A Bayesian Framework for Fault diagnosis of Hybrid Linear Systems

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Abstract

Fault diagnosis is crucial for guaranteeing safe, reliable and efficient operation of modern engineering systems. These systems are typically hybrid. They combine continuous plant dynamics described by continuous-state variables and discrete switching behavior between several operating modes. This paper presents an integrated approach for online tracking and diagnosis of hybrid linear systems. The diagnosis framework combines multiple modules that realize the hybrid observer, fault detection, isolation and identification functionalities. More specifically, a Dynamic Bayesian Network (DBN)-based particle filtering (PF) method is employed in the hybrid observer to track nominal system behavior. The diagnostic module combines a qualitative fault isolation method using hybrid TRANSCEND, and a quantitative estimation method that again employs a DBN-based PF approach to isolate and identify abrupt and incipient parametric faults, discrete faults and sensor faults in a computationally efficient manner. Finally, simulation and experimental studies performed on a hybrid two-tank system demonstrate the effectiveness of this approach.

1 Introduction

The increasing complexity of modern industrial systems motivates the need for online health monitoring and diagnosis to ensure their safe, reliable, and efficient operation. These systems are typical hybrid involving the interplay between discrete switching behavior and continuous plant dynamics. More specifically, the system configuration changes consist of known controlled mode transitions generated from external supervisory controller and autonomous mode transitions triggered by internal variables crossing boundary values. The continuous dynamic behavior is modeled by continuous-state variables that are a function of the particular discrete mode of operation. As a result, tasks like online monitoring and diagnosis have to seamlessly integrate continuous behaviors interspersed with discrete transitions that often require model switching to accommodate the discrete transitions [1].

For complex hybrid systems, faults will typically affect the continuous behavior and the discrete dynamics of the system. Some faults may be parametric, and they directly affect the continuous behavior, others are discrete, thus they directly affect the mode of system operation. Both types of faults also have indirect effects on the other type of behavior. Moreover, faults can have different time-varying profiles, such as abrupt faults, intermittent faults and incipient faults [2]. In addition, faults may occur in the plant, the actuators and the sensors. The diagnosis of multiple fault types in the same framework is challenging, because some faults may produce similar effects in the particular measurements. Therefore, the diagnosis approach should provide more discriminatory power.

Previous model-based diagnosis approaches of hybrid systems were developed separately for parametric faults or discrete faults. For example, [1], [3] combined system monitoring with an integrated approach: qualitative and quantitative fault isolation to generate, refine, and identify parametric faults. [4]-[5] are typical discrete fault diagnosis approaches, which modeled the discrete faults as fault modes, and relied on estimating the system behavior for diagnosis. In recent years, some integrated approaches have been proposed for diagnosis of parametric and discrete faults together. [6] introduced a global ARRs (GARRs)-based mode diagnoser to track discrete system modes, and combined it with a quantitative approach to diagnose discrete and abrupt or incipient parametric faults within a common framework. The approach presented in [7] monitored system behavior using a timed Petri-Net model and mode estimation techniques, and isolated the faults by means of a decision tree approach. Unfortunately, this method was application-specific, and was not generalized.

Our goal in this paper is to propose an integrated model-based approach to diagnose single and persistent incipient or abrupt parametric faults, discrete faults and sensor faults in hybrid linear systems. This extends our earlier work [8] from continuous systems to hybrid systems. A PF technique using switched DBN is adopted for tracking nominal hybrid system behavior. When a non-zero residual value is detected using a statistical hypothesis testing method, this fault detection scheme triggers the fault isolation and identification modules. We combine a fast qualitative fault isolation (Qual-FI) scheme using the hybrid TRANSCEND approach [1] with quantitative fault isolation and identification (Quant-FII) scheme based on a PF-based parameter estimation technique to support the diagnosis of multiple faults types in hybrid linear systems. The

Quant-FII scheme derives a switched faulty DBN model for each fault hypothesis that remains when the switch from Qual-FI to Quant-FII is initiated. In addition, Quant-FII is also designed to estimate possible parameter values [8].

The rest of this paper is organized as follows. Section 2 briefly presents the different models employed in our diagnosis approach and some basic definition of the different types of faults. A hybrid two-tank system is used as a running example to explain the hybrid bond graph modeling method and the derivation of temporal causal graph and DBN from hybrid bond graph models. Section 3 gives a brief overview of our diagnosis architecture, and then presents our online tracking and fault detection, qualitative fault isolation and quantitative fault isolation and identification schemes in some detail. Section 4 discusses the results of the application of our algorithm to the hybrid two-tank system. Finally, the discussion and conclusions of this paper are presented in the last section.

2 Theoretical Background

In this section, we formalize the basic definitions, concepts and notation of the modeling approach that goes in conjunction with our diagnosis architecture.

2.1 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 [9]. The nodes in bond graphs 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, drawn as half arrows, represent the energy exchange paths between the bond graph elements. Two junctions (1 and 0), also modeled as nodes, represent the equivalent of series and parallel topologies respectively.

