Analytic Redundancy, Possible Conflicts, and TCG-based Fault Signature Diagnosis applied to Nonlinear Dynamic Systems

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Abstract:
The FDI and DX communities have developed complementary approaches that exploit structural relations in the system model to find efficient solutions for the residual generation and residual evaluation steps in fault detection and isolation in dynamic systems. This paper compares three different structural techniques, two from the DX community and one from the FDI community. To simplify our comparison, we start with a common modeling approach that employs bond graphs. We describe the residual generation methods used by the three approaches, and apply them to a standard three tank configuration to demonstrate their diagnostic ability for continuous, nonlinear systems.

1. INTRODUCTION

The needs for increased performance, safety, and reliability of engineering systems provide the motivation for developing Integrated Systems Health Management (ISHM) methodologies. Our focus in this paper is on model-based approaches for online fault detection, isolation, and identification (FDII) in complex nonlinear systems. Model-based approaches to diagnosis are general, apply across multiple operating regions, and have the potential for overcoming the device dependency problem.

Traditionally, two different communities: (1) the Systems Dynamics and Control Engineering (FDI) community (e.g., [Gertler, 1998] and [Patton, et al., 2000]), and (2) the Artificial Intelligence Diagnosis (DX) community (e.g., [Hamscher, et al., 1992] and [Reiter, 1987]), have developed model-based diagnosis approaches. The two communities have employed different kinds of models, and made different assumptions concerning robustness of the generated solution with regard to modeling errors, measurement noise, and disturbances. However, there are common principles that govern the methods developed by the two communities. This was outlined in a 2002-03 study conducted by the French IMALAIA group [Cordier, et al., 2004], which laid the groundwork for a common terminology between Analytic Redundancy (ARR) methods used in the FDI community and conflict resolution methods used in the DX community. However, this analysis applied only to diagnosis methods for static systems.

More recently, the DX community has developed methods such as possible conflicts [Pulido and Alonso, 2000] [Pulido and Alonso, 2004] and analysis of temporal causal graphs [Mosterman and Biswas, 1999] [Manders et al., 2000] for diagnosis of continuous systems. These methods are based on the structural analysis of dynamic models, much like the ARR schemes developed by the FDI community. The two communities use different algorithms, but the overall framework for fault isolation is similar, defined by a two-step process: (i) residual generation, followed by (ii) residual evaluation [Gertler, 1998] [Patton, et al., 2000].

The goal of this paper is to make a systematic comparison of the algorithms used by the two communities. However, the comparison task can be complicated by the nature and form of the dynamic system models that form the basis for the model-based diagnosis algorithms. Therefore, to keep the scope of this paper manageable, we start with a common modeling framework,in our case, the bond graph modeling scheme [Karnopp, et al., 2000], and compare and contrast the ARR approach developed by [Samantaray et al., 2006] with possible conflicts [Pulido and Alonso, 2004], and temporal causal graph-based diagnosis methods [Mosterman and Biswas, 1999] for continuous nonlinear dynamic systems. In particular, the residual generation and evaluation algorithms used by the three methods are compared, and the similarities between the algorithms are established.

The rest of this paper is organized as follows. Section 2 briefly reviews the bond graph modeling approach, and a systematic method for deriving causal information from bond graphs. The bond graph model of a nonlinear, controlled three tank system is used as a running example to demonstrate the residual generation step for the three diagnosis algorithms. Section 3 describes the residual generation and residual evaluation schemes for the three algo-

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rithms, and then a comparative analysis of the approaches. Section 4 presents a comparison of the diagnosability capability of the three algorithms, and the conclusions of the paper.

