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Structural Approach for Distributed Fault Detection and Isolation

Hamed Khorasgani * **Daniel Jung** ** **Gautam Biswas** *

* *Inst. of Software-integrated Systems, Vanderbilt Univ., USA, e-mail:* {hamed.g.khorasgani,gautam.biswas}@vanderbilt.edu
** *Dept. of Electrical Engineering, Linköping University, Sweden, e-mail:* daner@isy.liu.se

Abstract:
This paper presents a framework for distributed fault detection and isolation in dynamic systems. Our approach uses the dynamic model of each subsystem to derive a set of independent, local diagnosers. If needed, the subsystem model is extended to include measurements and model equations from its immediate neighbors to compute its diagnosis. Our approach is designed to ensure that each subsystem diagnoser provides the correct results, therefore, a local diagnosis result is equivalent to the results that would be produced by a global system diagnoser. We discuss the distribute diagnosis algorithm, and illustrate its application using a multi-tank system.

Keywords: distributed fault diagnosis, residual generation.

1. INTRODUCTION

Analytical redundancy methods have been applied extensively for model based fault detection and isolation (FDI) of dynamic systems (Gertler, 1998; Bregon et al., 2014). Traditional approaches develop centralized diagnosers, e.g., the Aircraft Diagnostic and Maintenance Systems (ADMS) used on modern aircraft systems (Spitzer, 2007). However, as the complexity and size of systems, such as aircraft, automobiles, power plants, and manufacturing processes, have grown, distributed approaches to fault detection and isolation in large dynamic systems with many subsystems have become important (Leger et al., 1999; Shum et al., 1988). Transferring all of the collected sensor information to a central fault detection and isolation unit can be expensive and error prone. Centralized diagnosers may also be less reliable because they provide a single point of failure. Networking delays can also affect the timeliness of diagnosis decisions.

The computational intractability of centralized diagnosers for large systems is another reason for developing distributed diagnosers. In this paper, we adopt the approach of building individual diagnosers for each subsystem, taking into account that interactions with neighboring subsystems may have to be modeled to achieve globally correct diagnosis for each diagnoser.

The Dulmage-Mendelsohn (DM) decomposition (Dulmage and Mendelsohn, 1958) is a popular structural approach for designing FDI systems (Flaugergues et al., 2009; Krysander et al., 2008). Krysander and Frisk (2008) have used DM decomposition to address the sensor placement problem. In this paper, we adapt the DM decomposition approach to design and implement local diagnosers for each subsystem of a large, complex dynamic system. Unlike (Lafortune, 2007; Debouk et al., 2000) this method does not use a centralized coordinator and reduces the communication between subsystems to a minimum while still producing globally correct diagnosis results. Moreover, in the design process we do not need to have access to the global model.

The outline of the paper is as follows. Basic definitions and the multi-tank system as a running example are presented in Section 2. Section 3 formulates the problem. Our approach to distributed fault detection is presented in Section 4. The extension of the method to distributed fault isolation is presented in Section 5. Section 6 applies the method to the running example, a four-tank system and Section 7 concludes the paper.

2. BASIC DEFINITIONS AND RUNNING EXAMPLE

We use a four tank system (see Fig. 1) as a running example to discuss our distributed diagnosis algorithms. We assume each subsystem contains a tank, $T_i; 1 \leq i \leq 4$, and the outlet pipe to its right $P_i; 1 \leq i \leq 4$. Two of the subsystems, 1 and 3, also have inflows sources into their tanks. The system has eight sensors. Three sensors measure the pressure of T_1, T_2 and T_4 (p_1, p_2 and p_4, respectively). Three sensors measure the flow rates of P_1, P_2 and P_3 (q_1, q_2 and q_3, respectively). Two sensors measure the input flow rates, q_{in1} and q_{in2}. We assume the subsystems are disjoint, i.e., they have no overlapping components.

