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Active fault detection and constrained control of air handling unit

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Abstract: The paper deals with active fault detection and control for stochastic systems. An input signal generator for a given detector is designed such that detection and control aims are pursued. The detection aim is to minimize the probability of a wrong decision at the end of a finite horizon, and the control aim is to maintain the price of control actions below a given limit and satisfy some other design requirements. Since the control aim and other design requirements are enforced as constraints a constrained optimization problem is solved using the open loop information processing strategy. The proposed approach is applied to active detection of the stuck air mixing damper of an air handling unit.

Keywords: Active fault detection, optimization, air handling unit.

1. INTRODUCTION

The paper is motivated by the steadily increasing demand for energy-efficient building operation during recent years. Buildings and its appliances such as air handling units (AHU) account for 20–40 % of the total final energy consumption and its amount has been increasing at a rate 0.5–5 % *per annum* in developed countries (Perez-Lombard et al., 2008). Advanced building control and fault detection techniques have gained a lot of attention in the last two decades (Wong et al., 2005). Various advanced fault detection techniques such as neural networks (Lee et al., 1996), model based techniques (Hyvärinen, 1996) or expert rules (Trojanova et al., 2009) have been applied to AHU fault detection. Design of efficient AHU control algorithms based on distributed model predictive control (Ma et al., 2011), genetic algorithm (Xu et al., 2009) or particle swarm optimization algorithm (Kusiak and Li, 2010) was investigated recently.

Although many detection and control problems for AHUs have already been addressed using various approaches, a problem of simultaneous active fault detection and control have not been considered yet. The goal of the paper is to presents an approach that can be used for solving simultaneous active fault detection and control while respecting additional design constraints. A general formulation of active change detection and control for stochastic systems (Šimandl and Punčochář, 2009; Šimandl et al., 2011) provides a theoretical background and a unified framework for solving problems with detection and control aims. Within this unified framework, detection and control aims are included into a single criterion. As this approach might not be appropriate with regard to design requirements, alternative ways of expressing detection and control aims for multiple linear models were presented in (Široký et al., 2011). One of these alternative ways that consists in keeping a detection aim in a criterion and enforcing a control aim as a constraint is adopted in this paper, and the problem of active input signal generator design for a given detector is considered for a special class of nonlinear systems. The proposed active input signal generator is subsequently applied for simultaneous active fault detection and control of an AHU.

2. PROBLEM FORMULATION

The active fault detection and control problem is considered on a finite time horizon of length $F+1<\infty$ and it is assumed that the observed and controlled system can be described at each time step $k \in \mathcal{T} = \{0,1,\dots,F\}$ by the following model

$$\mathbf{x}_{k+1}{=}\mathbf{A}_{\mu_k}\mathbf{x}_k{+}{}^{\mathrm{L}}\mathbf{B}_{\mu_k}{}^{\mathrm{L}}\mathbf{u}_k{+}{}^{\mathrm{N}}\mathbf{B}_{\mu_k}\mathbf{H}_k(\mathbf{x}_k){}^{\mathrm{N}}\mathbf{u}_k{+}\mathbf{G}_{\mu_k}\mathbf{w}_k, \quad (1)$$

where $\bar{\mathbf{x}}_k = [\mathbf{x}_k^{\mathrm{T}}\ \mu_k]^{\mathrm{T}} \in \mathbb{R}^{n_x+1}$, $\mathbf{u}_k = [{}^{\mathrm{L}}\mathbf{u}_k^{\mathrm{T}}\ {}^{\mathrm{N}}\mathbf{u}_k^{\mathrm{T}}]^{\mathrm{T}} \in \mathbb{R}^{n_u}$ and $\mathbf{w}_k \in \mathbb{R}^{n_w}$ represent the state, the input and the state noise, respectively. The part of the state $\mathbf{x}_k \in \mathbb{R}^{n_x}$ is directly measured and used by an active detector and controller. The last element of the state $\mu_k \in \mathcal{M} = \{1,2\}$ is not measurable and represents the index of the model that is in effect at the time step k. The model for $\mu_k = 1$ represents the fault-free behavior of the system and the other model represents faulty behavior. In general, the evolution of the model index μ_k can be modeled as a