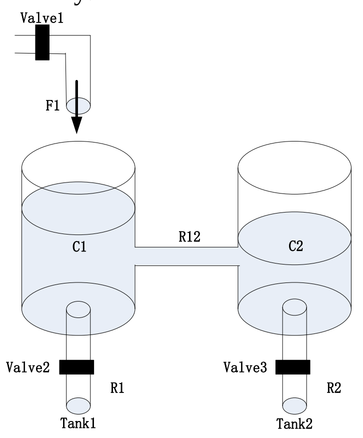

Figure 1 Schematics of hybrid two-tank system

Hybrid bond graphs (HBGs) extend BGs by introducing switched junctions to enable discrete changes in the system configuration [10]. The switched junctions may be dynamically switched on and off as system behavior evolves. When a switched junction is on, it behaves as a normal junction. When off, the 1 and 0 junctions behave as sources of zero flow and zero effort, respectively. The dynamic behavior of switched junctions is implemented by a finite state machine control specification (CSPEC). A CSPEC defines finite number of states, and captures controlled and autonomous changes.

The hybrid two-tank system, shown in Figure 1, is the running example we employ in this paper. This system consists of two tanks connected by a pipe, a source of flow into the first tank, and drain pipes at the bottom of each tank. Three valves valve1, valve2 and valve3 can be turned on and off by commands generated from the supervisory controller. When the liquid level in tanks 1 (h_1) and/or 2 (h_2) reaches the height at which pipe R_{12} is placed (h), a flow is initiated through pipe R_{12}. The autonomous mode changes associated with this pipe are triggered when the liquid level in tank1 and/or tank 2 goes above or below the height of the pipe R_{12}. We assume five sensors: M_1 and M_2 measure the outflow from tank 1 and tank 2, respectively. M_3 measures the flow through the autonomous pipe R_{12}, and M_4 and M_5 measure the liquid pressure in tank 1 and tank 2, respectively.

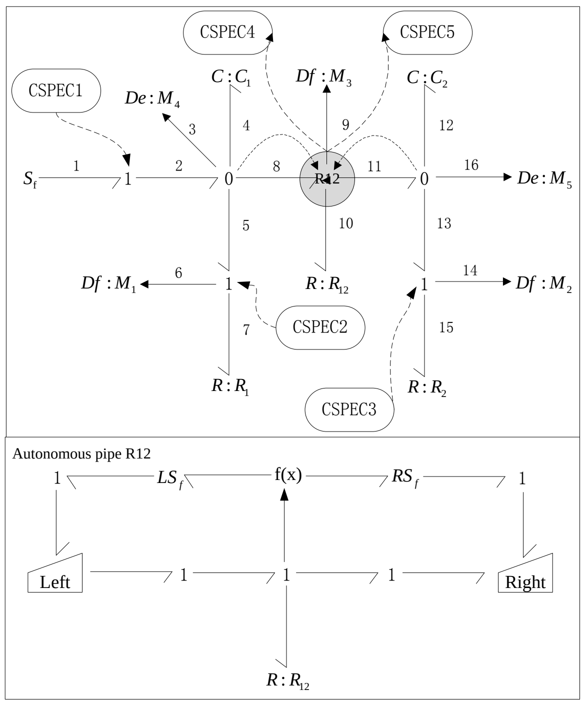

Figure 2 Hybrid bond graph of the plant

Figure 2 illustrates the HBG model for the plant in Figure 1 (The HBG model for autonomous pipe R_{12} is shown separately at the bottom part of Figure 2). The tanks and pipes are modeled as fluid capacitances *C* and resistances *R*, respectively. Measurement points occur at junctions. They are denoted by elements with symbols *De* for effort variable measurements and *Df* for flow variable measurements. Moreover, the two-tank system has five switched junctions: the CSPEC1, CSPEC2 and CSPEC3 describe the control logic for the three valves. CSPEC4 and CSPEC5 together capture the autonomous mode transitions of the connecting pipe between the two tanks. Figure 3 (a) shows the CSPEC for a valve controlled by the switching signal sw. Figure 3 (b) shows CSPEC4 that describes the state of the left tank. When the liquid height in tank1 is below that of the autonomous pipe R_{12}, that state is OFF. If the liquid level exceeds the height of the pipe, this CSPEC transitions to the ON state. Similarly, CSPEC5 denotes the state of the right tank, and the mode of the autonomous pipe depends on the combination of these two CSPECs. Table 1 shows the discrete mode for pipe R_{12} and the corresponding state of CSPEC4 and CSPEC5 in detail. The corresponding bond graph configurations are described in [15].