2. BOND GRAPH MODELING FOR DIAGNOSIS

Bond graphs are labeled, directed graphs, that present a topological, domain-independent, energy-based methodology for modeling the dynamic behavior of physical systems [Karnopp, et al., 2000] [Samantaray and Bouamama, 2008]. They provide a common modeling framework across multiple energy domains, (e.g., mechanical, electrical, fluid, and thermal). Building system models follows an intuitive approach where energy flow paths between system components are captured by a topological structure. In this structure, system components appear as nodes, and the energy flow paths appear as links or bonds. System component behaviors are modeled from a small set of primitive elements: (i) *energy storage* elements (capacities, C, and inertias, I); (ii) *dissipative* elements (resistors, R); (iii) *source* elements (sources of effort, S_e, and sources of flow, S_f), that add or remove energy from the system; and (iv) *junctions* (series, 1, and parallel, 0), that represent ideal energy connections for sets of elements. This representation provides a systematic framework for capturing causal relations between system variables. Standard mathematical models of dynamic system behavior, such as the state space and I/O formulations, can be systematically derived from bond graph models.

Our running example, the three tank system configuration, made up of three tanks $\{T_1, T_2, T_3\}$, and four valves V_0, V_1, V_2, and V_3 (see Fig. 1), resembles a continuous industrial process. Valves V_1, V_2, and V_3 are always completely open. We assume four sensors: two, $\{P_1, P_2\}$, measure the fluid pressure in tanks T_1 and T_3, the third, $\{F_1\}$, measures the in-flow into tank T_1, and the fourth $\{F_2\}$, measures the outflow from tank T_3. A control loop defined by a function $f(x)$, where x is the measured pressure in tank T_1 determines the opening of valve V_0. For this study, we consider seven different faults in the plant: change in tank T_1, T_2, T_3 capacities, and partial blocks in the valves V_1, V_2, V_3, and in the input pipe.

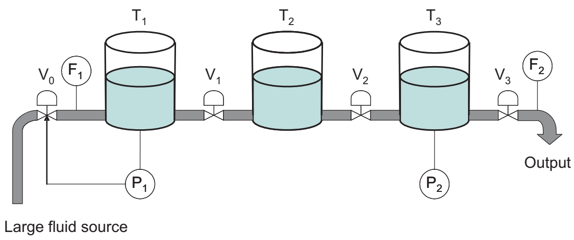

Fig. 1. Three tank schematic

Fig. 2 shows the bond graph model for the plant. The tanks are modeled as fluid capacitances, and the valves and pipes as resistances. 0− and 1− junctions represent the common effort (i.e., pressure) and common flow (i.e., flowrate) points in the system, respectively. Measurement points, shown as D_e and D_f components, are connected to junctions. The faults listed above appear as explicit parameters of the bond graph model.

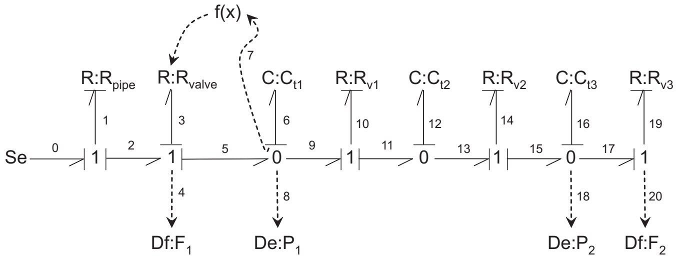

Fig. 2. Bond graph model of the plant. $f(x)$, a function of the tank pressure T_1 controls the resistance R_{valve} of valve V_0.

2.1 Deriving Temporal Causal Graphs

Causality can be automatically assigned to the bonds of a model using four types of causal constraints [Karnopp, et al., 2000]: (1) fixed causality for source elements, S_e, and S_f, (2) constrained causality for 0- and 1-junctions, (3) preferred (i.e., integral) causality for energy storage elements, C and I, and (4) arbitrary causality for dissipative elements, R. Temporal Causal Graphs(TCGs) developed by [Mosterman and Biswas, 1999] extend the traditional causal constraints described above, by including temporal constraints that are important for analysis of dynamic systems. They are directly derived from bond graph models by a simple extension to the causality algorithms (e.g., SCAP [Karnopp, et al., 2000]). For purposes of diagnosis, we exploit the causal and temporal relations between process parameters and the measurement variables provided by the TCG for residual generation and analysis.