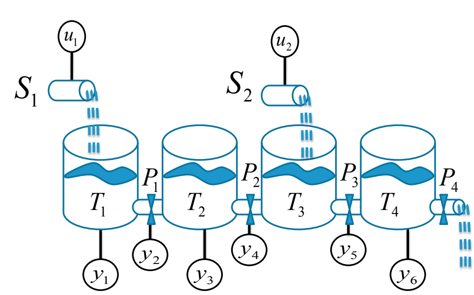

Fig. 1. Four-tanks system.

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More generally, we assume a system, S is made up of n of subsystems, $S_1, S_2, ...S_n$. Each subsystem is described by a dynamic system model.

Definition 1. (Subsystem model). A subsystem model M_i ($1 \leq i \leq n$) is a tuple of (V_i, C_i, F_i), where V_i is the set of variables, C_i is the set of constraints and F_i is the set of system faults associated with the subsystem.

The overall set of system faults, $F = \bigcup_{i=1}{}^{n} F_i$, is the union of faults associated with each subsystem.

For illustration, the first subsystem in our running example is described by the set of following equations:

$$
\begin{aligned}
c_1 &: \dot{p}_1 = \frac{1}{C_{T1} + f_1}(q_{in1} - q_1) & c_4 &: q_{in1} = u_1 \\
c_2 &: q_1 = \frac{p_1 - p_2}{R_{P1} + f_2} & c_5 &: p_1 = y_1 \\
c_3 &: p_1 = \int \dot{p}_1 \, dt & c_6 &: q_1 = y_2.
\end{aligned} \tag{1}
$$

C_{Ti} is the nominal capacity of tank T_i, R_{Pi} is the nominal resistances of pipe P_i, $C_1 = \{c_1, c_2, c_3, c_4, c_5, c_6\}$ is the set of behavior constraints associated with this subsystem, $V_1 = \{\dot{p}_1, p_1, p_2, q_{in1}, q_1\}$ is the set of variables for the first subsystem model and $F_1 = \{f_1, f_2\}$ is the set of faults for this subsystem. Note that V_1 does not include known variables such as measurements, ($u_1, y_1,\ y_2$), or system parameters, ($C_{T1},\ R_{P1}$).

Similarly, the second subsystem model is defined by the following equations:

$$
\begin{aligned}
c_7 &: \dot{p}_2 = \frac{1}{C_{T2} + f_3}(q_1 - q_2) & & \\
c_8 &: q_2 = \frac{p_2 - p_3}{R_{P2} + f_4} & c_{10} &: p_2 = y_2 \\
c_9 &: p_2 = \int \dot{p}_2 \, dt & c_{11} &: q_2 = y_4.
\end{aligned} \tag{2}
$$

For this subsystem the set of constraints is $C_2 = \{c_7, c_8, c_9, c_{10}, c_{11}\}$, the set of variable is $V_2 = \{\dot{p}_2, p_2, p_3, q_1, q_2\}$ and $F_2 = \{f_3, f_4\}$ is the set of faults. Note that the initial conditions for constraints c_3, c_9 and other integral equations in the paper are assumed to be known.

Definition 2. (Neighboring Subsystems). Two subsystems, and, therefore, their corresponding models, M_i and M_j are defined to be neighbors if and only if they have at least one shared variable.

In the running example, subsystem models M_1 and M_2 are neighbors and their shared variables are $V_1 \cap V_2 = \{p_2, q_1\}$.

The DM decomposition divides a system model into three parts: (1) under-determined, (2) exactly determined and (3) over-determined (Flaugergues et al., 2009). The over-determined part introduces redundancy in the system model and can be used for fault detection and isolation. Fig. 2 represents DM decomposition of the first subsystem. This subsystem model has a just determined part ($M_1{}^0$) and an over-determined part ($M_1{}^+$). The shared variables between a subsystem and the other subsystems in the running example are circled in the figures.

