems, and then discusses the details of three main function modules: system monitoring, mode diagnoser and parametric FII. Experimental results are presented in Section 5. Finally, Section 6 contains the discussion and conclusions.

2. DESCRIPTION OF THE APPLICATION

The Advanced Water Recovery System (AWRS), which was designed and built for long-duration manned missions at the NASA Johnson Space Center (JSC) (Bonasso et al., 2003), is a key unit of Advanced Life Support Systems (ALS). The AWRS is composed of four main components: Biological Waste Processor (BWP), Reverse Osmosis (RO) Subsystem, Air Evaporation Subsystem (AES), and Post Processing Subsystem (PPS). In this paper, we focus on the diagnosis of faults in the RO subsystem (see Figure **1**), a hybrid dynamic system with discrete and continuous dynamics. More specifically, the RO subsystem cycles through three modes of operation, that is determined by a four-way multi-position valve. The feed pump is on in all modes, and it pulls the effluent from the BWP to provide a steady stream of input flow for the system. In the primary mode (M1), the input liquid mixes with the effluent from primary loop, as it flows through a tubular reservoir. The recirculation pump boosts the liquid pressure as it flows into the membrane. Clean water leaves the system on the other side of the membrane, and the remaining water with concentrated brine flows back through the return loop to be re-circulated.

As the time elapses, particulate matter collects on the membrane, increasing its resistance to the flow. Therefore, the outflow from the system decreases. After a time interval, the system transitions to the secondary mode (M2), where the length of the feedback loop is reduced, which causes the flow rate to increase, and the outflow of clean water to increase correspondingly. However, this also results in increasing brine concentration in the remaining effluent in the loop, and the collection of impurities in the membrane also increases at a faster rate. After some time, the concentration reaches a level where very little water can be pushed through membrane, and a transition is executed to the purge mode (PM). In this mode, the recirculation pump is turned off, and the valve position is set to allow the effluent with concentrated brine to flow into the AES, where the remaining water is recovered by an evaporation method. The above three modes constitute a whole operating cycle[1], and then the system goes back to primary mode for the second period.

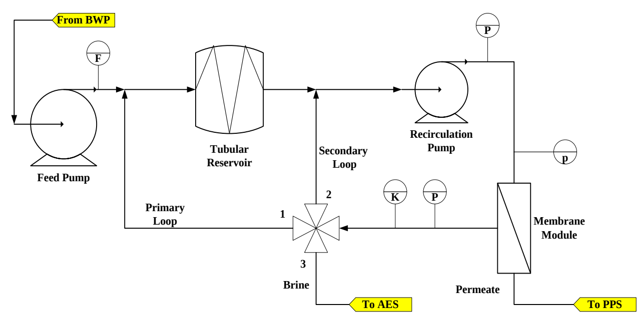

Figure 1. Process diagram for RO subsystem

As can be seen from Figure **1**, five sensors are used to collect observation for our monitoring and diagnosis experiments: 1) the outflow from the feed pump, F_{fp}; 2) the pressure immediately after the recirculation pump, P_{pump}; 3) the pressure of the permeate at the membrane, P_{memb}; 4) & 5) the pressure and conductivity of the liquid in the return path of recirculation loop P_{back} and P_K.

[1] In reality, there is a fourth mode where clean water is pumped in the reverse direction through the membrane to remove particulate matter from its surface.

3. MODELING APPROACH

In this section, we formalize the basic definitions, concepts and notation of modeling approach for our fault diagnosis approach.

3.1. Hybrid Bond Graphs

Bond graphs (BGs) are a domain-independent topological-modeling language that captures energy-based interactions among the processes that make up a physical system (Karnopp et al., 2012). The nodes in BGs represent components of dynamic systems including energy storage elements (capacities, C and inertias, I), energy dissipation elements (resistors, R), energy sources (effort source, Se and flow source, Sf) and energy transformation elements (gyrators, GY and transformers, TF). Bonds show the energy exchange paths between bond graph elements, drawn as half arrows. Two junctions (0- and 1-junctions) model the equivalent of series and parallel topologies respectively.

Hybrid bond graphs (HBGs) extend BGs by introducing switched junctions to enable discrete changes in the system configuration (Mosterman and Biswas, 1998; Roychoudhury et al., 2011). The switched junctions may be dynamically switched on and off as system behavior evolves. When a switched junction is on, it behaves as normal junction. When off, 1-junction and 0-junction behave as source of zero flow and zero effort respectively. The dynamic behavior of a switched junction is implemented by a finite state machine (FSM) control specification (CSPEC). State transitions are defined by external control signals and internal variables crossing pre-specified threshold values. The output of a CSPEC determines whether the junction is on or off (Daigle et al., 2008). As a running example, the HBG for the RO subsystem is shown in Figure **2**.