The TCG for the three tank plant (Fig. 1) is shown in Fig. 3. Junctions and resistors define instantaneous magnitude relations, and capacitors and inertias define temporal effects on causal edges. For this example, to simplify the TCG structure, all = links and corresponding variables have been removed.

2.2 Constituent Equations

Using the constituent equations for components and junctions and following the causal links, one can systematically derive state space and input/output models of system behavior [Karnopp, et al., 2000] [Roychoudhury, et al., 2007]. Example constituent equations are: (1) $e_6 = \frac{1}{C_{t1}} \int f_6 dt$ for capacitor C_{t1}, where e_6 and f_6 correspond to the pressure in the tank, and net flowrate into the tank (i.e., the difference between input and output flowrate), respectively, and (2) $f_9 = f_{10} = f_{11}$ and $e_9 = e_{10} + e_{11}$ for a 1−junction in Fig. 2.

3. STRUCTURAL METHODS FOR RESIDUAL GENERATION AND ANALYSIS

This section discusses the ARR, PC, and TCG approaches to residual generation.

3.1 ARRs: The Diagnostic Bond Graphs approach

An Analytical Redundancy Relation (ARR) [Cordier, et al., 2004] is a constraint deduced from the model of the system containing only measured variables. The constraint

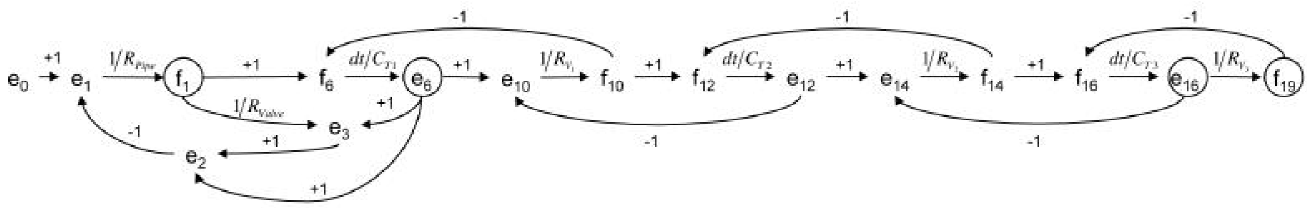

Fig. 3. Temporal causal graph of the three tank system.

also includes a subset of potential fault parameters of the system, and the fault isolation task links measured deviations in the variables to possible fault parameters. Fault isolation, i.e., residual evaluation can be defined as a logical combination of measurement deviations and implicated fault parameters.

ARRs are derived from the set of over-determined equations obtained from the structural system model. In the bond graph framework, this translates to first generating equations that correspond to the conservation laws at each 0− and 1− junction (see section 2.2), and manipulating these equations till only known (i.e., measured and input) variables remain. For example, starting with the equation $e_9 = e_{10} + e_{11}$ in section 2.2, the next substitution would generate, e_9 = measurement P_1, and $P_1 = R_{v_1}.f_{10} + \frac{1}{C_{t2}} \int f_{12}.dt$, and this substitution process would continue till all variables, such as f_{10} and f_{12} are substituted by other measurements, such as F_1, F_2 and P_2. Once the right form of equation is generated, a check is made to see if this equation (residual) is structurally independent of previously generated ones. However, this method for ARR derivation from bond graphs incurs high computational costs for equation derivation and structural equivalence checking, and the method cannot be applied when unknown variables cannot be eliminated because of the presence of algebraic loops and nonlinear non-invertible constraints [Medjaher, et al., 2005]).

