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Brief paper

Model-based fault detection, estimation, and prediction for a class of linear distributed parameter systems ☆

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ABSTRACT

This paper addresses a new model-based fault detection, estimation, and prediction scheme for linear distributed parameter systems (DPSs) described by a class of partial differential equations (PDEs). An observer is proposed by using the PDE representation and the detection residual is generated by taking the difference between the observer and the physical system outputs. A fault is detected by comparing the residual to a predefined threshold. Subsequently, the fault function is estimated, and its parameters are tuned via a novel update law. Though state measurements are utilized initially in the parameter update law for the fault function estimation, the output and input filters in the modified observer subsequently relax this requirement. The actuator and sensor fault functions are estimated and the time to failure (TTF) is calculated with output measurements alone. Finally, the performance of detection, estimation and a prediction scheme is evaluated on a heat transfer reactor with sensor and actuator faults.

1. Introduction

The design of fault detection and prediction scheme is a critical part of improving system reliability (Jiang, Marcel, & Vincent, 2006). Therefore several model-based detection and prognostics schemes have been introduced in the literature for industrial systems, which are traditionally described by ordinary differential equations (ODEs). A robust prognostic scheme was developed by Hansen, Hall, and Kurtz (1995). Fault diagnosis for gearbox was introduced by utilizing a mathematical model of the physical systems (Bartelmus, 2001). Vania and Pennacchi (2004) proposed a detection and isolation scheme by using system representation. Isermann (2004) introduced a model-based fault detection and diagnosis scheme by generating symptoms. Jiang and Chowdhury (2005) utilized an adaptive observer to handle a fault distribution function. Biswas, Koutsoukos, Bregon, and Pulido (2009) developed complementary approaches in fault detection and isolation in dynamic systems.

An adaptive threshold was generated in the research of Meseguer, Puig, and Escobet (2006) to evaluate the fault detection residual. Chinnam and Baruah (2003) and Kwan, Zhang, Xu, and Haynes (2003) developed a stochastic process model to approximate the fault and estimate the remaining useful life (RUL) or time to failure (TTF) of the system whereas the RUL was estimated in Wang and Vachtsevanos (2001) by applying the dynamic wavelet neural network (NN).

A variety of industrial systems including fluid flows, thermal convection and chemical reaction processes are classified as distributed parameter systems (DPS) since the system state changes with both time and space. Therefore, the ODE models given by lumped parameter representation for DPS are unsuitable to mimic their behavior (Patan & Ucinski, 2005). Instead, the state of a DPS is described by a partial differential equation (PDE).

Several fault detection and diagnosis schemes have been introduced in the literature for DPS. Christofides (2001) approximated DPS with finite dimensional ODEs; then, the reduced order ODE model was utilized in the development of fault detection and diagnosis schemes. A detection observer based on the approximate finite dimensional slow subsystem was introduced to detect and isolate faults in Demetriou and Ito's research (2002). Baniamerian and Khorasani (2012) introduced a finite-dimensional geometric method for fault detection and isolation (FDI) of parabolic PDEs by constructing a set of residuals such that each one is only affected by a fault.

Despite these interesting results, these detection and diagnosis schemes (Baniamerian & Khorasani, 2012; Demetriou & Ito,

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2002) used a finite dimensional ODE representation of DPS; consequently, they may suffer from false and missed alarms due to model reduction. In addition, the fault can change the dynamics of the overall system, thereby causing the reduced order model and resulting fault detection and diagnostics scheme to be inaccurate.

By contrast, this paper introduces a novel fault detection and estimation scheme by using a novel observer, which is designed directly based on PDE representation of DPS. Initially, a Luenberger-type observer was designed using healthy DPS dynamics to estimate system state and output. The estimated and measured system outputs are compared to generate the detection residual, which is shown to converge under healthy operating conditions in the absence of disturbance and uncertainty. A fault on the DPS can act as an external input to the detection residual dynamics causing the residual to increase. The fault is detected when this residual exceeds a predefined threshold.

Upon detecting a fault, an adaptive term is added to the observer to learn the fault function. Although the fault detection observer only requires the system output, the parameter update law requires the system state to be available at all positions, which is a major drawback.

Therefore, by using the linear property of the PDE representation, an input filter along with two output filters are utilized to develop a new observer, which allows the determination of a parameter update law that tunes unknown fault parameter estimation with measured system output alone. Upon detecting a fault by using the filter-based observer, the detection and estimation scheme is revisited.

With state and output availability, the detection residual and parameter estimation errors are shown to be bounded in the presence of any bounded uncertainties or disturbances while asymptotic convergence is demonstrated in the absence of these terms. In addition, with output alone the detection residual and parameter estimation errors are shown to be bounded under faults with bounded uncertainties or disturbances. Moreover, by comparing the estimated fault parameters with their failure limits, an explicit formula for online estimation of TTF or RUL is proposed.