According to the definition of HBGs, a system mode is described by a unique state combination of all the switched junctions. Two typical switched junctions are common in hybrid physical systems: (1) A switched junction associated with a particular discrete component that can operate in multiple states. (e.g., a valve or a relay in hydraulic and electrical systems, respectively); and (2) the combination of the state of multiple switched junctions may define the mode of a system component. If this is the case, the faulty system component also should be defined by the combination of these junctions.

Previously, (Daigle et al., 2010a; b) have considered the first situation. This case is relatively simple. The discrete faults can be easily introduced into corresponding CSPEC definitions as unobservable fault events. The Qual-FI scheme yields fault signatures that can be used to generate and refine the set of possible discrete faults and parametric faults, and employs temporal causal graph (TCG) with extended fault signatures for diagnosis (Mosterman & Biswas, 1999; Narasimhan & Biswas, 2007). However, when the second situation occurs, since the faulty system component involves multiple switched junctions, the traditional method for defining and processing discrete faults cannot be applied.

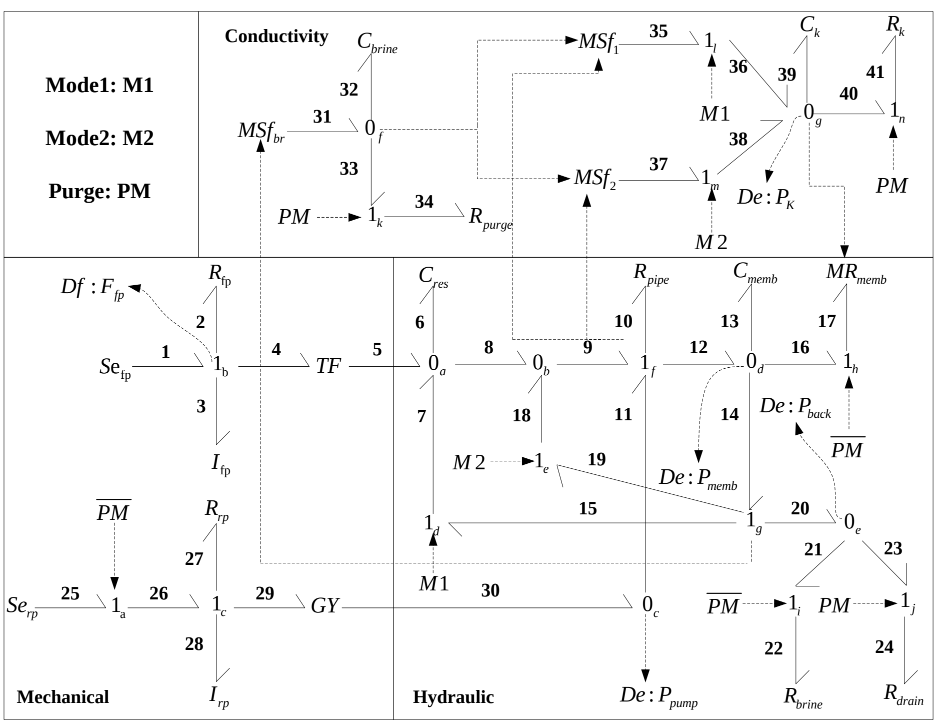

Figure 2. Hybrid bond graph of the RO subsystem

For example, in the RO subsystem, described earlier in Section 2, a multi-position valve controls system configuration, and mode changes in this valve correspond to multiple coupled switched junctions. In primary mode, switched junctions $1_a, 1_d, 1_h, 1_i$ and 1_l are ON, and $1_g, 1_m, 1_j, 1_k$ and 1_n are OFF. In secondary mode, 1_g and 1_m become ON, and 1_d and 1_l are OFF. Besides three nominal modes, discrete faults in RO subsystem can be classified into two categories: 1) *stuck-at faults*, i.e., though a valve may be commanded to transition into a new mode, it remains stuck at the current mode, and 2) *uncommanded transitions*, i.e., a valve may unexpectedly transition to a new mode without a trigger signal. Figure **3** shows the mode transition automaton for RO subsystem. As can be seen from this figure, the nominal mode transition is autonomous when the corresponding transition constraint function is satisfied. $\tau_{ij'}$ denotes the unobservable fault transition from nominal mode *i* to fault mode j'. If *i* is equal to *j*, it is a stuck-at fault transition. Otherwise, the uncommanded transition occurs.

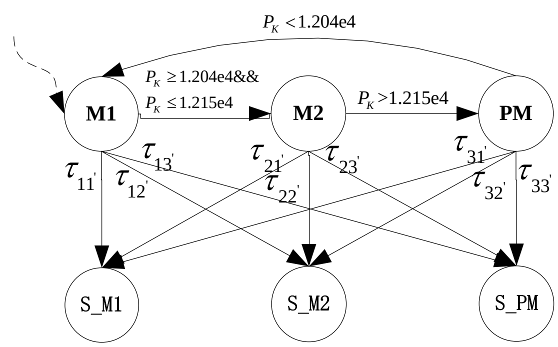

Figure 3. The mode automaton for RO subsystem

3.2. Dynamic Bayesian Networks (DBNs)

A DBN is a two-slice temporal Bayes net for modeling dynamic systems. It captures the uncertainty in estimating the values of the system variables any time slice *t* given the values at time slice *t-1*(Murphy, 2002). A dynamic system consists of four different types of stochastic variables: the continuous state variables X_t, other hidden variables Z_t, input variables U_t and measured variables Y_t. The relations between the state variables from time step *t* to time step *t+1* can be generated using the discrete time form of the state space model. The hidden and output variable values at any time step *t* are related to the state variables at the same time step.

