Using Bond Graphs for Diagnosis of Dynamic Physical Systems

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Abstract

Modeling and analyzing dynamic system behavior is the key to successful diagnosis of complex continuous engineering systems. The bond graph modeling language provides a systematic framework for compositional modeling of dynamic physical systems from physical principles. A description of the important properties of this modeling paradigm as they pertain to diagnosis is presented. This modeling technique facilitates the explication of causal interactions and temporal relations between parameters by drawing upon fundamental laws of energy conservation and continuity. This representation is exploited to develop a diagnosis algorithm that generates fault candidates from multiple measurement snapshots.

1 Introduction

Developing reliable and efficient diagnosis methodologies for dynamic and continuous engineering systems poses a significant challenge to both researchers and practitioners. Dynamic systems are time-varying, have memory (i.e., future behavior is a function of both input and internal state), and system parameters are continuous-valued. Important distinctions can be made between modeling steady state versus dynamic behavior of continuous systems. Steady state behavior occurs at fixed operating regions and defines equilibrium behavior. A system may have multiple operating regions of interest, and each region defines a steady state behavior with a corresponding system model. Each model presents a static (or fixed) relation among sets of components. On the other hand, dynamic behavior of a continuous system is described by the system assuming different states over time, and individual states need not represent equilibrium behavior. Component interactions, in this case, are no longer defined statically, but evolve as the system goes through different states. For example, steady state or equilibrium behavior of a gear train can be described by its transmission ratio, whereas dynamic behavior focuses on torque generated, which is a function of time varying parameters such as force and angle. Typically, a normally operating system is described in terms of steady state behavior and static models. However, when fault situations occur, caused by failed components, external disturbances, and control changes, system behavior is dynamic. Therefore, system models for the analysis of dynamic system behavior are the key to developing successful diagnostic methodologies.

Component-oriented models use system descriptions in the form of a topology of interconnected components, and behavior descriptions specified for the individual components. Prediction of system behavior is accomplished by *compositional modeling*[1; 4; 10] and simulation. Component-oriented diagnosis identifies sets of components whose deviant behavior can explain observed discrepancies in system behavior.

Traditional model-based diagnosis methodologies have focused on consistency-based techniques[5] but this approach is more applicable to static or steady state diagnosis. The qualitative models used by most of these systems cause ambiguities in generating and analyzing behavior, and this can lead to computational intractability in diagnosis and monitoring tasks. Also, none of these systems deal with the notion of tracking model changes caused by faults. MIMIC[3], a system developed for monitoring and diagnosis, hypothesizes faults using a pre-determined fault tree; a qualitative simulation based on QSIM[7], using pre-enumerated fault models corresponding to fault hypotheses, matches predicted behaviors with actual observations to discriminate among multiple hypotheses. For MIMIC to work successfully, it is necessary that all faults that may occur in the system are modeled a priori. So, for a large fault space this approach is impractical. Kramer et al.[11; 8] describe a diagnosis methodology that uses causal models represented as signed directed graphs (SDGs) derived from physical mechanisms. Deviations from a steady state are tracked by linear first order differential equation models and explicit structure in the SDGs that describes various kinds of compensatory and feedback mechanisms. The diagnosis algorithm traces causal relations to identify preliminary causes for observed deviations, which are then related to component malfunctions.

Our goal is to develop effective mechanisms for diagnosis and monitoring of the dynamic behavior of complex engineering systems. Having recognized that modeling is the crucial problem, we identify important features of

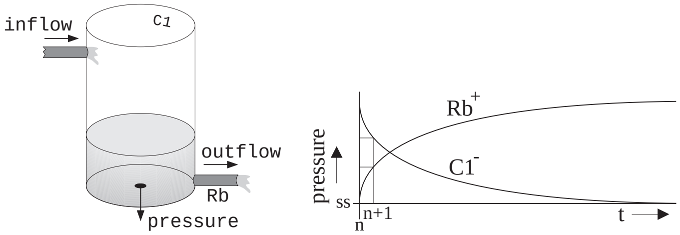

Figure 1: **One Tank Flow System**

dynamic physical system behavior that traditional methods with their focus on diagnosis inference methods have ignored, and use these features to perform effective diagnosis of dynamic systems. The diagnosis and monitoring algorithm will require the ability to:

- model dynamic behavior of complex systems to explicitly reason about temporal attributes of system parameters, and relate behavior changes back to component parameters,
- use qualitative and quantitative information to reason about system behavior, and
- switch system models dynamically as faults cause structural and behavioral changes.

