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Adaptive sliding mode observer for sensor fault diagnosis of an industrial gas turbine ☆

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ABSTRACT

Sensors are one of the crucial components in gas turbines and the failure in sensor measurements can lead to serious problems in maintaining their safety and performance requirements. Our aim in this paper is to develop an adaptive sliding mode observer for sensor fault diagnosis in an industrial gas turbine. The proposed observer has a robustness against gas turbine parameter uncertainties caused by degradations without any priori knowledge about the bounds of faults and parameter uncertainties. The efficiency of the proposed fault diagnosis approach is validated with Matlab/Simulink simulations and the realistic gas turbine data extracted from the PROOSIS software.

1. Introduction

Recent years have witnessed an increasing research interest in fault diagnosis of gas turbines with the main aim to enhance their reliability, efficiency and safety. Security and safety measures and the need for reducing the life cycle cost make it necessary to move towards more advanced fault diagnosis methodologies satisfying the above requirements. Like all physical systems, gas turbines are prone to faults occurring in their different components such as actuators and sensors and it is vital to have a monitoring system which is able to observe the engine and to diagnose the health of the system. In this paper, our work is focused on sensor faults that reflect wrong and faulty measurements in gas turbines. Moreover, different types of components degradation can also happen in gas turbines such as the blockage of the inter-compressor piping, compressor, or combustor, compressor or turbine fouling, and turbine erosion. In this paper, a fault diagnosis approach is developed for sensor fault detection, isolation and identification in an industrial gas turbine which guarantees at the same time the robustness against degradation in the engine components.

In the literature, Fault Detection and Isolation (FDI) of gas turbines is mainly based on the most popular procedure called Gas Path Analysis (GPA). This method allows observing measurements such as the rotor speed, the engine temperatures and pressures as well as the fuel flow rate (Urban, 1972; Volponi, Daguang, DePold, & Ganguli, 2003) in order to achieve fault diagnosis of actuators, sensors and engine components. In this context, sensor fault diagnosis algorithms are based on either data-based or model-based approaches.

Data-based approaches analyze a large amount of the gas turbine engine historical data for different healthy and degraded conditions. The neural network-based approaches have been extensively used for the gas turbine fault diagnosis (Korbicz, Kościelny, Kowalczuk, & Cholewa, 2004; Ogaji, Singh, & Probert, 2002; Sadough Vanini, Khorasani, & Meskin, 2014; Vishwanath Rao, 2009; Volponi et al., 2003). Their main disadvantage is the continuous need for retraining the network after any change in the system due to deterioration or aging. Genetic algorithms have also been used for sensor fault diagnosis of the gas turbine (Korbicz et al., 2004; Ogaji et al., 2005; Sampath & Singh, 2006). They are characterized by simple implementation of sensor fault detection and accommodation, ability to detect small deviations in the component performance parameters with the robustness and consistency in the presence of noise. Their drawbacks rely on identifying only one fault component with a very long run and convergence time. Hybrid diagnosis approach is also proposed while combining the genetic algorithm with the neural network (Sampath & Singh, 2006) in order to enhance the ability to detect small deviations and to successfully identify 95% of fault cases on the gas turbine engine.

On the other hand, model-based fault diagnosis methods are utilizing the mathematical linear or nonlinear representation of the gas turbine based on the thermodynamic equations and characteristics of each component (Aretakis, Mathioudakis, & Stamatis, 2004; Kobayashi & Simon, 2007; Korbicz et al., 2004; Lu, Chen, Huang, Zhang, & Liu, 2013; Simani & Patton, 2008). Based on real-time

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nonlinear on-board aircraft engine, sensor FDI approaches utilizing Kalman filters are proposed (Borguet & Léonard, 2009; Kobayashi & Simon, 2004, 2007; Lu et al., 2013) in which the filters are designed after linearizing the model around different operating points. However, their robustness is limited to a small range of health degradation and a periodic update of the algorithm is required which is impractical. Fault isolation with these Kalman filters is limited to the previously known faults, and they cannot cover all the operating points to accommodate the long-term engine degradation.

Another popular FDI approach is the multiple-model based algorithm (He, Tan, Wang, & Kong, 2010; Kiyak & Caliskan, 2011; Kobayashi & Simon, 2004; Korbicz et al., 2004; Meskin, Naderi, & Khorasani, 2013; Naderi, Meskin, & Khorasani, 2012; Tang, Zhang, DeCastro, Farfan-Ramos, & Simon, 2010; Vanini, Meskin, & Khorasani, 2014; Wei & Yingqing, 2009) that consists of a bank of fault diagnosers, one related to each fault and one for the healthy operation mode. These approaches can be categorized into neural networks techniques, filtering techniques, and unknown input observers for FDI purposes. In Vanini et al. (2014), an auto-associative neural network approach is developed to detect and identify both sensor and component faults in a jet engine. The advantages rely on the fact that no mathematical model is used for training and simple decisions are made for fault identification. Online sensor faults diagnosis with linear Kalman filters in Kobayashi and Simon (2004), Wei and Yingqing (2009), Meskin et al. (2013) and nonlinear Kalman filters in Naderi et al. (2012) are considered for jet engines. In He et al. (2010), H_∞-based FDI approach is proposed which assures the robustness in the presence of measurement noise while no component degradation is considered. In the context of fault diagnosis by observers, a nonlinear adaptive FDI approach is proposed in Tang et al. (2010) with adaptive thresholds for detecting and isolating sensor faults, actuator faults, and component faults in aircraft engines. However, the weak points remain in considering only one fault at a time and a need for real-time adaptive neural network to compensate the modeling errors. Later on, sensor fault diagnosis approach based on unknown input observers is developed in Kiyak and Caliskan (2011) and a structure of fuzzy logic rules is also designed for the determination of the fault severity. The main common drawback of all multiple-model approaches is the redundancy of using a bank of diagnosing systems. Besides, FDI via threshold methods is restrictive and the definition of a suitable threshold for each of the working conditions is a critical and difficult task. Moreover, hierarchical framework is required for tackling concurrent multiple faults, which increases the computational complexity of implementing multiple-model FDI methods.