Since the TCG structure describes the causal and temporal constraints between system variables, the DBN can be easily constructed from TCG. In our work, we obtain the TCG systematically from the HBG model of RO subsystem for a given mode, and then generate the corresponding DBN. For lack of space, the DBN model construction process is not shown in this paper, but can be found in (Roychoudhury, et al., 2008, 2009).

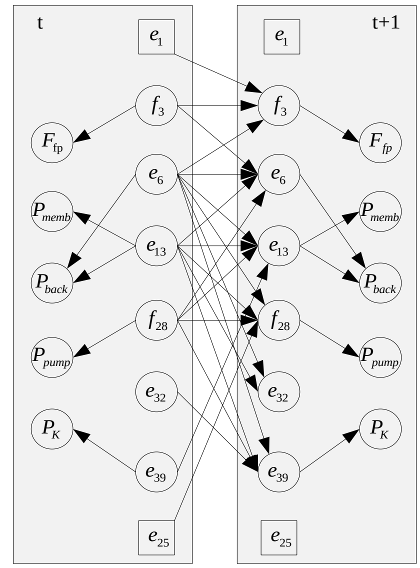

Figure 4. Nominal DBN for RO subsystem

Table 1. The details of system variables for RO subsystem

System Variables	Name	Description	Mode
State Variables X_t	f_{3_t}	The outflow at the feed pump	All
	f_{28_t}	The outflow at the recirculation pump	All
	e_{6_t}	The pressure of the liquid in the tubular reservoir	All
	e_{13_t}	The pressure of the liquid in the membrane	All
	e_{32_t}	The pressure of the liquid in the pipe carrying brine	All
	e_{39_t}	The conductivity of the liquid in the return path	All
Input Variables U_t	e_1	The effort source value for the feed pump	All
	e_{25}	The effort source value for the recirculation pump	M1/ M2

The nominal DBN model for the RO subsystem in primary mode is shown in Figure 4. The nodes at time step *t* include the following stochastic variables: $X_t = \{f_{3_t}, f_{28_t}, e_{6_t}, e_{13_t}, e_{32_t}, e_{39_t}\}$, and $Y_t = \{F_{fp_t}, P_{memb_t}, P_{back_t}, P_{pump_t}, P_{K_t}\}$ respectively.

Input variables $U_t = \{e_{1_t}, e_{25_t}\}$ are deterministic, and no hidden variables $Z_t = \{\varnothing\}$ appear in the RO subsystem. Table **1** describes state and input variables in more details (The measured variables are shown in Section 2). The particular mode of operation that the variables may/may not be active is also indicated.

For each abrupt parametric fault candidate, we invoke a separate fault model by incorporating an extra state variable that denotes the fault parameter into the nominal DBN model. The fault DBN model for the RO subsystem in primary mode with an abrupt fault in R_{fp} is shown in Figure 5. We replace every occurrence of constant R_{fp} in the nominal model with the stochastic variables $R_{fp}(t)$, and add the corresponding links. Table 2 lists potential parametric faults in the RO subsystem.

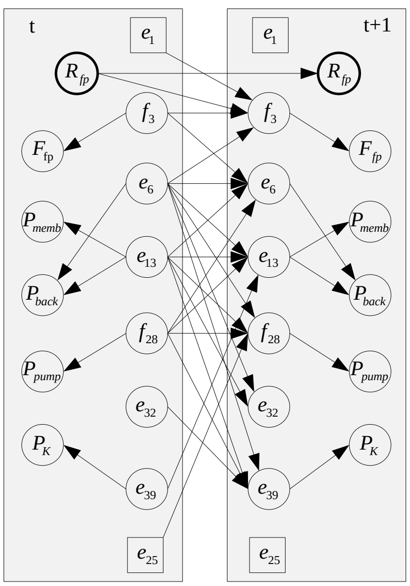

Figure 5. Fault DBN for RO subsystem in primary mode with abrupt fault in R_{fp}

Table 2. Potential parametric faults of RO subsystem

Name	Description
R_{fp}	Increase in friction in the feed pump
R_{rp}	Increase in friction in the recirculation pump
I_{fp}	Decrease in inertia of the feed pump
I_{rp}	Decrease in inertia of the recirculation pump
TF	Decrease in the feed pump efficiency
GY	Decrease in the recirculation pump efficiency
C_{res}	Buildup of impurities in the tubular resistance
C_{memb}	Buildup of impurities in the membrane
R_{pipe}	Partial blockage in pipe carrying water to the membrane
R_{brine}	Partial blockage in the pipe carrying brine
R_{drain}	Partial blockage in the pipe to the AES

4. FAULT DIAGNOSIS METHOD OF HYBRID SYSTEMS

The computational architecture of our online monitoring and fault diagnosis methodology for isolation and identification of discrete mode and continuous parameter faults in hybrid systems consists of four main parts: (1) system monitoring module, (2) mode diagnoser module, (3) parametric FII module, and (4) online model transformations module, as shown in Figure 6.

