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Fault diagnosis based on dissipativity property

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ABSTRACT

In this paper, a novel fault diagnosis scheme for linear process systems using dissipativity theory is developed. Dissipativity (supply rate) of a process is an input/output property, which may not be valid when a fault occurs. For a given process, dissipativity is not a unique property, with different dissipative supply rates reflecting different aspects of its dynamics. In this approach, the dissipativity of a process is “shaped” such that it is fault-sensitive (i.e., no longer valid when faults occur) and fault-selective (i.e., no longer valid when one particular fault occurs). By adopting the storage functions and supply rates in the quadratic difference form (QdF), the dissipativity conditions are represented as quadratic functions of the input/output trajectories of the process, which captures much more detailed dynamical features compared to conventional dissipativity (e.g., QSR-type supply rates). These dissipativity properties are determined offline by solving an optimization problem with linear matrix inequality constraints. The online diagnosis algorithm involves checking of inequalities on input/output trajectories, which is much simpler compared to the diagnosis approaches based on observers or parameter estimation. The proposed approach is illustrated using a case study of fault diagnosis of a heat exchanger.

1. Introduction

Modern industrial processes are becoming very complex. The increasing dependence of complex processes on automatic control systems can make the plants susceptible to faults such as sensor/actuator failures. Therefore, fault detection (i.e., to identify if there is a fault) and diagnosis (i.e., to determine what fault occurs) are becoming an important issue in process control practice. Model-based fault detection approaches, including observer-based, parity equation-based and parameter estimation-based methods, utilize the mathematical models of the processes (referred to surveys Venkatasubramanian et al., 2003; Frank et al., 2000). The general procedure of observer-based methods usually involves two steps, residual generation and decision making (Frank, 1990), as depicted in Fig. 1. The residuals are shaped such that they are sensitive to abnormal conditions. An example of observer-based method is the fault detection filter, proposed in Beard (1971) and Jones (1973). Parity equation based methods (e.g., Chow and Willsky, 1984) generate parity vector (residuals), that is used to check the consistency between process model and process outputs (Gao et al., 2015). While they are simpler than observer-based approaches, parity equation based methods can be less effective in detecting faults and are limited to faults that do not include gross parameter drifts (Venkatasubramanian et al., 2003). Another fault detection method is based on parameter estimation, which is formed on the basis of system identification techniques (Simani et al., 2013). The basic idea is to identify the actual process parameters online, and compare them with the parameters of the fault-free process model.

Many of the above fault detection methods have been extended for fault diagnosis (Ding, 2008). For observer-based methods, a bank of observers, one for each fault or a group of faults, are required for fault diagnosis. One intuitive idea is to make a residual sensitive to the fault that is concerned and robust to all other faults (i.e., structure residual fault isolation Gertler, 1988). Alternatively, the residual can be shaped to be robust to all but one fault and also robust against uncertainties (i.e., generalized residual fault isolation Frank, 1990). Generally, a fault diagnosis method needs to generate several representative symptoms. For example, in Isermann (2011), fault-symptom tables have been used, and systematic treatment of fault-symptom trees is based on approximative reasoning with if-then-rules by fuzzy logic. However, the implementation of above observer based approach can be complex, especially for large scale chemical processes (Venkatasubramanian et al., 2003). Fault diagnosis methods based on parameter estimation methods are suitable for the diagnosis of multiplicative faults (with process parameter changes), but they require dynamic process input excitation which is often infeasible in online monitoring (Isermann, 2011).

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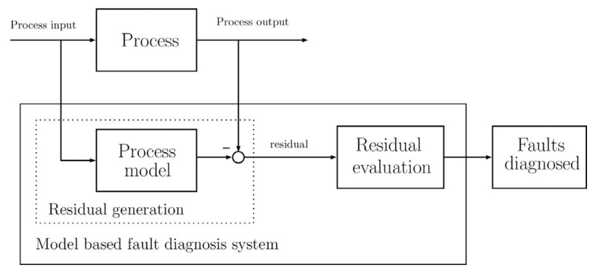

Fig. 1. Model-based fault diagnosis scheme.
Adapted from Ding, 2008.

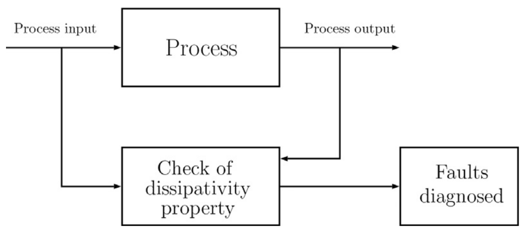

Fig. 2. Dissipativity-based fault diagnosis scheme.