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Markov chain with given transition probabilities. Here it is assumed that there is no switching between models during the considered horizon. The part of the input ${}^{\mathrm{L}}\mathbf{u}_k \in {}^{\mathrm{L}}\mathcal{U}_k \subseteq \mathbb{R}^{n_{\mathrm{L}}}$ affects the system in a linear way, and the other part ${}^{\mathrm{N}}\mathbf{u}_k \in {}^{\mathrm{N}}\mathcal{U}_k \subseteq \mathbb{R}^{n_{\mathrm{N}}}$ affects the system through a given nonlinear matrix-valued function $\mathbf{H}_k : \mathbb{R}^{n_x} \to \mathbb{R}^{n_H \times n_{\mathrm{N}}}$. The sets ${}^{\mathrm{L}}\mathcal{U}_k$ and ${}^{\mathrm{N}}\mathcal{U}_k$ determine admissible inputs and stem from physical, logical or design considerations. The state noise $\mathbf{w}_k$ is the white Gaussian noise with zero mean value and identity covariance matrix. Further it is assumed that the pdf of initial state $p(\bar{\mathbf{x}}_0) = p(\mathbf{x}_0)P(\mu_0)$, where probability $P(\mu_0)$ is given and $p(\mathbf{x}_0)$ is Gaussian distribution with the known mean value $\mathbf{x}_{0|-1}$ and the covariance matrix $\mathbf{P}_{0|-1}$. Finally, the matrices $\mathbf{A}_{\mu_k}$, ${}^{\mathrm{L}}\mathbf{B}_{\mu_k}$, ${}^{\mathrm{N}}\mathbf{B}_{\mu_k}$, $\mathbf{G}_{\mu_k}$ of appropriate dimensions are known for all $\mu_k \in \mathcal{M}$.

The active fault detector and controller consists of a given detector and an input signal generator to be designed. At each time step $k \in \mathcal{T}$, it is assumed that the given detector has the following form

$$d_k = \sigma_k(\mathbf{x}_0^k, \mathbf{u}_0^{k-1}) = \arg\max_{\mu_k \in \mathcal{M}} P\left(\mu_k | \mathbf{x}_0^k, \mathbf{u}_0^{k-1}\right), \quad (2)$$

where $P(\mu_k|\mathbf{x}_0^k, \mathbf{u}_0^{k-1})$ is the conditional probability of model μ_k, and d_k is the decision that can be regarded as an estimate of the model valid at the time step k. Since every possible active detector and controller must be a causal system, an input signal generator can generally be described as

$$\mathbf{u}_k = \boldsymbol{\gamma}_k(\mathbf{I}_0^k), \quad (3)$$

where $\mathbf{I}_0^k = [\mathbf{x}_0^k, \mathbf{u}_0^{k-1}, d_0^{k-1}]$ is the information vector containing all data received up to the time step k and the function $\boldsymbol{\gamma}_k : \mathbb{R}^{(n_x+n_u)k+n_x} \times \mathcal{M}^k \to \mathbb{R}^{n_u}$ describes the input signal generator at the time step $k \in \mathcal{T}$. Note that the notation $\mathbf{x}_i^j$ is used to denote the sequence of variables or functions from the time step i to the time step j. If $i > j$ then the sequence is empty, and it is simply left out from the expression. The aim of the design is to determine the sequence of functions $\boldsymbol{\gamma}_0^F$ such that the behavior of the active fault detector and controller is optimal in some sense.

To evaluate the quality of the active fault detector and controller, a criterion is needed. It is assumed that the detection and control aims can be expressed using two independent cost functions $L_k^{\mathrm{d}}(\mu_k, d_k) : \mathcal{M} \times \mathcal{M} \to \mathbb{R}^+$ and $L_k^{\mathrm{c}}(\mathbf{x}_k, \mathbf{u}_k) : \mathbb{R}^{n_x+n_u} \to \mathbb{R}^+$, respectively. In this paper the following aims and corresponding cost functions are considered. The detection aim is to minimize the probability of making a wrong decision at the final time step of the finite horizon. Such an aim can be expressed by the following detection cost function

$$L_k^{\mathrm{d}}(\mu_k, d_k) = \begin{cases} 1 & \text{if } k = F, d_F \neq \mu_F, \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

The control aim consists in minimizing the price of control actions measured by the control cost function

$$L_k^{\mathrm{c}}(\mathbf{x}_k, \mathbf{u}_k) = \sum_{i=1}^{n_u} |\mathbf{p}_{k,i}^{\mathrm{T}} \mathbf{u}_{k,i}|, \quad (5)$$

where the subscript i denotes the ith element of a vector, and $\mathbf{p}_k \in \mathbb{R}^{n_u}$ is a given vector of unit prices of individual inputs.