Given system input *u(t)* and system output *y(t)* in time series form, the dynamic behavior evolution of the system is monitored by a hybrid observer using a switched DBN-based PF approach. The fault detection scheme continually compares observed output *y(t)* and estimated output $\hat{y}(t)$ computed by the observer. Any statistically significant difference triggers the mode diagnoser module. The objective of mode diagnoser is to establish whether the discrepancies observed in system behavior tracking is attributed to a discrete fault or a parameter fault. If the possible fault is identified to be a parameter fault, the parametric FII module is activated to generate and refine parametric fault candidates, and compute fault magnitude using an estimation method.

In the online model transformation module, the HBG model is used to generate the BG and TCG corresponding to the current estimated mode of operation. Our online model transformation module provides the nominal DBN model constructed from the TCG to the hybrid observer. Similarly, the fault DBN model for Quant-FII scheme can also be derived by incorporating the fault parameter as a stochastic variable into the DBN. In addition, TCG is adopted by Qual-FI scheme to complete qualitative fault reasoning. The whole process of online model transformation should be rerun, if the HBG executes a mode change. In the following sections, we describe these schemes of our diagnosis methodology in greater detail.

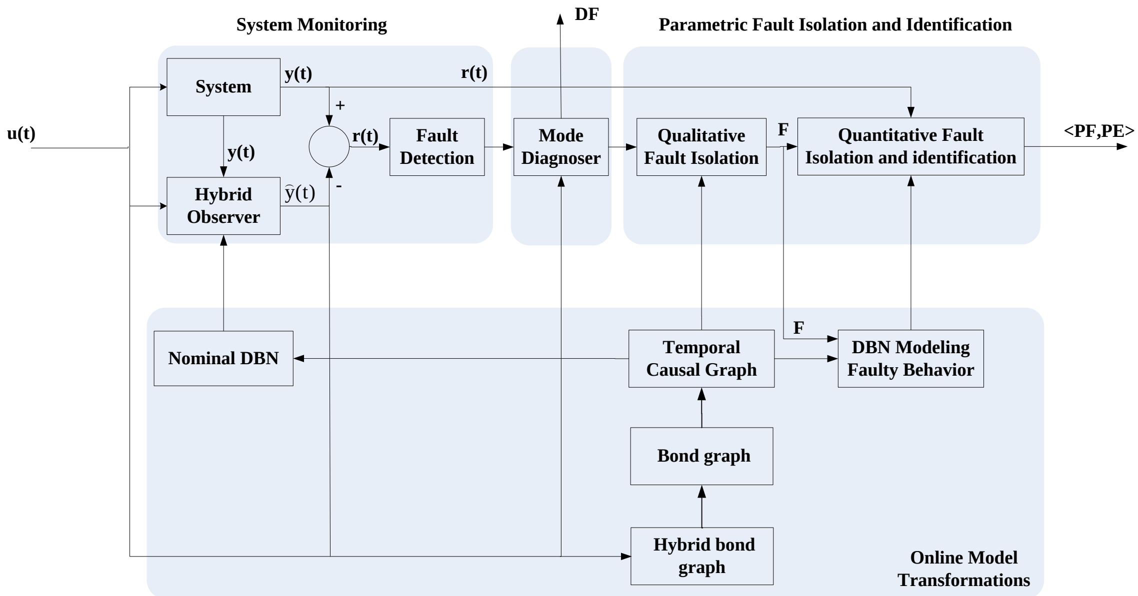

Figure 6. Diagnosis architecture of hybrid systems

4.1. System Monitoring

Our hybrid observer follows the classic hybrid systems approach, where the evolution of the system dynamics is assumed to take place at two distinct time rates: 1) discrete mode changes occur instantaneously at a time point; 2) continuous behavior evolves at the sampling period T_s (Mosterman and Biswas, 1998). For the discrete mode change behaviors, the CSPECs corresponding to each switched junction in the HBG model execute mode transitions. In a particular system mode, the PF technique is employed to estimate linear/nonlinear continuous behavior using the corresponding DBN model. Modeling uncertainty and measurement noise are assumed as uncorrelated Gaussian distributions with zero mean. In order to process the interaction between continuous behavior and discrete mode changes, not only external control signals but also internal autonomous mode changes need to be considered in our hybrid observer. Moreover, each discrete mode transition triggers a reconfiguration in the HBG model, a new DBN model will be regenerated automatically, and PF method resumes in new discrete mode.