The contributions of this paper include: (a) the development of a novel model-based detection and estimation scheme by using the PDE-based detection observer with detectability conditions, (b) the design of the detection, estimation and prediction scheme by using a filter-based observer, which not only requires the system output alone but also allows the estimation of actuator and sensor faults, and (c) TTF prediction with outputs alone.

This paper is organized as follows. A class of linear DPS described by a parabolic PDE is introduced in Section 2. Then the detection and estimation scheme is developed in Section 3, when the state is measurable and in Section 4 with output alone. Finally, Section 5 applies the proposed scheme to a heat transfer reactor in simulations.

2. Background and system description

The notations used in this paper are standard. A scalar function $v(x) \in L^2(0,1)$ is a square integrable on Hilbert space $L^2(0,1)$ with the norm defined as $\|v\|_2 = \sqrt{\int_0^1 v^2(x)dx}$. Throughout the paper the norm of a function $v(x,t)$ is denoted by $\|v(t)\|$ and the norm of $\partial v(x,t)/\partial x$ is expressed as $\|v_x(t)\|$.

Consider a class of linear DPS expressed by the following parabolic PDE with Dirichlet actuation given by

$$v_t(x,t) = \varepsilon v_{xx}(x,t) + \lambda v(x,t) + d(v(x,t),x,t) \tag{1}$$

where x is the space variable and $t \ge 0$ is the time variable with boundary conditions defined by

$$v_x(0,t) = -qv(0,t), \qquad v(1,t) = U(t), \qquad y(t) = v(0,t) \tag{2}$$

where $v : [0,1] \times R^+ \to R$ represents the distributed state of the system; $d(v(x,t),x,t)$ stands for the system uncertainty or disturbance; $U(t)$ denotes control input, $\lambda > 0$ is a positive constant; ε and q are constant scalars; $v_t = \partial v/\partial t$, $v_x = \partial v/\partial x$ and $v_{xx} = \partial^2 v/\partial x^2$ are partial derivatives of v and $y(t)$ is the system output.

Assumption 1. The system uncertainty or disturbance is bounded above such that $\|d(v,x,t)\| \le \bar{d}$ for all (v,x) and $t \ge 0$, where $\bar{d} > 0$ is a known constant. A more specific representation can be found in Baniamerian and Khorasani (2012); Yao and El-Farra (2011).

In this paper, an actuator and sensor fault type at the boundary condition are considered and will be described next.

2.1. Actuator fault

Under a multiplicative actuator fault at the boundary condition of the DPS, the system in (1) and (2) can be described by

$$v_t(x,t) = \varepsilon v_{xx}(x,t) + \lambda v(x,t) + d(v(x,t),x,t), \tag{3}$$

subject to the boundary conditions given by

$$v_x(0,t) = -qv(0,t), \qquad v(1,t) = \theta U(t), \qquad y(t) = v(0,t), \tag{4}$$

where θ is the multiplicative fault parameter bounded by $|\theta| \le \theta_{\max}$. Alternatively, the boundary condition with the actuator fault can be expressed as $v(1,t) = U(t) + h(U(t),t)$, where $h(U(t),t) = \Theta U(t) = (\theta - 1)U(t)$ and $\Theta = \theta - 1$.

Moreover, the fault function can be written as

$$h(U(t),t) = \Omega(t - t_i)\Theta U(t), \tag{5}$$

where t_i is the time of fault occurrence and $\Omega(t - t_i)$ is the time profile of the fault defined by $\Omega(\tau) = \begin{cases} 0, & \text{if } \tau < 0 \\ 1 - e^{-\kappa\tau}, & \text{if } \tau \ge 0 \end{cases}$, where κ represents the fault growth rate, which should be a constant. This time profile allows both incipient and abrupt faults with different growth rates κ to be represented. However, for fault prediction, incipient faults are considered.

2.2. Sensor fault

Under a sensor fault, the system measured output is written as

$$y(t) = \theta_s v(0), \tag{6}$$

where θ_s is a positive scalar representing a multiplicative sensor fault bounded by $\theta_{s\min} \le |\theta_s| \le \theta_{s\max}$. Under healthy conditions, the value of θ_s is taken as unity whereas it changes in the presence of a sensor fault. The following standard assumptions are required in order to proceed.

Assumption 2. There exists a stabilizing controller that guarantees the boundedness of the system state under healthy operating conditions.

Remark 1. This assumption separates a fault with instability of the system. For fault detection, the closed-loop DPS should be stable. Smyshlyaev and Krstic (2004) proposed a state and output feedback controller by using the backstepping approach to stabilize the parabolic PDE by using a control input which is a function of output $y(t)$.

Assumption 3. The fault type is known. Moreover, a single fault occurs on the system at any given time.

Remark 2. This assumption is used for fault estimation.