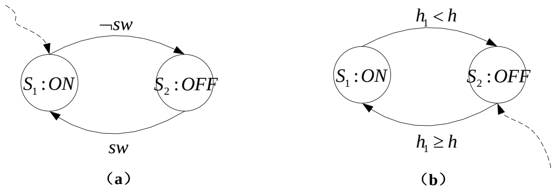

Figure 3 (a) Controlled transition; (b) Autonomous transition for CSPEC4

Table 1 Four different possible configurations for autonomous pipe R_{12}

Mode	Constraint Function	CSPEC4	CSPEC5
1	$h_1 \geq h \cap h_2 < h$	ON	OFF
2	$h_1 < h \cap h_2 \geq h$	OFF	ON
3	$h_1 < h \cap h_2 < h$	OFF	OFF
4	$h_1 \geq h \cap h_2 \geq h$	ON	ON

The temporal causal graph (TCG) is a signal flow diagram that captures the causal and temporal relations between system variables, and can also be systematically derived from a BG [11]. In our work, we can efficiently reason about the qualitative behavior of each continuous mode of hybrid system behavior using the TCG when a fault is detected. Formally, a TCG is defined as follows [2]:

Definition 1 (Temporal Causal Graph): A TCG is a directed graph that can be denoted by a tuple <*V*, *L*, *D*>. $V = E \cup F \cup S \cup M$ is a set of vertices involving effort variables *E*, flow variables *F*, discrete fault event *S* and measurement *M* in hybrid bond graph model. *L* is a label set $\{1, -1, =, p, p^{-1}, N, Z, p \cdot dt, p^{-1} \cdot dt\}$. The propagation type of first seven labels is instantaneous, and the last two are temporal. $D \subseteq V \times L \times V$ is a set of edges.

For lack of space, the TCG for hybrid two-tank system is not shown in this paper, but the algorithms for deriving TCGs directly from bond graph model can be found in [2]. It should be noted that for each mode of operation, the TCG may need to be re-derived to capture the changes in the BG model configuration when mode transitions occur.

2.2 Dynamic Bayesian Networks

Assuming that the system is Markovian and time-invariant, we can model the system as a two-slice temporal Bayes net that illustrates not only the relations between system variables at any time slice *t*, but also the across-time relations between the variables [12]. The system variables consists of four different set of variables (X_t, Z_t, U_t, Y_t), which denotes the continuous state variables, other hidden variables, input variables and measured variables for dynamic system, respectively. The relations between these variables can be generated as equations in the state space formalism. The across-time links between the successive times slice *t* and *t+1* are derived as transition equations between the state variables in the system. Since the TCG describes the causal constraints between system variables, the DBN can be easily constructed from TCG. More details of this process are presented in Lerner, et al. [13].

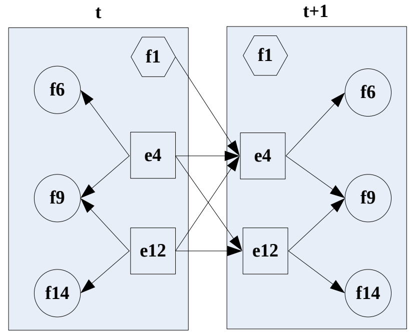

Figure 4 Nominal DBN

When all the valves are ON and the liquid level in tank1 and tank2 are above the height of the autonomous pipe R_{12}, the nominal DBN model for hybrid two-tank system is shown in Figure 4. This DBN model derived from the TCG as the following random variables: the continuous state variables $X = \{e_4, e_{12}\}$ presents the pressures at the bottom of each tank, input variables $U = \{f_1\}$ denotes the input flow into tank 1, and measured variables $Y = \{f_6, f_9, f_{14}\}$ indicates the outflow from tank1, the flow through the autonomous pipe R_{12} and the outflow from tank 2.

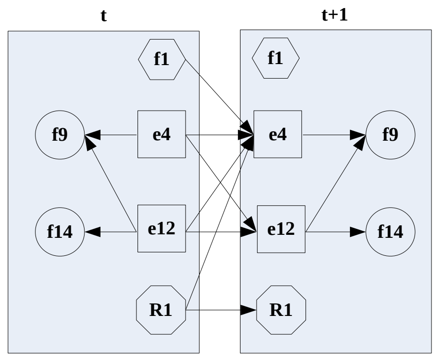

Figure 5 Single DBN model for both abrupt and incipient parametric fault

Since the discrete faults only influence the system mode, but not parameter variables, the DBN fault model corresponding to discrete fault will be constructed from the TCG in the particular discrete mode. For parametric faults, the DBN fault model is generated on the basis of nominal DBN model by augmenting a new random variable for each fault candidate. Figure 5 shows DBN model with parametric faults represented explicitly for the hybrid two-tank system.

The abrupt fault R_1^{+a} and incipient fault R_1^{+i} are represented in the same model. When the fault occurs, fault parameter R_1 becomes the additional state variable that need to be tracked.

2.3 Modeling Faults

In this paper, we focus on the diagnosis of persistent single faults. We consider incipient or abrupt parametric faults and discrete faults occurring in hybrid linear systems, as well as sensor faults. The precise definition for these faults can be given as follow.

Definition 2 (Incipient parametric fault): An incipient fault profile is defined by a gradual drift in the corresponding component parameter value *p(t)* from the fault occurrence time t_f . The incipient fault parameter $p^i(t)$ can be described by:

$$p^i(t) = \begin{cases} p(t) & t \le t_f \\ p(t) + d(t) = p(t) + \sigma_p^i (t - t_f) & t > t_f \end{cases} \tag{1}$$

where $d(t) = \sigma_p^i (t - t_f)$ is a linear function with a constant slope σ_p^i that added to the nominal parameter value from the time point of fault occurrence. Our approach to isolation and identification of incipient fault parameters is to calculate this constant slope σ_p^i [8].