The fault detection scheme continually monitor each measurement residual defined by $r_i(t) = y_i(t) - \hat{y}_i(t)$, where $y_i(t)$ is the measured variable from sensor *i* at time step *t*, and $\hat{y}_i(t)$ is the estimated value generated by the observer. Due to measurement noise and modeling errors, $r_i(t)$ is also nonzero when no fault occurs in the system. Therefore, our fault detection scheme employs a Z-test statistical technique (Biswas et al., 2003) for robust fault detection. The Z-test uses a sliding window to compare the current signal deviation with normal known measurement residual. The confidence level, length of current and normal data set and other relevant parameters determine the performance of fault detection scheme.

4.2. Mode Diagnoser

Our diagnosis methodology depends on the analysis of residuals generated from fault detection module, which indicates the consistency of the real system observation and estimated system behavior. For hybrid systems, the deviated residual detected by statistically method is not necessarily an indication of a fault. A typical reason is inaccurate mode estimation resulting from autonomous mode changes under nominal system operation. Take the RO subsystem for example. Figure **7** shows the system monitoring results for the P_{back} and P_{memb} signals assuming 40db additive noise. The top two figures describe the comparison of estimated and measurement variables, while the bottom figures represent the corresponding residuals. We can easily see that the abnormal residuals will be generated from secondary to purge mode in every cycle, because of the inaccurate autonomous mode transition and the large, abrupt changes in P_{back} and P_{memb} in short time. Apparently this erroneous estimation will affect the FDI process in a significant way.

A feasible solution is to trigger the traditional Qual-FI scheme and refine the fault hypothesis set until all of them are refuted. However, pruning parametric faults in Qual-FI scheme is complicated, because autonomous mode transitions need to be considered when a mismatch occurs between predicted fault signatures and observed in measured residuals (Narasimhan & Biswas, 2007). As a result, this approach will make the overall computations intractable.

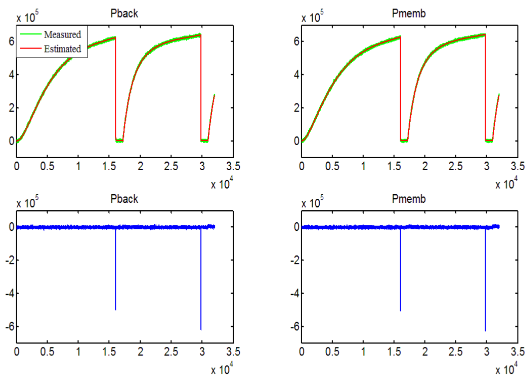

Figure 7. The system monitoring results using 40db noise

Algorithm 1: Mode diagnoser

Input: Current estimated mode $\hat{q}_k$, Possible mode hypotheses $H = \varnothing$

Roll-back n mode transitions and generate possible mode hypotheses

For i=0:n **do**

Generate the possible nominal successor mode $h_{N_{k-i}}$ and discrete faults $h_{DF_{k-i}}$ for current estimated mode $\hat{q}_{k-i}$, and save them $H = H \cup h_{N_{k-i}} \cup h_{DF_{k-i}}$

End For

Roll-forward to refine the mode hypotheses

For $\forall h \in H$ **do**

If the controlled mode change $\sum_c$ or autonomous mode change occurs $\sum_a$

Execute mode change $h = \delta(h, \sum_c | \sum_a)$

End If

If a mismatch is detected $\neg P(h)$

Delete this mode hypothesis $H = H - h$

End If

End For

Analysis the result of mode diangoser

$Length(H) == 0 \Rightarrow$ Parametric fault

$Length(H) == 1 \,\&\&\, h \subset DF \Rightarrow$ Discrete fault

$Length(H) == 1 \,\&\&\, h \subset N \Rightarrow$ Inaccurate mode estimation

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In addition, hybrid systems diagnosis comprises of both parametric faults and discrete faults. Unlike parametric faults, all discrete faults introduce jumps in system variable values (Dressler & Struss, 1996), so we first analyze discrete faults during fault isolation and identification process. Moreover, processing discrete faults first postpones triggering of the Qual-FI scheme, which reduces the computational complexity of the diagnoser.

On the basis of the above considerations, this paper introduces the concept of mode diagnoser. The key idea is to find the possible nominal system modes and discrete faults using a quick roll-back process, and refine these mode hypotheses using a fast roll-forward process. The true discrete system mode will survive if inaccurate mode estimation or discrete faults occur. In contrast, all hypothesized discrete fault modes are refuted denotes the parametric faults.