Since the detection and control cost functions usually represent two conflicting aims, it is necessary to express a desired compromise between them (Široký et al., 2011). Here it is assumed that the overall price of control actions has to be kept under a given limit while the probability of making a wrong decision at the final time step is minimized. Therefore, the goal is to minimize the criterion

$$J(\boldsymbol{\gamma}_0^F) = \mathrm{E}\left\{\sum_{k=0}^{F} L_k^{\mathrm{d}}(\mu_k, d_k)\right\}, \quad (6)$$

where $\mathrm{E}\{\cdot\}$ is the expectation operator, and the control aim is enforced as the constraint

$$\mathrm{E}\left\{\sum_{k=0}^{F} L_k^{\mathrm{c}}(\mathbf{x}_k, \mathbf{u}_k)\right\} \leq L_{\max}^{\mathrm{c}}, \quad (7)$$

where $L_{\max}^{\mathrm{c}} > 0$ is maximum acceptable value of the control criterion.

Besides the requirements on detection and control, there may be some additional constraints that are connected with control aim or other design requirements. Since the system is described by a stochastic model, it is not possible to satisfy constraints with certainty except for few special cases. Therefore, the concepts of expectation constraints and chance constraints were developed (Ruszczyński and Prékopa, 2003). The instantaneous linear constraints on the expected value of the state $\mathbf{x}_k$ conditioned by the fault-free behavior are considered in the form

$$\mathbf{C}_k \,\mathrm{E}\{\mathbf{x}_k | \mu_k = 1\} + \mathbf{c}_k \leq \mathbf{0}, \quad (8)$$

where the inequality is taken element-wise, $\mathrm{E}\{\cdot|\cdot\}$ denotes the conditional expectation operator, $\mathbf{C}_k \in \mathbb{R}^{n_c \times n_x}$ and $\mathbf{c}_k \in \mathbb{R}^{n_c}$ are a given matrix and a vector, respectively. The number of constraints is denoted n_c. Failed system can be constrained as well, however, the goal of active fault detection is to detect a failure not to handle it. Therefore only the fault-free behavior is constrained.

3. ACTIVE FAULT DETECTOR AND CONTROLLER DESIGN

3.1 Linearization by state feedback

The problem of active fault detection and control for multiple linear models was considered in (Blackmore et al., 2008; Punčochář and Šimandl, 2009), where an upper bound was used for designing a suboptimal active fault detector and controller. This upper bound is known as the Bhattacharyya bound and requires to compute the predictive means and covariance matrices of output (state) which can be easily done for a linear model. To preserve this advantageous properties of linear models, the nonlinear model will be transformed into a linear one by introducing a virtual input that will replace the nonlinear term in model (1).

A virtual input ${}^{\mathrm{N}}\bar{\mathbf{u}}_k \in \mathbb{R}^{n_H}$ is defined as

$${}^{\mathrm{N}}\bar{\mathbf{u}}_k = \mathbf{H}_k(\mathbf{x}_k)\, {}^{\mathrm{N}}\mathbf{u}_k, \quad (9)$$

and the corresponding set of admissible virtual inputs can be obtained as

$${}^{\mathrm{N}}\bar{\mathcal{U}}_k(\mathbf{x}_k) = \left\{{}^{\mathrm{N}}\bar{\mathbf{u}}_k : {}^{\mathrm{N}}\bar{\mathbf{u}}_k = \mathbf{H}_k(\mathbf{x}_k)\, {}^{\mathrm{N}}\mathbf{u}_k, {}^{\mathrm{N}}\mathbf{u}_k \in {}^{\mathrm{N}}\mathcal{U}_k\right\}. \quad (10)$$

Using this virtual input, the nonlinear model (1) can be rewritten as a linear one