In this work, we assume every fault parameter, f is included in exactly one constraint equation, c_f. This is not a restricting assumption because if we have more than a fault in a constraint we can consider the other faults as new variables and then add new constraints for each of these new variables making the variable equal to the fault. Given that, the local detectability can be defined as:

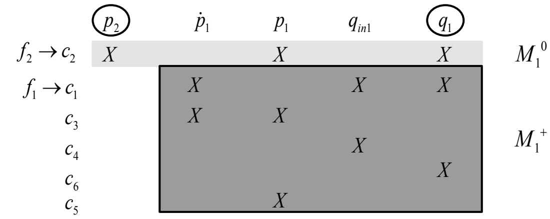

Fig. 2. DM decomposition of the first subsystem model.

Definition 3. (Locally detectable) A fault $f \in F_i$ is locally detectable if $c_f \in M_i{}^+$, where $M_i{}^+$ is the over-determined part of subsystem model M_i.

Consider *Definition* 3 and Fig. 2. Fault f_1 is locally detectable because $c_1 \in M_1{}^+$ but f_2 is not locally detectable since $c_2 \notin M_1{}^+$. To detect f_2, the diagnosis subsystem needs to have an extra constraint.

Definition 4. (Augmented subsystem model) Given subsystem model M_i and constraint $c_k \notin M_i$, the augmented subsystem model $M_{i_{c_k}} = (M_i|c_k)$ is ($V_{i_{c_k}}$, $C_{i_{c_k}}$, $F_{i_{c_k}}$), where $V_{i_{c_k}}$ is the union of V_i and variables appear in c_k, $C_{i_{c_k}}$ is the union of C_i and c_k and $F_{i_{c_k}}$ is the union of F_i and the possible fault associated with c_k.

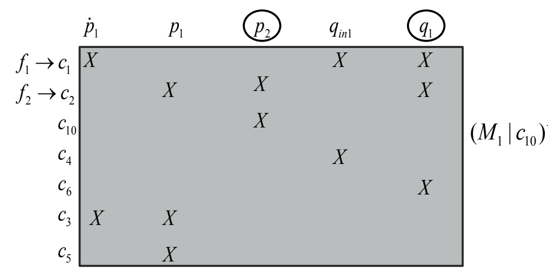

Fig. 3. DM decomposition of $M_{1_{c_{10}}} = (M_1|c_{10})$.

For example in the running example $M_{1_{c_{10}}} = (M_1|c_{10})$ is ($V_{1_{c_{10}}}$, $C_{1_{c_{10}}}$, $F_{1_{c_{10}}}$), where $V_{1_{c_{10}}} = \{\dot{p}_1, p_1, p_2, q_{in1}, q_1\}$, $C_{1_{c_{10}}} = \{c_1, c_2, c_3, c_4, c_5, c_6, c_{10}\}$ and $F_{1_{c_{10}}} = \{f_1, f_2\}$. Note that c_{10} did not add any new variables or faults to the subsystem model. Fig. 3 represents the DM decomposition of the augmented subsystem model $M_{1_{c_{10}}}$. This figure shows that $c_2 \in M_{1_{c_{10}}}{}^+$, and, therefore, f_2 is locally detectable for the augmented subsystem model $M_{1_{c_{10}}}$.

Definition 5. (Locally isolable) A fault $f_i \in F_i$ is locally isolable from fault $f_j \in F$ if $c_{f_i} \in (M_i \backslash c_{f_j})^+$, where $(M_i \backslash c_{f_j})^+$ is the over-determined part of subsystem model M_i without c_{f_j}.

Fig. 4 shows DM decomposition of the $M_{1_{c_{10}}} \backslash c_1$.

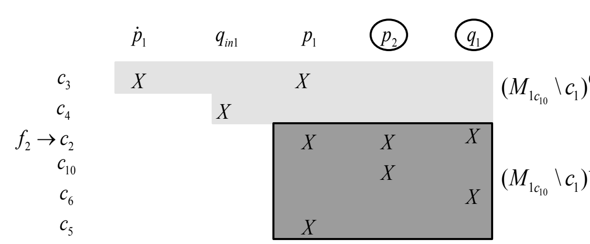

Fig. 4. DM decomposition of $M_{1_{c_{10}}} \backslash c_1$.

c_2 is in the overdetermined part of the augmented subsystem model, therefore f_2 is locally isolable from f_1 in the augmented subsystem model.