In this paper, we address the first two issues. We adopt the bond graph[12] methodology for describing dynamic behavior of the system under scrutiny. In this work, we do not discuss sensor-related issues or address the task of measurement accuracy and interpretation. Our focus is on the characteristics of the bond graph model that assist in the development of efficient and effective diagnosis algorithms to relate measurement deviations to system component faults.

2 Modeling for Diagnosis

Diagnosing dynamic systems requires the ability to analyze time-varying system behavior. We assume that the system under scrutiny was working normally in steady state, and one or more faults cause the system to deviate from steady state and exhibit transient behavior. With time, the system may again achieve steady state behavior, which may or may not correspond to the original steady state operation of the system. Our diagnosis methodology is initiated once *discrepancies* are detected. System behavior is *tracked* to identify faults (system component malfunctions) using a combination of transient and steady state analysis. Note that system behavior is captured as a temporal sequence of snapshots.

Consider a simple tank system with a constant inflow source at the top, and an outflow pipe at the bottom (Fig. 1). For a fixed inflow rate and outflow resistance, the level of liquid in the tank and the outflow rate attain steady state values. Consider two faults that can occur in the system: (i) an object falls into the tank, instantaneously decreasing its capacity, (ii) a blockage in the pipe causes the output resistance to increase. Suppose we are monitoring the pressure at the bottom of the tank at discrete times. Up to a certain time stamp n, this pressure was at the steady state value; at time stamp $n+1$ the value is observed to be higher than normal. On reasoning backwards from this measurement, either of the two faults listed above are plausible causes but it is not possible to determine the true fault assuming only one has occurred, from this one measurement. If we continue to monitor the pressure, one of two situations are observed: (i) The pressure decreases down toward its previous steady state value, or (ii) the pressure increases to a different steady state value. In the first case, the tank capacity is implicated, and, in the second case, the pipe resistance is implicated. This simple example illustrates that diagnosis of dynamic continuous systems requires the analysis of temporal system behavior to differentiate among possible faults.

Diagnosis of continuous dynamic systems requires the following steps:

1. Given a measurement set, use causal analysis to identify the possible faulty components in the system.
2. For each faulty component set, propagate effects of the fault(s) to predict future values for the measured variables.
3. Use temporal analysis to eliminate possible faults whose predicted behaviors do not match observed measurement values.

In some situations, new steady state behavior of the faulty system may have to be derived to differentiate among possible candidate sets. Bond graph models of physical systems provide a comprehensive scheme for modeling all of the above information[1; 12].

3 Bond Graphs as Diagnosis Models

Bond graph models provide a systematic framework for analyzing dynamic system behavior[1]. This framework can be exploited to generate: (i) constraints among locally related variables from the causal links associated with the bonds of the graph, (ii) temporal relations from analytic models of system behavior, and (iii) steady state behavior. The causal links are used to generate fault hypotheses, while a combination of causal, temporal, and steady state analysis provides the information necessary to discriminate among these hypotheses.

3.1 The Causal Graph

A causal relation is an interaction between two events where one event can be identified as the cause and the other as its result. These causal relations can be assigned to bond graph elements based on local information. For example, a flow source has flow causality, a capacitance a preferred effort causality, and a resistance can have either. This information then algorithmically propagates through the graph to assign causality to every element. A formal algorithm for generating a causal graph for the system can be established based on the SCAP algorithm[12].

The first step in the diagnosis task constructs a *causal graph* from the bond graph model of the system. Effort and flow variables in the system are represented