A summary of the advantages and disadvantages of each sensor fault diagnosis approach is presented in Table 1. After the comparative study of the previously adopted methodologies for sensor fault diagnosis of the gas turbine, the problem is addressed from the model-based perspective. More precisely, the main aim of this paper is the development of robust sensor fault diagnosis for the newly developed nonlinear model for an industrial gas turbine (Tsoutsanis, Meskin, Benammar, & Khorasani, 2013). Sliding mode approach is a strong approach to adopt (Perruquetti & Barbot, 2002; Yan & Edwards, 2007) due to its robustness against parametric uncertainties and perturbations as well as the guaranteed finite time convergence. In the sliding mode approach, the system trajectories are constrained to evolve after a finite time on a suitable sliding surface usually given by the difference between the observer and the system outputs. In this paper, the adaptive sliding mode technique is adopted which ensures the adaptation of the observer gain in such a way to be as small as possible and sufficient to overcome the uncertainties and perturbations caused by degradation and faults occurring to the gas turbine components without any *a priori* knowledge about the bounds of these uncertainties (Huang, Kuo, & Chang, 2008; Lee & Utkin, 2007; Plestan, Shtessel, Bregeault, & Poznyak, 2010). In the literature, the adaptive sliding mode technique was mainly addressed for control of single-input-single-output systems. In this paper, Lyapunov stability conditions and all the theoretical derivations are included for the development of a novel adaptive sliding mode observer for fault diagnosis and to guarantee the stability, finite-time convergence and robustness of the proposed approach.

After the convergence of the output error towards zero and maintaining the sliding motion, the sliding mode observer is able not only to detect and isolate sensor faults, but also to reconstruct them by analyzing the so-called "equivalent output estimation error injection" concept (Tan & Edwards, 2002; Utkin, 1992). Fault reconstruction is a powerful alternative to fault identification using multiple-model techniques in which the fault with predefined severity can only be identified. Therefore, instead of the bank of dissimilar residual signals used to infer the location of the fault in the system, the sliding mode approach provides a direct way for fault isolation as well as a direct estimate of the size and severity of the fault, which is of the high importance in the gas turbine.

The paper is organized as follows. Section 2 presents the healthy and degraded gas turbine modeling. In Section 3, an adaptive sliding mode observer is designed for estimating faults on output sensors in the gas turbine. The performance of the proposed fault diagnosis approach is evaluated via Matlab/Simulink in Section 4 and in Section 5, its robustness is validated with the data extracted from PROOSIS software. Finally, Section 6 concludes the work.

Notation: In this paper, $\mathbb{R}^{+n}$ represents the set of vectors in $\mathbb{R}^n$ with positive elements. $(\cdot)^{\mathrm{T}}$ denotes the transpose of a vector and $|\cdot|$ denotes the absolute value. Finally, $||\cdot||$ represents the Euclidean norm or its induced norm.

2. Gas turbine dynamical model

The engine model consists of a compressor, combustor, turbine and power turbine as shown in Fig. 1. A double-shaft model is considered where one turbine drives the compressor and another one drives the generator, with exhaust from the compressor turbine powering the power turbine. The outlet variables of the engine components are numbered from stage 3 to stage 6, while the stage numbers 1 and 2 correspond to the ambient and the compressor inlet variables, respectively. For instant, the outlet temperature and pressure of the compressor are denoted by T_3 and P_3, respectively.

2.1. Healthy gas turbine model

In order to develop a model-based fault diagnosis technique for a given gas turbine, an appropriate mathematical model of the system is required. A variety of gas turbine modeling techniques has been proposed in the literature with the main aim of representing as accurately as possible the gas turbine behavior in both steady and transient operations (Sanghi, Lakshmanan, & Sundararajan, 2000). In this paper, the mathematical model introduced in Tsoutsanis et al. (2013) which captures the nonlinear dynamical behavior of the gas turbine is considered. The developed model combines two fundamental approaches for simulating the performance of the gas turbine: the Constant Mass Flow iterative (CMF) and the Inter-Component Volume (ICV) methods (Crosa, Ferrari, & Trucco, 1995; Walsh & Fletcher, 2004). The steady state model is based on the CMF method and also used for initializing the transient simulation which is based on the ICV method (Tsoutsanis et al., 2013). The engine model is represented by a set of first order differential equations where dynamic