To solve these problems, [Samantaray et al., 2006] propose a method where sensor variables are represented as sub-graphs that are derived by inverting the causality associated with the sensor variable bond. For example, the measurement $D_e : P_1$ may be imposed as the effort enforcer in Fig. 2, and this would put the capacitance C_{t1} in derivative causality. This ensures the decoupling of the residuals. Five different configurations for these subgraph models are considered: (1) inverted causality in an effort or flow sensor, (2) non-inverted causality in an effort or flow sensor, and (3) inversion of a signal sensor, D_s, to a signal source, S_s (this is a special case for dealing with controllers). The bond graph of the system with all these substitutions using preferred derivative causality is called the *Diagnostic Bond Graph* (DBG) [Samantaray and Bouamama, 2008].

Fig. 4 shows the DBG of the three-tank system with the causality on the sensors inverted. Table 1 shows the fault signature matrix derived from the DBG with the faults as rows, and the four ARRs as columns. Entry $(i, j) = 1$ in this table implies that ARR_j is sensitive to $fault_i$. A 0 implies the ARR is not affected by the corresponding fault. Column I shows the isolation capabilities of this approach. An entry of 1 for a fault in this column implies

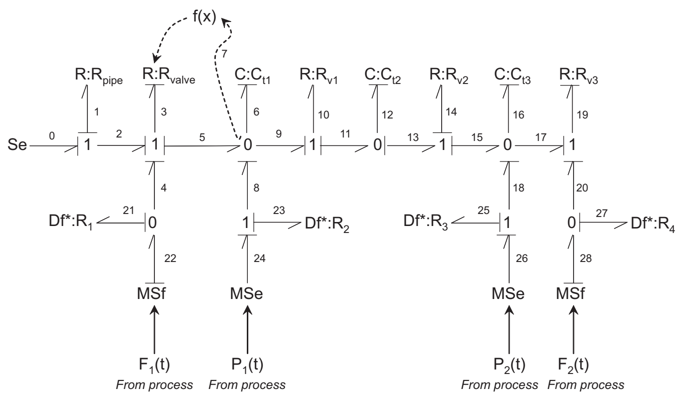

Fig. 4. DBG of the three-tank system including the flow measurements that correspond to the residuals ($Df^* : R_1$, $Df^* : R_4$), and the pressure measurements that correspond to the residuals ($Df^* : R_2$, $Df^* : R_3$).

that it is uniquely isolable, a 0 implies that it is not. For our example, fault parameters C_{t_2}, R_{v_1}, and R_{v_2} cannot be uniquely isolated.

Table 1. Signature matrix of the analytical redundancy relations found for the laboratory plant.

	ARR_1	ARR_2	ARR_3	ARR_4	I
C_{t_1}	0	1	0	0	1
C_{t_2}	0	1	1	0	0
C_{t_3}	0	0	1	0	1
R_{v_1}	0	1	1	0	0
R_{v_2}	0	1	1	0	0
R_{v_3}	0	0	0	1	1
R_{pipe}	1	0	0	0	1

3.2 Possible conflict(PCs) for Consistency based Diagnosis

The possible conflicts methods is related to consistency based diagnosis approaches commonly employed in the DX community [Reiter, 1987]. Possible conflicts (PCs) [Pulido and Alonso, 2000] [Pulido and Alonso, 2004], represent subsystems that produce conflicts when faults occur. Like ARRs, they are *minimal subsets of equations* with the analytical redundancy property to detect and isolate faults [Pulido and Alonso, 2004]. PCs are computed using a three steps process: (1) Generate an abstract representation of the system, as an hypergraph (H_{SD}), (2) Derive *Minimal Evaluation Chains*, i.e., the smallest connected subsystems ($H_{ec} \subseteq H_{SD}$) that define an over constrained set of relations, which can be solved locally, and (3) Generate solutions by local propagation; each possible solution is called a *Minimal Evaluation Model*, or MEM, and it can be used to predict the behavior of a subsystem.