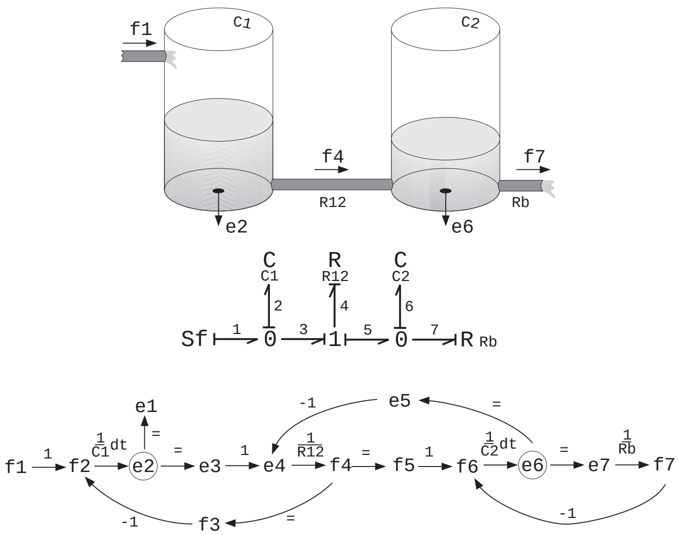

Figure 2: **Bond Graph and Causal Graph: Two connected tanks containing a fluid.**

as vertices, and the relations between them as directed edges. Typically junctions impose *equality* or *summation* between sets of effort or flow variables. Equalities are marked with an = sign on the corresponding edges and summation is expressed as +1 or −1 depending on the direction of the power flow on the bonds of the associated variables. Otherwise, relations between effort and flow variables are derived from the *constituent* relations of the corresponding elements. For example, the $e_i \rightarrow f_i$ link for a resistor is labeled $\frac{1}{R}$, whereas the same link for a capacitive element is labeled $\frac{1}{C}dt$. The labels for junctions, transformers, and resistive elements represent instantaneous *magnitudinous* relations, whereas the energy storage links have both *magnitudinous* and finite *temporal* properties. In other words, the energy storage elements introduce an *integrative* effect. The rate at which the effect of a fault is manifested at a measured variable, is a function of the magnitudinous and temporal values associated with the path that links the observed parameter to the fault.

An example of a connected two tank system, its bond graph, and its causal graph is shown in Fig. 2. The causal properties of the bonds are reformulated into the causal graph form starting from the flow source f_1. A number of negative feedback loops, a phenomenon ubiquitous to passive elements in a physical system, become apparent in the causal graph.

3.2 Rate of Change

An important mechanism for distinguishing between faults is that they may affect measured variables at different temporal rates. The differences in the response time can be observed by studying sequences of measurement values and using the rate of change to discriminate among the suspected components.

The bond graph model provides for a systematic derivation of response times for measured variables[2]. For example, if R_{12} in Fig. 2 is hypothesized to deviate

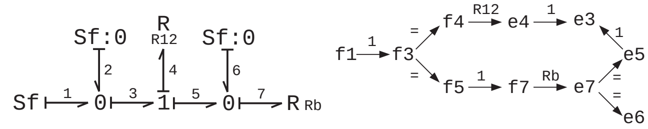

Figure 3: **Two Tank System: Bond Graph of Steady state model**

above normal, e_3 and e_6 are affected. The response time of the deviations of these two signals provides a temporal ordering that can be used to verify or refute the R_{12}^{+} hypothesis.

3.3 Steady State Analysis

When the transient effects of the fault have died out, the system reaches a new steady state. Analysis of this steady state may provide valuable diagnostic information that can be used to prune the hypothesis space. Steady state behavior can be derived systematically from a bond graph model by observing that, in steady state, the energy stored in the capacitive and inductive elements does not change. Therefore capacitances can be replaced by a constant flow source (with 0 flow) and inductances by a constant effort source (with 0 effort). This causes changes to the causality assignment in the bond graph. A steady state causal graph for the two tank system is shown in Fig. 3. As an example, from the steady state model we can derive that e_5 (which equals e_6) can only be different in steady state if R_b changes. No other component parameter deviation affects the steady state value of e_5.

4 The Diagnosis Algorithm

Following up on the discussion in Section 2, the diagnostic algorithm can be described in terms of the following steps:

1. Consistency and causal graph propagation.
   - Establish consistency across = edges at junctions.
   - Propagate measured variables backward to identify fault hypotheses.
2. Temporal behavior propagation. Trace the effect of each fault hypothesis and match the observed and predicted values over time to discriminate among possible hypotheses. To this end:
   - Propagate *forward* the effects of component parameter deviations, and increase the order of the derivative each time an edge with an integrating effect is traversed.
   - Determine rates of change for observed variables.
3. Analysis of steady state behavior after transients have died out.
   - Predict steady state behavior for each of the suspect components.
   - Identify possible *inverse responses* based on steady state behavior.