Definition 3 (Abrupt parametric fault): An abrupt parametric fault is characterized by step changes in nominal component parameter value *p(t)* from the fault occurrence time t_f . The abrupt fault parameter $p^a(t)$ is given by:

$$p^a(t) = \begin{cases} p(t) & t \le t_f \\ p(t) + b(t) = p(t) + \sigma_p^a \cdot p(t) & t > t_f \end{cases} \tag{2}$$

where $b(t) = \sigma_p^a \cdot p(t)$ is a step function that gets added to the parameter value from the time point of fault occurrence. σ_p^a is the percentage change in the parameter expressed as a fraction, and our goal is to estimate this value [8].

Definition 4 (Discrete fault): A discrete fault manifests as a discrepancy between the actual and expected mode of a switching element in the model [2].

Discrete faults occur in discrete actuators, like valves and switches that operate in discrete modes (e.g., *on* and *off*). Consider the example of a valve, it may be commanded to close, but remain stuck open. Also, it may unexpectedly open or close without a command. This type of fault manifests as an unexpected system mode change, unlike parametric faults, which cause deviations in continuous behavior.

Definition 5 (Sensor fault): A sensor fault is a discrepancy between the measurement and actual value in the model.

In this paper, we only consider sensor bias fault, which can be represented as:

$$m^b(t) = \begin{cases} m(t) & t \le t_f \\ m(t) + \Delta_m^b & t > t_f \end{cases} \tag{3}$$

where *m(t)* is the true value, and Δ_m^b is the sensor bias term.

3 Diagnosis Approach of Hybrid Linear Systems

Our integrated diagnosis approach for hybrid linear systems (See Figure 6) combines the Hybrid TRANSCEND approach [2] with switched DBN-based PF scheme [14] together, which diagnoses abrupt or incipient parametric faults, discrete faults and sensor faults in a common framework. It includes three main parts: system monitoring, qualitative fault isolation (QFI) and quantitative fault isolation and identification (QFII). These three steps are summarized below.

Initially, a nominal DBN is constructed from the current TCG model. A hybrid observer uses a PF-based nominal DBN model to track the system behavior in individual modes of operation. At the same time, a finite automata method in hybrid bond graph scheme implements the CSPECs, executes controlled and autonomous mode changes, and determines the system model for hybrid observer.

The fault detection continually monitors the statistically significant deviations between the observation *y(t)* and estimation $\hat{y}(t)$ generated by hybrid observer. Once a fault is determined, QFI is triggered to generate the initial fault hypothesis, and refine them as additional deviations are observed. When remaining fault hypothesis set satisfies particular condition, the QFII scheme is invoked to run in parallel with QFI. The goal of this scheme is to refine the fault hypothesis further and estimate the value of the fault parameter. The following subsections describe these steps in more detail.

3.1 Online Tracking and Fault Detection

Since the hybrid system is piecewise continuous, discrete mode changes of the hybrid system have to be detected accurately as the continuous behavior of the system evolves. In our work, we have designed hybrid observers that are based on the nominal DBN-based PF scheme to track the continuous behavior in individual modes of operation. PF is a general purpose Markov chain Monte Carlo method that approximates the belief state using a set of samples or particles, and keeps the distribution updated as new observations are made over time. Moreover, the PF approach for DBNs exploits the sparseness and compactness of the DBN representation to provide computationally efficient solutions, because each measured variable in a DBN typically depends on some but not all continuous state variables.

For discrete mode changes, the finite state machine (FSM) for each switched junction determines mode transitions. Since the continuous behavior and discrete mode changes will interact with each other as system evolves, the FSM needs to execute controlled or autonomous mode changes. Explicit controlled changes are relatively simple, but the autonomous mode changes depend on the internal continuous variables. If mode changes occur, the hybrid observer will regenerate the nominal DBN model from TCG in new mode, and use the PF to continuously track system dynamic behavior. The online tracking algorithm for hybrid systems is shown in Algorithm 1.