The set of constraints in a MEC with a MEM is called a *Possible Conflict* (PC). When MEMs are evaluated with available observations and produce inconsistencies, then the PC is confirmed as a conflict. The method for generating PCs is different from the ARR approach, but the ARRs described in the last section and the PCs are structurally equivalent [Pulido, et al., 2007]. Causal assignments in ARRs and MEMs can be paired up and shown to be equivalent. Possible Conflicts represent the same structural information for all the MEMs obtained from a MEC. It has been shown that the calculation of PCs use the minimality criteria in terms of sets of constraints but ARRs use the structural independence criterion. For diagnosis, discrepancies between model predictions and measurements are linked back to individual PCs, from which fault hypotheses are derived. Like the ARR scheme, fault hypotheses consistent across all observed discrepancies are retained.

The hypergraph, H_{SD}, can be derived from the bond graph model using a procedure similar to deriving the TCG (see section 2.1). The difference is that no causal information is required, and no specific details about temporal information is included. Later, when the MECs are constructed, causal information between the effort and flow variables are used to generate the directed and-or graph of each MEC. For example, the first $1-$junction in the bond graph model establishes the relation between variables, e_0, e_1 and e_2 ($e_1 = e_0 - e_2$). Similarly, e_1 is related with f_1 through the resistor element. Causal relations from the bond graph model and more explicitly represented in the TCG, help establish the directionality and sequence of computations to derive MEMs from the AND-OR graph.

The three tank model produced 53 MECs, 4 MEMs, and 4 PCs. Fig. 5 illustrates a possible conflict. The right part of the figure represents the discrepancy node for this possible conflict, e_6. This node compares the value of the effort e_6 computed using the MEM represented in the left part of the figure with the sensor reading P_1. The computation of the required value(s) in the MEM occurs bottom-up, i.e., we start with sensor P_2 and compute effort e_{16}. Using efforts e_{16} and e_{12}, we compute effort e_{14}, and so on. Dashed lines in the MEM represent temporal constraints that are solved by integration (i.e., simulation).

Table 2 lists the resulting signature matrix with faults as rows and the PCs as columns. Again, column I shows the isolation capabilities of the approach. Like the ARR scheme, faults in C_{t_2}, R_{v_1}, and R_{v_2} cannot be uniquely isolated.

3.3 The TCG Approach

The TCG approach to online fault detection and isolation is implemented as the TRANSCEND system [Mosterman and Biswas, 1999] [Biswas et al., 2003]. Unlike the ARR and PC schemes, the fault detection approach is implemented as an independent process with an observer and a statistical fault detector, but we do not focus on that difference in this paper. The fault isolation scheme

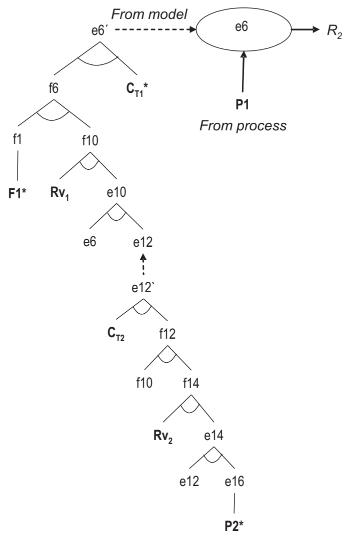

Fig. 5. Possible Conflict PC_2 found for the three-tank system. C_{t1}, C_{t2}, R_{v1}, and R_{v2}, are the parameters implicated by this PC. e_6, e_{12}, and f_{10} are values computed for each time step. F_1, P_1, and P_2 are the measurements.

Table 2. Signature matrix of the possible conflicts found for the laboratory plant.

	PC_1	PC_2	PC_3	PC_4	I
C_{t_1}	0	1	0	0	1
C_{t_2}	0	1	1	0	0
C_{t_3}	0	0	1	0	1
R_{v_1}	0	1	1	0	0
R_{v_2}	0	1	1	0	0
R_{v_3}	0	0	0	1	1
R_{pipe}	1	0	0	0	1

is implemented a three step process: (1) hypothesis generation after fault detection, (2) fault signature generation for all hypothesized faults, and (3) hypothesis refinement through progressive monitoring. Again, the online FDI algorithm is not the focus of this paper. Instead we focus on the fault signature generation process, and its relation to residual generation by the ARR and the PC methods described earlier.