The mode diagnoser algorithm using the combination of roll-back and roll-forward process is summarized as Algorithm 1. Once a statistically significant non-zero residual is determined, the mode diagnoser is invoked immediately. Considering that a discrete fault or a nominal mode transition may have occurred in a mode prior to the current mode hypothesized by the hybrid observer, the mode diagnoser algorithm reasons backwards, envisions past system modes, and hypothesizes that either a discrete fault mode or a nominal mode transition may have occurred in one of the past modes. After that, the roll-forward process applied for the refinement of discrete mode hypotheses is activated. Since the inaccurate mode estimation resulting in significant non-zero residuals is inevitable, we typically assume that the measurements estimated using real discrete mode will converge to the observed measurements within s_d time steps from the possible fault occurrence time t_{fo} . Ideally, after a predefined finite number of time steps, only the measurement estimated by correct discrete mode should converge to the observation.

4.3. Parametric Fault Isolation and Identification

Once the mode diagnoser rejects all the possible discrete mode faults, the parametric FII module combining Qual-FI scheme by means of Hybrid TRANSCEND methodology in (Narasimhan & Biswas, 2007) and extended Quant-FII scheme is activated to generate and refine parametric fault hypotheses, and calculate the fault magnitude.

4.3.1. Qualitative Fault Isolation

Our qualitative fault isolation scheme is based on qualitative fault signatures describing the transient response of the dynamic system to abrupt parametric faults (Biswas, et al., 2003; Narasimhan & Biswas, 2007). A qualitative fault signature is expressed as the qualitative value of zeroth, first, and higher order time-derivative on a measurement residual.

The zeroth symbols are labeled as normal (0), above normal (+) and below normal (-). Similarly, derivatives are denotes as no change (0), increase (+) and decrease (-) from the nominal behavior, respectively. Ambiguity in a signature is represented by a *. Since the first change and slope value provide all the discriminatory evidence for qualitative fault isolation in dynamic system (Manders et al., 2000), we condense higher order signatures to magnitude change symbol and the first nonzero derivative change. Therefore, the formal definition of qualitative fault signature can be given as follow:

Definition 1 (Qualitative Fault Signature): Given a fault *f*, a measurement *m* and current system mode *q*, the qualitative fault signature is denoted as a tuple $QFS(f, m, q) = (s_0, s_1)$, where $s_0, s_1 \in \{0, +, -, *\}$ represents the magnitude and slope symbol respectively (Manders et al., 2000).

Figure 8 shows the schematic for qualitative fault isolation. The symbol generator models the residual deviation at fault detection time as zeroth fault signature. Hybrid hypothesis generation reasons backward to find all possible modes that fault may occur in prior to the current mode, and applies the back-propagation algorithm to generate fault hypotheses that are consistent with the observed deviation in individual mode. Starting with each fault hypothesis, hybrid signature generation employs a forward-propagation algorithm to yield fault signatures in corresponding discrete mode for abrupt fault hypothesis.

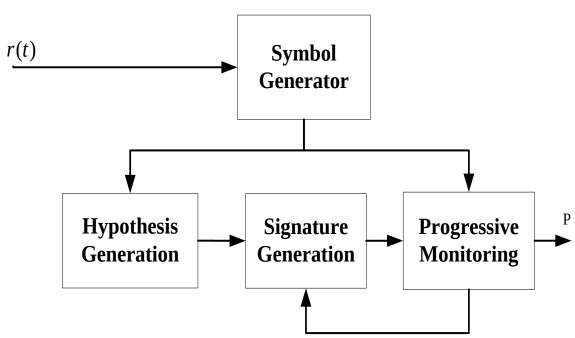

Figure 8. Schematic of qualitative fault isolation

As more measurements deviate from nominal, progressive monitoring compares the predicted fault signatures with the observed deviations. A match implies support for the fault hypothesis, and any inconsistency indicates that assumed fault hypothesis or system mode is not correct. In case of an inconsistency, autonomous mode change needs to be considered, and hypothesis signature generation updates predicted fault signatures in all possible successor modes .We assume that no more that *n* autonomous mode changes have occurred. Once an inconsistency occurs and the times of autonomous mode changes exceed *n*, this fault candidate is dropped.

4.3.2. Quantitative Fault Isolation and Identification

The Quant-FII scheme is activated when Qual-FI scheme satisfies any of the following conditions: the fault candidates are refined to a pre-specified number *k*, Qual-FI scheme cannot prune the remaining fault candidates further, or a predefined time steps *l* have passed. We restrict the length of Qual-FI scheme as a predefined value, and assume that no autonomous change occurs during this period (Biswas, et al., 2003; Roychoudhury, et al., 2009).

We construct multiple faulty DBN model to track the system behavior from the possible fault occurrence time t_{fo}. A separate PF algorithm is applied to estimate all stochastic variables including possible fault candidates. Ideally, only the estimated variables generated by true fault DBN model will gradually converge to the observed measurements after a finite number of time steps l_d. Therefore, a Z-test scheme is invoked to determine the statistically significant deviation between estimation and measurement from time step $t_{qz} = t_{fo} + l_d$. Moreover, since all the DBN models run in parallel with Qual-FI scheme, our fault isolation and identification scheme drops a fault candidate if Qual-FI scheme prunes the fault candidates or the significant difference in a fault DBN model is determined by Quant-FII scheme. Finally, a post processing step is required to calculate the bias term for true abrupt fault.