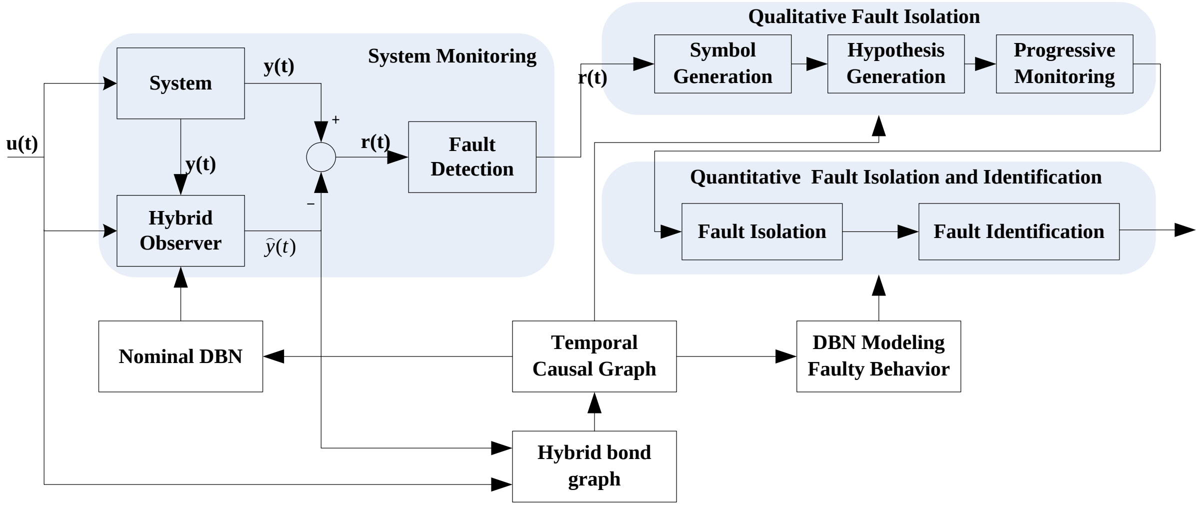

Figure 6 The diagnosis architecture

Algorithm 1: Online tracking algorithm

Input: Number of particles, N; a initial DBN model $D=\{X,Z,U,Y\}$

For each particle *i*, from 1 to N do

Sample X_0^i from the prior probability distribution

Assign Y_0^i as the measurement at time step 0

End For

For each time-step t>0 do

If the controlled or autonomous mode change occurs

Regenerate a DBN model D' from TCG in new system configuration

End If

Prediction: Sample each particle in DBN model D'

Weighting: Compute the weight considering the observation

Resampling: Normalize the weighted samples, and resample N new samples

Calculate the estimated continuous state variables X_t and Y_t at time step *t*

End For

The fault detection module compares the measured variable y(t) from sensors with its estimate, $\hat{y}(t)$ computed by the hybrid observer at each time-step *t*. Ideally, any inconsistency $r(t)=y(t)-\hat{y}(t)$ implies a fault, and invokes the qualitative fault isolation module. However, to account for noise in the measurements and modeling errors, statistical techniques are employed to determine significant deviations from zero for the residual. In this paper, a Z-test, which uses a sliding window to compute the residual mean and variance, is adopted by reliable fault detection with low false-alarm rates [3].

3.2 Qualitative Fault Isolation

The QFI scheme is based on qualitative fault signature (QFS) method, which was proposed by Mosterman and Biswas [11] and then extended by Narasimhan and Biswas [1] to hybrid systems. Daigle, et al. [2] extended this method to model discrete and sensor faults in continuous and hybrid systems. All of these methods are based on a formal definition of fault signature as follows:

Definition 6 (Qualitative Fault Signature): Given a fault f and measurement m, the qualitative fault signature can be denoted by $QFS(f,m)=\{(s_1s_2,s_3),s_1,s_2\in(+,-,0,*),s_3\in(N,Z,X,*)\}$; where ± and 0 indicate an increase, decrease, and no change for residual magnitude or slope. N, Z and X imply zero to nonzero, nonzero to zero, and no discrete change behavior in the measurement from the estimate. * denotes the ambiguity in the signatures.

Table 2 Selected fault signature for hybrid two-tank system for the mode when all the valves are open and liquid level in both tanks are above the height of the autonomous pipe

Fault	f_6	f_9	f_{14}
C_1^{-a}	$(+-,X)$	$(+-,X)$	$(0+,X)$
C_1^{-i}	$(0+,X)$	$(0+,X)$	$(0+,X)$
R_1^{+a}	$(-+,X)$	$(0+,X)$	$(0+,X)$
R_1^{+i}	$(0-,X)$	$(0+,X)$	$(0+,X)$
$v1.off$	$(0-,X)$	$(0-,X)$	$(0-,X)$
$v2.off$	$(-*,X)$	$(0+,X)$	$(0+,X)$
f_6^+	$(+0,*)$	$(00,X)$	$(00,X)$
f_6^-	$(-0,*)$	$(00,X)$	$(00,X)$

When measurement deviations are detected, the symbol generator module in QFI scheme is triggered to calculate the QFS for the current mode of operation. However, since the fault may have occurred but not detected in an earlier mode, the fault hypothesis generation module rolls back to find the previous modes in which fault may have occurred, and generate fault hypothesis set $F=\{(f_i,\lambda_i,q_i)\}$, where λ_i denotes the deviation of fault parameter value, and q_i indicates the possible modes. The progressive monitoring module applies the forward propagation algorithm to continually refine the fault candidates in the fault hypotheses set. For hybrid systems, the progressive monitoring also has to include forward propagation through mode changes, which makes the tracking algorithm much more complex. Narasimhan and Biswas [1] discuss the details of the roll back and roll forward algorithms used to support the progressive monitoring task. When a fault signature is no longer consistent with the observed measurements, and the changes cannot be resolved by autonomous mode transitions, this fault candidate is dropped.

The selected qualitative fault signature for hybrid two-tank system in particular mode is shown in Table 2. For incipient parametric faults, the QFS is shown as $(0\tau, s_3)$, where τ is the first nonzero symbol in the QFS for the abrupt faults with same system parameter. Sensor faults only affect the measurement provided by the sensor, so other measurements that are not affected are denoted by 00.