The residual generation scheme used in TRANSCEND models the deviations in measurements and the fault effects using a qualitative reasoning framework. Deviation in individual measurements are represented as a $\pm$ change in the magnitude and slope of a measured signal residual (i.e., $y(t) - \hat{y}(t)$), where a $\pm$ value indicates a change above (below) normal for a measurement residual (or a positive (negative) residual slope). A 0 implies no change in the measurement value (or a 0 (flat) residual slope). Note that for dynamic systems, both the measurement deviation and slope can change with time, i.e., a measurement representation can go from $(+, +)$ to $(+, 0)$ or $(+, -)$. Fault parameter changes are also represented as $\pm$ values. For example, $R^{+}{}_{pipe}$ implies a fault where the pipe resistance increases above normal, and $R^{-}{}_{pipe}$ implies a fault where the pipe resistance decreases to below its nominal value.

Fault signatures, i.e., the effect of a fault on a measurement are also expressed in the qualitative framework defined above. More formally, a qualitative fault signature is expressed as: *Given a fault f , and measurement m, a qualitative fault signature, $FS(fm)$, of order k, is an ordered $(k+1)$-tuple consisting of the predicted magnitude and 1^{st} through k^{th} order time-derivative effects of a residual signal of measurement m, defined from the time point of occurrence of fault f, expressed as qualitative values: below normal (−), normal (0), and above normal (+).* Typically k is chosen to be the order of the system [Manders et al., 2000].

Given a set of possible fault parameters and a set of measurements associated with a system, the qualitative fault signatures can be derived from the TCG model of the system by forward propagation from the fault parameter along the edges of the TCG to the measurement node [Mosterman and Biswas, 1999]. All deviation propagations start off as 0^{th} order effects (magnitude changes). When an integrating edge in the TCG is traversed, the magnitude change becomes a first order change, i.e., the first derivative of the affected quantity changes. Each subsequent traversal of an integral edge increases the order of the fault signature by 1. As an example, the fault signature for ${R^+}_{pipe}$ on pressure measurement P_1 is $(0,+)$, indicating an increase in pipe resistance will cause no change in tank 1 pressure at the point of fault occurrence, and a gradual increase in pressure after the occurrence of the fault.

Table 3 lists the fault signatures derived for all possible single faults on the four measurements P_1, P_2, F_1, and F_2. An additional symbol used in the fault signatures is $*$, which captures indeterminate effects due to the qualitative framework used for signatures as discussed above [1]. Column I shows isolation capabilities (1 implies isolable, 0 implies not uniquely isolable) of this approach. The additional direction of change information helps improve discriminability. For example, fault C_{T_2} is uniquely isolable in the TCG approach but not in the PC and ARR approaches. Like the ARR and PC approach, faults R_{v_1} and R_{v_2} cannot be uniquely isolated.

The fault signature generation algorithm is computationally efficient when compared to traditional ARR and PC schemes. It is linear in the size of the TCG with no algebraic loops, and a low order polynomial when algebraic loops are present. However, with the use of the DBG structure, the ARR scheme can be made equivalent in complexity to the TCG scheme.

Table 3. Fault Signature matrix for the TCG approach

	P_1	P_2	F_1	F_2	I
C_{T_1}	$+*$	$0+$	$**$	$0+$	1
C_{T_2}	$0+$	$0+$	$0*$	$0+$	1
C_{T_3}	$0+$	$+-$	$0*$	$+-$	1
R_{V_1}	$0-$	$0+$	$0*$	$0+$	0
R_{V_2}	$0-$	$0+$	$0*$	$0+$	0
R_{V_3}	$0-$	$0-$	$0*$	$+-$	1
R_{pipe}	$0+$	$0+$	$+*$	$0+$	1

[1] An indeterminate effect occurs when there are at least two paths of the same order in the TCG that propagate + and - effects, so the resultant effect is unknown.