5. EXPERIMENTAL RESULTS

To demonstrate the efficiency and accuracy of our comprehensive online monitoring and fault diagnosis framework for hybrid systems, we have conducted a set of simulation experiments on the RO subsystem (See Figure 1) for several fault scenarios. System behavior is simulated using Matlab Simulink for two full cycles of operation, which result in a simulation length of 32000 seconds. Zero mean and 40db Gaussian white noise was added to the measurements. In this paper, we illustrate two fault scenarios in more detail.

The first scenario comprises a stuck switch fault. The four-way multi-position valve should be transitioned to secondary mode at 27240s in the second operating cycle but remains stuck at the primary mode. Figure 9 shows the comparison of actual and estimated values of a set of measured variables for this fault scenario. First, due to the residuals generated by inaccurate mode estimation, mode diagnoser is triggered in the secondary mode of the first operating cycle at 16048s. Three different mode candidates: purge mode for nominal mode transition and the ‘stuck at’ discrete fault in the primary mode (S_M1) and purge mode (S_PM) are generated. At 16099s, the discrete fault ‘S_M1’ becomes inconsistent with the measurements and is pruned. In the remaining mode candidates, since the discrete fault ‘S_PM’ shows the same continuous behavior as nominal purge mode, these two modes cannot be distinguished if no discrete mode transition occurs. In our work, we preserve the nominal purge mode as the current real mode. (Even though the discrete fault 'S_PM' is the true one, it could be detected again shortly after the next mode transition). This refined process is presented in Table 3. Soon after, fault detection signals another deviation at 28938s. The mode diagnoser rolls back to find the two possible fault occurrence modes: primary mode and secondary mode, and generates the possible mode transitions shown in Table 4. As more observations are obtained, mode diagnoser prunes this set of mode candidates. Finally, the discrete fault S_M1 is correctly identified as the fault.

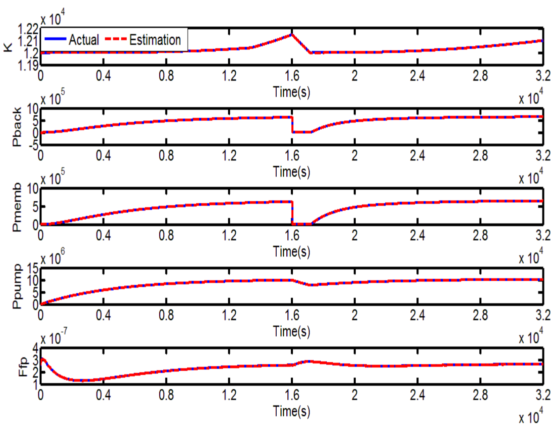

Figure 9. Estimated results if a discrete fault stuck at primary mode

Table 3. The refine process of nominal mode transition in first operating cycle

Mode Candidate	Previous Mode	Transition Occurrence Time	Refine Time
PM	M2	16048	Y
S_M1	M2	16048	16099
S_PM	M2	16048	X

Table 4. The refine process of discrete fault valve stuck at 27240s

Mode Candidate	Previous Mode	Transition Occurrence Time	Refine Time
M2	M1	27244	28938
S_M1	M1	27244	Y
S_M3	M1	27244	27295
PM	M2	28938	28990
S_M1	M2	28938	29179
S_M3	M2	28938	28990

In the second fault scenario, a decrease in the recirculation pump efficiency is introduced in gyrator GY as an abrupt parametric fault with magnitude 10% at 20000s. Table 5 shows the fault diagnosis process for this scenario. The fault detection scheme detects a significant negative deviation for pump pressure P_{pump} with 4 seconds delay. The mode diagnoser module is triggered immediately to generate possible mode candidates: M2, S_M2 and S_PM. At 20057s, all the mode candidates are dropped, and it is determined that the fault is a parametric fault. As a result, the Qual-FI scheme is activated to generate the initial fault candidate set, $F = \{GY^{-a}, R_{rp}^{+a}, I_{fp}^{-a}, C_{res}^{-a}\}$. The next observed change, the pressure at membrane P_{memb} also shows a negative deviation at 20096s. I_{fp}^{-a} and C_{res}^{-a} conflicts with this observation. Possible autonomous mode change is executed to create a new trajectory for these three fault candidates (For lack of space, we do not show this trajectory in detail). After that, P_{back} and F_{fp} decrease successively, but these observations cannot eliminate the remaining candidates set $F = \{GY^{-a}, R_{rp}^{+a}\}$. Further refinement in the fault can only be done by Quant-FII scheme. We predefine 1000 as the number of samples in Quant FII scheme. The fault DBN model using R_{rp}^{+a} is eliminated at 20305s, and GY^{-a} consistent with the observed measurements. The estimation of fault models GY^{-a} is presented in Figure 10. Therefore, GY^{-a} is isolated as the true fault. The PF correctly identifies the fault magnitude to be about a 10.1047% step decrease in GY (See Figure 11), while the true fault magnitude is 10%.