3.3 Quantitative Fault Isolation and Identification

Quant-FII scheme will be activated when any of the following conditions are fulfilled: 1) All the measurements have deviated from nominal, so the remaining fault candidates cannot be refined further only by the Qual-FI scheme; 2) The number of fault candidates has been reduced to a predefined value *k*; 3) A predefined time *l* has elapsed. We restrict the length of Quant-FII scheme as a pre-specified value, and assume that no autonomous change occurs during this period.

The steps describing this scheme are illustrated as follows: First, a separate DBN faulty model will be constructed for each remaining fault candidate in the hypothesis set. Second, we combine each switched DBN faulty model with PF method to estimate the system behavior. Similar to fault detection scheme, a Z-test method is employed to detect the inconsistency between estimated values from PF and measurements. Ideally, only the correct true fault model will converge to the observed values of the measurements. Once the deviation is determined, the corresponding fault candidate will be dropped. This scheme runs in parallel with the qualitative fault isolation scheme, and if a controlled mode change occurs, these two schemes need to reload the DBN model for new system mode. This is the big difference between continuous systems and hybrid systems.

If the fault hypothesis cannot be refined further or only a single parametric or sensor fault candidate is left, fault identification scheme will be activated to identify the abrupt or incipient parametric fault in the same model and estimate the fault parameter value. We can use the PF result of the fault parameter to calculate the abrupt parameter fault magnitude σ_p^a, incipient parameter fault slope σ_p^i or sensor fault bias term Δ_m^b.

4 Experimental Results

To demonstrate the effectiveness of our approach, we apply it to the hybrid two-tank system in Figure 1. In this plant, the incipient parametric faults are modeled as gradual decrease in tank capacity and gradual increases in pipe resistances and denoted as $C_1^{-i}, C_2^{-i}, R_1^{+i}, R_2^{+i}$ and R_{12}^{+i} respectively. The abrupt parameter faults are modeled as step decrease in tank capacity and step increases in pipe resistances and represented as $C_1^{+a}, C_2^{+a}, R_1^{+a}, R_2^{+a}$ and R_{12}^{+a} respectively. We consider discrete faults in each controlled valves including the valve gets stuck and valve changes mode without a command. For sensor faults, bias faults causing abrupt changes in the measurement are considered.

We assume that the tanks are initially empty, and start to fill in at a constant rate. The initial configuration of the system is all the valves are set to open. We will denote the system mode as q_{ijkm}, where *i*, *j* and *k* are the modes of valve1, valve2 and valve3 respectively, and *m* is the mode of autonomous pipe R_{12}. More specifically, the mode of valves includes $S_1 : on, S_2 : off, S_3 : Stuck\_on$ and $S_4 : Stuck\_off$. Therefore, the initial mode of the system is q_{1113}. At time step t=6.7s, the liquid level in tank 1 reaches the height of autonomous pipe R_{12}. The system mode transitions from q_{1113} into q_{1111}. Now the autonomous pipe R_{12} acts as an outflow pipe for the tank 1 but as flow source for the tank 2. As system evolves, the liquid level in tank 2 will also reach the autonomous pipe at time step t=53s. After that, system mode changes into q_{1114}. The experiments have been run for a total of 400s using a sampling period 0.1s. Gaussian white noise with zero mean and variances 0.018 is added to measurements.

4.1 Incipient Parametric Fault in R1

In this first experiment, we present our diagnosis approach for a fault scenario. A 10% rate of increase in pipe R_1 is injected as the incipient fault at time step t = 60s.

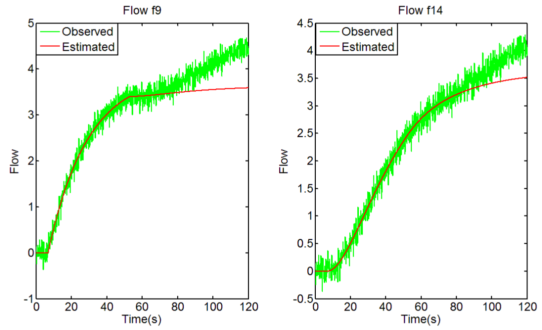

Figure 7 Observed and estimated result for nominal DBN model

We only consider the measurement M_3 and M_2 for the flow f_9 through the autonomous pipe R_{12} and the output flow f_{14} from tank 2. At time step t=82s, the fault detection scheme detects an increase in the flow f_9, resulting in the initial fault hypothesis $F = \{(C_1^{-a}, q_{1114}), (C_1^{-i}, q_{1114}), (R_1^{+a}, q_{1114}), (R_1^{+i}, q_{1114}), (v2.off, q_{1414}), (f_9^{+}, q_{1114})\}$. At 88.4s, the flow f_{14} shows an increase above nominal (+). A possible autonomous transition is executed for the current inconsistent candidate (f_9^{+}, q_{1114}). After that, the first order change of flow f_9 is determined to decrease and increase in mode

q_{1414} and q_{1114} at time steps t=94.8s and 97.7s, respectively, and finally the possible fault hypotheses are $F=\{(C_1^{-i},q_{1114}),\ (R_1^{+a},q_{1114}),(R_1^{+i},q_{1114})\}$. According to the fault signatures in mode q_{1114}, these three candidates cannot be refined further using observed deviations. Figure 7 represents observed and estimated result generated by the nominal DBN model.