4. DISCUSSION AND CONCLUSIONS

How are fault signatures related to residual generation, and more specifically to ARRs and PCs? There are differences between the algorithms used for generating the ARRs, PCs, and FSMs. But the equivalence in their methodological approaches can be attributed to the relation between diagnostic bond graphs with inverted causality and the TCG scheme that is based on preferred causality. The DBG structures imply that the ARR relations are derived as transfer functions from measurement to input. All fault parameter values included in this transfer functions are possible candidates if the corresponding ARR value is non zero. Residual analysis is performed by performing a logical 'AND' on the individual ARR results. A single fault hypothesis is established if a particular fault parameter appears in all non zero ARRs, and does not belong to an ARR that remains 0.

For the TCG scheme, the analysis is along the preferred causality direction, i.e., from the fault parameter to the measurement, conditioned the inputs. Therefore, the transfer function is derived from inputs to measurements in the direction of preferred causality. Fault hypotheses are established by matching fault signatures to individual measurement deviations (magnitude change and slope), and a single fault hypothesis is established, only when one fault parameter is consistent with all of the observed measurement changes. Due to shortage of space, we do not present a formal analysis of the equivalence in this paper, but we will present this in a future expanded journal paper.

The PC scheme is between the ARR and the TCG methods. It derives PCs by combining constituent equations, till the resultant equation contains just measurement and input (i.e., known) variables and system parameters. Since it uses the equation framework like the ARRs, its discriminability is identical to the ARR scheme. However, PC schemes are designed to use mixed integral and derivative causality relations, and, therefore, they can produce different fault signature matrices with different diagnosability properties [Pulido, et al., 2007] [Svard and Nyberg, 2008]. It remains to be seen if we can formally establish whether the use of mixed causality residual generation approaches increases the theoretical diagnosability of the system given a set of measurements. An important issue to be considered is that the structure of each PC or ARR can be seen as equivalent to a minimal subset of over-determined equations within the TCG, i.e, PCs and ARRs identify minimal structures in TCGs, which can form the basis for fault isolation using minimal fault signature matrices.

Another difference is the way each approach deals with temporal information. Whereas ARRs and PCs only model the causal and the temporal information between variables and their derivatives [Blanke, et al., 2003], the qualitative fault signatures approach uses a more informative structure, the temporal causal graph. The additional information helps relate the direction of change in a variable to a fault hypothesis. This approach uses qualitative information to drive the diagnosis task. The use of this kind of information allows one to obtain a more informed fault isolation space than the PCs or the ARRs, and this results in better discriminability for the TCG scheme. [Ligeza and Gorny, 2000] have proposed a TCG-like scheme, where they derive the TCG structure from a Simulink model of a system as opposed to a bond graph. The generality of this approach for non linear systems still needs to be established. Koscielny, et al. [Koscielny, et al., 2006] define discriminability matrices that take into account the sign of the observed deviation, but these deviations are obtained from experts' heuristic knowledge. All three methods discussed in this paper, derive discriminability and fault signature information systematically from the bond graph model of the system.

A more comprehensive comparison of different compilation methods for diagnosis is presented in [Pulido and Alonso, 2004]. In this paper, we keep our focus on methods that exploit the causal structure implied by the bond graph models, which facilitates the residual generation process, and reduces the computational complexity for all three methods. In future work, we will develop a more systematic comparison framework that is supported by systems dynamics theory, and can be described formally within the BRIDGE framework to capture discriminability of sets of measurements and diagnosability of systems. We will also extend our approach to cover sensor and actuator faults, in addition to the parametric faults that we have discussed in this paper. Last, it is important to extend the comparison to different and more complex forms of nonlinear systems, where both quantitative analysis becomes more complex, and qualitative analysis looses discrimination power.

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