In this paper, a fault diagnosis approach is developed based on dissipativity theory. Dissipativity theory, introduced by Willems (1972), has become an important tool for system analysis and control design (e.g., Sepulchre et al., 1997; Ydstie and Alonso, 1997; Bao and Lee, 2007). Dissipativity (represented by a supply rate) is an input/output property of a system (Willems, 1972), representing the features of process dynamics, such as the gain and phase conditions and their combinations (Rojas et al., 2008). When a fault (e.g., a multiplicative fault, which is modeled by parameter changes (Ding, 2008)) occurs, it can be identified by checking the change of dissipativity property, as depicted in Fig. 2. The dissipativity property of a process is not unique. For the same process, different aspects of the process dynamics can be captured by different supply rates. In this paper, the dissipativity properties of a process are shaped to be sensitive to different faults (fault-selective). The dissipativity shaping problem is formulated in linear matrix inequality (LMI) constraints, which can be easily solved offline using any semi-definite programming tools. Furthermore, a robust dissipativity condition is also developed, which is incorporated in the proposed fault diagnosis approach to reduce the rates of false alarm caused by uncertainties. Compared to existing approaches, the proposed approach is simpler to implement, as it does not require observers or parameter estimation.

Passivity condition (a special case of dissipativity) was used for fault detection and diagnosis for passive electronic circuits, as shown in Chen et al. (2010). However, the passivity condition is very coarse and may not capture sufficient dynamic details of process input output relationship, leading to limited capacity in fault detection and diagnosis. Another issue in existing passivity based approach is that it needs the full state information as the storage function is defined on state variables, which are usually unavailable in practice. To overcome the above problems, dissipativity in the quadratic difference forms (QdF) (the discrete-time version of the dissipativity in quadratic differential forms developed by Willems and Trentelman (1998)) is adopted in this work, where both the storage functions and supply rates are defined as functions of input/output trajectories (as in Kojima and Takaba, 2005, 2006; Kaneko and Fujii, 2003). This eliminates the need for state estimation for fault diagnosis. Furthermore, as a more general form of dissipativity, the QdF supply rates and storage functions can capture much more details of the dynamic features (e.g., the gain, phase or their combination *at different frequencies*) of the process, comparing to traditional QSR dissipativity (Pendharkar and Pillai, 2008; Tippett and Bao, 2014), leading to much more effective fault diagnosis.

This paper is organized as follows. The framework for analyzing faults using dissipativity theory is introduced in Section 2. The developments of the novel dissipativity-based fault diagnosis method is presented in Section 3. The robust dissipativity condition for the proposed fault diagnosis approach is developed in Section 4. The proposed approach is illustrated on a heat exchanger case study in Section 5, followed by the discussion and conclusion in Section 6.

2. Fault analysis using dissipativity theory

In this section, some important concepts of dissipativity theory and quadratic difference form (QdF) are introduced, followed by the framework of dissipativity based fault analysis, which is different from classical fault detection and diagnosis methods based on analytical redundancy.

2.1. Introduction to dissipativity theory

The dissipativity theory was first introduced by Willems (1972), as a framework for analyzing dynamical systems. While inspired by a class of systems which dissipate energy, the concept of dissipative systems is developed for general systems where the energy can be abstract and not necessarily physical (Willems, 1972; Bao and Lee, 2007).

Consider a linear time-invariant process defined by the following state space equations

$$x_{k+1} = Ax_k + Bu_k$$
$$y_k = Cx_k + Du_k \quad (1)$$

where $x \in \mathcal{X} \subset \mathbb{R}^n$ are process variables, k is the time step, $u \in \mathcal{U} \subset \mathbb{R}^p$ is the input vector and $y \in \mathcal{Y} \subset \mathbb{R}^q$ is the output vector.

Definition 1 *(Willems, 1972).* Consider the system described by (1). Define a function $s(u_k, y_k)$ on input and output variables, called the supply rate. The system is said to be dissipative with respect to the supply rate $s(u_k, y_k)$ if there exists a positive semi-definite function $V(x_k)$ defined on the states, called the storage function, such that the following dissipativity inequality is satisfied

$$V(x_{k+1}) - V(x_k) \leq s(u_k, y_k). \quad (2)$$

for all $x_k \in \mathcal{X}$, $u_k \in \mathcal{U}$ and k.

The following (Q,S,R) type supply rate is commonly used:

$$s(u, y) = y^\top Qy + 2y^\top Su + u^\top Ru. \quad (3)$$

As aforementioned, full state measurements are usually unavailable in online monitoring and process control practice (Venkatasubramanian et al., 2003). Therefore the traditional dissipativity condition given in (2), with storage function defined on state variables, cannot be directly used for fault detection and diagnosis. To overcome this difficulty, in this work, the behavior systems approach developed by Willems (2007) is adopted. For continuous time systems, Willems and Trentelman introduced storage functions and supply rates in the "quadratic differential forms" (QDF) which are functions of the input and output and their derivatives (Willems and Trentelman, 1998). This was later extended to "quadratic difference forms" (QdF) for discrete time systems by Kojima and Takaba (2005, 2006), as follows:

Definition 2. Adopted from Kojima and Takaba (2005)

Consider the system described by the model in (1). Define the extended input and output as