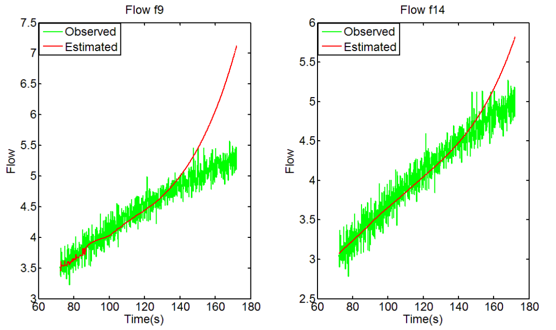

Figure 8 Estimated observation using fault model C_1^{-i}

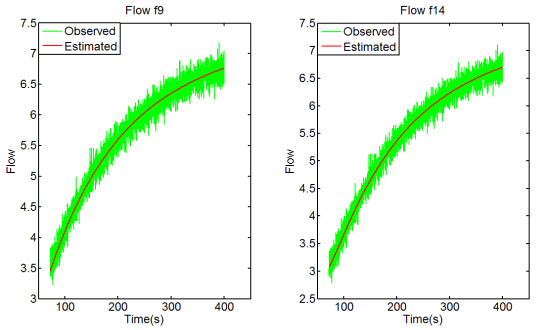

Figure 9 Estimated observation using fault model $R_1^{+a/i}$

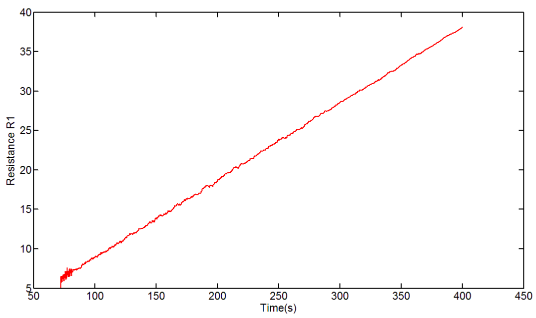

Figure 10 Estimated value of true fault parameter R_1^{+i}

The QFII scheme is initiated at time step t=72s, and two separate DBN fault model using C_1^{-i} and $R_1^{+a/i}$ are constructed. As more measurements are obtained, the Z-tests indicate a deviation in the measurement estimates obtained by the fault model C_1^{-i}, and the estimation generated by possible true fault model $R_1^{+a/i}$ is consistent with measurement. The quantitative fault identification part estimates the value of R_1, and determines that R_1 indeed has an incipient fault. While the actual fault slope is 0.1, the estimated slope is 0.1009. The estimation using two faulty models are shown in Figure 8 and Figure 9 respectively, and the plot for estimated value for R_1 is presented in Figure 10.

4.2 Discrete Fault in Valve 2

In this subsection, we investigate an unexpected switch fault: valve 2 closes without a command at time step t=80s. We only consider the flow f_6 and flow f_9 in this experiment.

Figure 11 shows the observed and estimated outputs using nominal DBN model. The fault is detected at time step t=80.1s, and the symbol generator reports a decrease in flow f_6. QFI scheme generates the fault hypothesis set $F=\{(R_1^{+a},q_{1114}),(R_1^{+i},q_{1114}),(v1.off,q_{4114}),(v2.off,q_{1414}),$ $(f_6^{-},q_{1114})\}$. At time step t=80.6s, the symbol generator determines the flow f_6 to Z in mode q_{1114} and q_{4114}, because of estimated flow $\hat{f}_6 \neq 0$ and the observation $f_6=0$. This symbol eliminates all the parametric faults and discrete fault $v1.off$ from current trajectory. At 83.6s, the flow f_{10} shows a positive deviation (+), so the fault candidate $(v2.off,q_{1414})$ is correctly isolated. In this experiment, the real fault candidate is isolated by the QFI scheme, so the QFII scheme is not invoked.

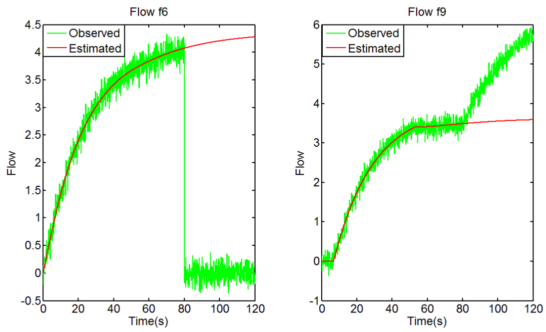

Figure 11 Observed and estimated result for nominal DBN model

We also perform several additional experiments with different fault types, fault magnitude, noise level and fault occurrence time, and obtain satisfactory results. For lack of space, we do not discuss these results in detail.