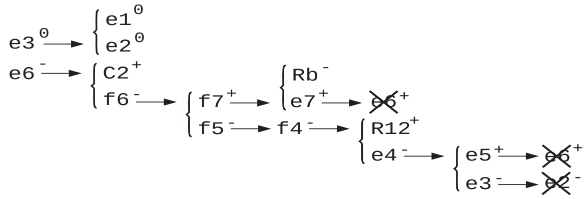

Figure 4: **Backward tracing of the diagnosis model.**

4.1 Consistency and causal graph propagation

Vertices corresponding to observed variables are assigned their measured values. A variable is assigned the value 0 if the measurement is normal, + if the measurement is above normal, and − if the measurement is below normal. Assuming faults do not change physical system configuration, junctions are not under diagnostic scrutiny, therefore, junction relations are assumed to remain consistent. To establish this consistency among variable values, qualitative assignments across all = edges in the causal graph is performed.

Normal values are first propagated along = edges in the causal graph. Each vertex encountered along the propagation is labeled normal. Next, deviant measurement values are propagated backward until a normal value is reached or a conflicting assignment arises. Each vertex encountered along the propagation is labeled + or − depending upon the edge connecting the vertex to its successor and the label of that successor.

For example, suppose the pressure at the bottom of the tank C_2 (e_6) is observed to be low (−) and the pressure at the left of the connecting pipe (e_3) is normal (0) in the two tank system (Fig. 2). First, consistency is established across the = edges by labeling e_1 and e_2 (Fig. 4). Tracing the causal relations upstream implicates the tank capacity C_2 (+), the outflow resistance R_b (−), and the resistance of the connecting pipe, R_{12} (+). Backward propagation stops at the conflicting value for e_6 because of the negative feedback of the loops for e_6 and e_2.

Causal graph propagation identifies an initial set of hypotheses. As a next step, temporal behavior and/or steady state analysis is used to distinguish among multiple hypotheses.

4.2 Temporal Behavior

Initial fault hypotheses are verified by propagating their behavior and matching them with observed variable values. A qualitative propagation for each fault hypothesis, achieved by propagating *forward* the effects of that fault, generates the $0^{th}, 1^{st}$, and 2^{nd} order derivative for each measured variable. The order of the derivative of the temporal effect is increased every time an integrating edge is traversed in the causal graph. The qualitative values so derived constitute the *signature* for the observed value for that hypothesis. If the signatures of all observed values are consistent with the actual observations, then the fault hypothesis is accepted, otherwise it is rejected.

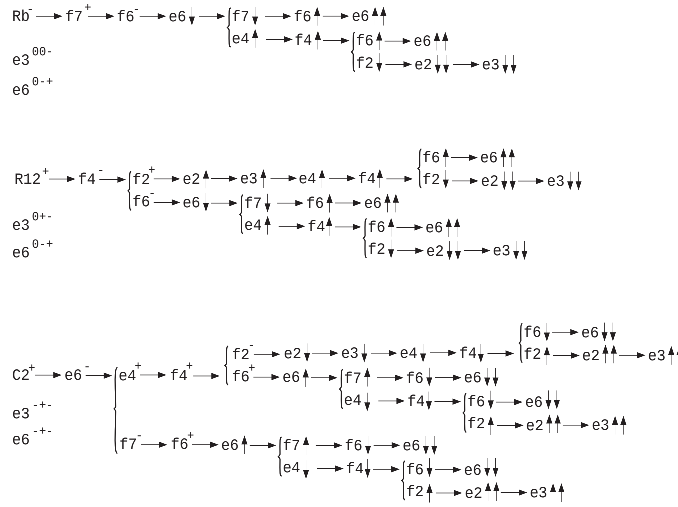

Figure 5: **Forward tracing of the diagnosis model, incorporating integrating effects, to predict behavior.**

Continuing the two tank example, causal graph propagation identifies R_{12}^{+}, R_b^{-}, or C_2^{+} as possible fault hypotheses. The detailed prediction trace for each fault is shown in Fig. 5. The measured variable e_6 shows identical response for both resistance deviations, i.e., decreasing with a decreasing slope (e_6^{0-+}). The superscripts represent the $0^{th}, 1^{st}$, and 2^{nd} order derivatives respectively. Note that no explicit magnitude for e_6 is specified in its trace that yields the signature, which implies that this value must start off from its normal value. On the other hand, the capacitance deviation, causes a discontinuous drop in the value of e_6, which then increases with a decreasing slope e_6^{-+-}.