Table 5. The diagnosis process for abrupt parametric fault GY^{-a} with fault size 10% at 20000s

FDI	Time	Symbolic	Candidate Set
Mode Diagnoser	20004		M2,S_M2,S_PM
	20056		M2,S_M2
	20057		X
Qual-FI	20004	$P_{pump}:(-,\cdot)$	$GY^{-a}, R_{rp}^{+a}, I_{fp}^{-a}, C_{res}^{-a}$
	20096	$P_{memb}:(-,\cdot)$	GY^{-a}, R_{rp}^{+a}
	20114	$P_{back}:(-,\cdot)$	GY^{-a}, R_{rp}^{+a}
	20308	$F_{fp}:(-,\cdot)$	GY^{-a}, R_{rp}^{+a}
Quant-FI	20305		GY^{-a}
Parameter Estimation			Fault magnitude: -0.101047

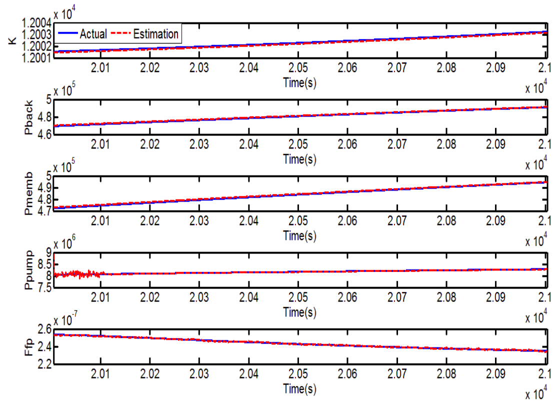

Figure 10. Quant-FI result for fault model GY^{-a}

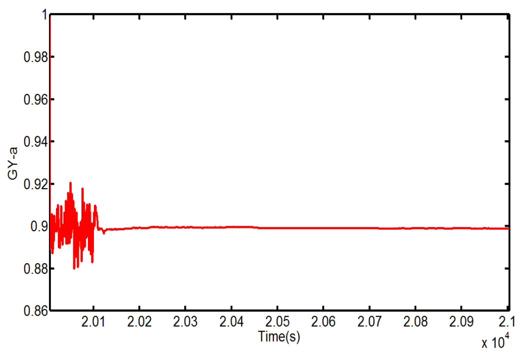

Figure 11. Estimated parameter for GY^{-a}

6. DISCUSSION AND CONCLUSION

In this paper, we employ the HBGs as the core of our modeling framework. Unlike our previous work (Narasimhan & Biswas, 2007; Daigle et al., 2010a; b), a DBN-based PF technique for continuous systems (Roychoudhury, et al., 2008; 2009) is extended to track hybrid system behavior and identify parametric faults and calculate the fault magnitude after a fault has been isolated. DBNs provide a compact and factored representation of the system model and exploit the conditional independence among variables. PF is an anytime algorithm which can be applied to large systems with nonlinearities and complex dynamics. There are three differences between our method and traditional PF method for hybrid systems in (Wang & Dearden, 2009). First of all, our method is a deterministic method, which only tracks a single trajectory when system behavior is nominal. The traditional PF method is a non-deterministic probabilistic method that captures multiple possible trajectories at each time-step. Moreover, our method considers discrete faults and parametric faults, while the traditional PF method only captures discrete faults abstracted as discrete fault modes in hybrid system model. Finally, although traditional PF method employs one step look-ahead technique to alleviate the problem of sample impoverishment, where there are not enough particles that can transition into a faulty mode with very low likelihood, they only track partial fault candidates with high probability. In contrast, we avoid sample impoverishment problem by constructing a separate fault model for all the fault candidates generated and refined by Qual-FI scheme, so all the possible fault candidates are considered in this paper. Second, a novel mode diagnoser is introduced to indentify real discrete system mode. Three different cases resulting in significantly residuals are taken into account. Our mode diangoser analyzes inaccurate mode estimation and discrete faults prior to parametric faults, and if all the discrete mode candidates are rejected, parametric FII module will be triggered to isolate parametric faults. This strategy considers false-alarm situation resulted from inaccurate system tracking, and improves the computational efficiency of our previous work. Third, our comprehensive online monitoring and diagnosis methodology of hybrid system handles multiple forms of faults including discrete faults and abrupt parametric faults, and has been demonstrated its effectiveness by applying to a real-world system: RO subsystem of an ALS.

In future work, since the centralized model-based diagnosis scheme has more computational complexity and memory requirements and the actual systems are often large and complex, we intend to employ distributed diagnosis strategy to relieve the computational burden of our diagnosis methodology. In addition, extending our framework to deal with multiple faults to adapt real systems is also another research direction.

ACKNOWLEDGEMENT

This research was supported by China Scholarship Council under contract number 201306020068. The work was performed in Prof. Biswas' lab at the Institute for Software Integrated Systems (ISIS), Vanderbilt University, USA.

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