5 Conclusion

In this paper, we presented an integrated approach for online monitoring and diagnosis of incipient or abrupt parametric faults, discrete faults and sensor faults in hybrid linear systems. First of all, we adopt the HBGs to model the system, and construct the diagnosis models, i.e., the TCGs and the DBN models from the HBG model in different modes. A PF method based on the switched DBN model is employed for online monitoring of the system dynamic behavior. Once the discrete finite automaton in the HBGs detects the controlled or autonomous mode changes, HBGs will regenerate the TCGs and DBN model in new mode. These modeling approaches guarantee that the hybrid systems can be tracked correctly.

Then, we demonstrate that we can accommodate discrete faults and sensor fault models into the TCG and DBN models that represent dynamic system behavior. As a result, our model-based approach can diagnose parametric, discrete and sensor faults within the same modeling and tracking framework. Finally, QFI scheme using Hybrid TRANSCEND approach and QFII scheme by means of switched DBN-based PF approach are combined together into a common framework, which provides more discriminatory power and less computational complexity.

This work builds on approaches presented in [1][2][11][14]. [1] extends our previous work [11] from continuous systems to hybrid systems, but previous diagnosis framework could only handle abrupt parametric faults. Soon after, Daigle [2] further extended the work in [1] to capture discrete faults and sensor faults. Roychoudhury [8][14] combined a qualitative fault isolation scheme with an efficient DBN approach to diagnose both abrupt and incipient parametric faults for continuous systems. This paper proposes a comprehensive diagnosis methodology, which extends DBN-based PF observer [8][14] to track behavior of linear hybrid systems within and across mode changes, and combines qualitative fault isolation scheme in [2] with PF-based quantitative fault isolation and identification scheme in [8][14] to diagnose multiple fault types.

This method has been successfully applied to a hybrid two-tank system, and experimental results demonstrate the effectiveness of the approach. However, since the application in this paper is only a relatively simple hybrid linear system, our future work will scale up this methodology for more realistic linear and nonlinear hybrid systems. Moreover, distributed diagnostics techniques can efficiently decrease the computational complexity for complex real systems, so this is also a research direction in future [16].

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References

[1] Narasimhan, S. and Biswas, G. Model-based diagnosis of hybrid systems. *Systems, Man, and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 37(3): 348-361, 2007.

[2] Daigle M J. *A qualitative event-based approach to fault diagnosis of hybrid systems*. PhD thesis, Vanderbilt University, 2008

[3] Biswas, G., Simon, G., Mahadevan, N., Narasimhan, S., Ramirez, J. and Karsai, G. A robust method for hybrid diagnosis of complex systems. *Proceedings of the 5th Symposium on Fault Detection, Supervision and Safety for Technical Processes*, 1125-1131, 2003

[4] Dearden, R. and Clancy, D. Particle filters for real-time fault detection in planetary rovers. In *Proceedings of the Thirteenth International Workshop on Principles of Diagnosis*, 2002

[5] Hofbaur, M. W. and Williams, B. C. Hybrid estimation of complex systems. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 34(5): 2178-2191, 2004.

[6] Levy, R., Arogeti, S., and Wang, D.. An integrated approach to mode tracking and diagnosis of hybrid systems. *IEEE Transactions on Industrial Electronics*, 61(4), 2024–2040, 2014.

[7] Zhao, F., Koutsoukos, X., Haussecker, H., Reich, J. and Cheung, P. Monitoring and fault diagnosis of hybrid systems. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 35(6), 1225-1240, 2005

[8] Roychoudhury, I., Biswas, G., Koutsoukos, X.. Comprehensive diagnosis of continuous systems using dynamic bayes nets. *Proceedings of the 19th International Workshop on Principles of Diagnosis*. 151-158, 2008

[9] Karnopp, D. C., Margolis, D. L. and Rosenberg, R. C. System Dynamics: Modeling, Simulation, and Control of Mechatronic Systems. Wiley. 2012

[10] Roychoudhury, I., Daigle, M. J., Biswas, G. and Koutsoukos, X. Efficient simulation of hybrid systems: A hybrid bond graph approach. *Simulation*, 87(6), 467-498, 2011.

[11] Mosterman, P. J., and Biswas, G. Diagnosis of continuous valued systems in transient operating regions. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 29(6), 554-565, 1999.

[12] Murphy, K. P. *Dynamic bayesian networks: representation, inference and learning*. PhD thesis, University of California, Berkeley. 2002

[13] Lerner, U., Parr, R., Koller, D. and Biswas, G. Bayesian fault detection and diagnosis in dynamic systems. In *AAAI/IAAI*, 531-537, 2000.

[14] Roychoudhury, I. *Distributed diagnosis of continuous systems: Global diagnosis through local analysis*. PhD thesis, Vanderbilt University. 2009

[15] Narasimhan, S. *Model-based diagnosis of hybrid systems*. PhD Dissertation, Vanderbilt University. Department on Electrical Engineering and Computer Science, August 2002.

[16] Roychoudhury, I., Biswas, G., & Koutsoukos, X. (2009). Designing distributed diagnosers for complex continuous systems. Automation Science and Engineering, IEEE Transactions on, 6(2), 277-290.