Fig. 6 shows the continuous behavior of e_3 and e_6 for R_{12}^{+} and $R_b{}^{-}$, respectively. Even though e_6 exhibits different *temporal behavior* quantitatively for the two faults, their qualitative signatures look the same, therefore, this measurement alone could not differentiate between the two faults. However, the signatures of e_3 are different for the two faults. R_b^{-} yields e_3^{00-} (second order behavior with a negative slope) while R_{12}^{+} results in e_3^{0+-} (first order behavior with a positive slope). Over time if e_3 falls below normal the cause is R_b^{-} while if e_3 deviates above normal, the cause is established to be R_{12}^{+}.

The response times (or the rates of response) can be used to discriminate hypotheses by studying the first order *rate of change* of the observed variables. For example, if R_{12} deviates above normal, signatures e_3^{0+-} and e_6^{0-+} are observed. If the rate at which e_3 increases is larger than the rate at which e_6 falls, e_3 falling below its normal threshold would be detected *before* e_6. From the bond graph it can be seen that the rates of change of e_6 and e_3 are $R_{12} * C_1$ and $R_{12} * C_2$, respectively. If C_1 is less than C_2, the response of e_3 is faster than e_6, i.e., e_3 is observed to have dropped below normal first. If this behavior is not observed, R_{12}^{+} can be eliminated from the hypotheses set. Note that this analysis is independent

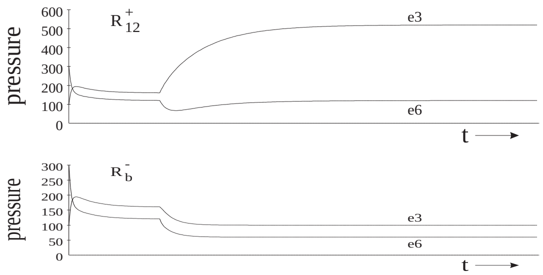

Figure 6: **Fault behavior for R_{12}^{+} and R_b^{-}.**

of the actual value of the possibly deviant R_{12}.

4.3 Steady State

In the final stage, the causal structure of the system in steady state can be used to identify the effect of each of the implicated component parameters. Because of the predictive power of the steady state analysis, it is not required to wait until the system reaches steady state. For example, for resistance failures, e_6 in Fig. 5 has the temporal signature e_6^{0-+}. This can be asymptotic behavior towards a new, lower, steady state value or the effort value can go back up (an inverse response) to attain its original value. The steady state analysis reveals either of these to happen. So, if the effort value starts going back up, it can be immediately inferred that the element causing the corresponding steady state behavior is faulty, without waiting for the signal to actually reach steady state.

This is illustrated in Fig. 6 which shows the fault behavior for, ${R_{12}}^{+}$ and ${R_b}^{-}$, respectively. From the steady state analysis (see Fig. 3), it is observed that for R_b^{-} the pressure e_6 $(= e_7)$ in steady state is low and a change in R_{12} does not affect the steady state value of the observed variable e_6. This information can be used to make a distinction between causes for the fault behaviors. Notice that steady state analysis introduces additional information that makes it possible to discriminate between R_{12}^{+} and R_b^{-} based on measurements of e_6 only.

5 Discussion

Bond graphs are a powerful tool for building consistent, composable, and hierarchically structured models of dynamic physical systems across domains in a manner that their physical correctness can be guaranteed. We show how an explicit representation of causal relations between system parameters and variables facilitates component oriented fault diagnosis. Palowitch's [11] causal models are obtained by categorizing analytic system descriptions into classes of physical mechanisms. While the classes are chosen with care to conform to physical principles, the bond graph framework provides a more systematic procedure for identifying causality. Moreover, a combination of qualitative causal relations, quantitative magnitude relations, and response times associated with state variables is exploited to refine the diagnosis task. By curtailing spurious behavior, and, therefore, spurious candidate generation, the computational intractability problems faced by MIMIC[3] may be mitigated.

Future work will focus on developing algorithms to efficiently identify interacting, multiple faults. Bond graph switching[9] to represent discontinuous behaviors to instantiate alternative topologies for the system is also being investigated.

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