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Robust fuzzy scheduler fault tolerant control of wind energy systems subject to sensor and actuator faults

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ABSTRACT

In this paper, new robust fuzzy scheduler fault tolerant control is proposed to tackle multivariable nonlinear systems subject to sensor faults, actuator faults and parameter uncertainties. Takagi–Sugeno fuzzy model is employed to represent the nonlinear wind energy systems, and then a model-based fuzzy scheduler controller design use the concept of general-distributed compensation. Takagi–Sugeno fuzzy systems are classified into three families based on the input matrices and a fault tolerant control synthesis procedure is given for each family. In each family, sufficient conditions are derived for robust stabilization, in the sense of Lyapunov method and Taylor series stability, for the Takagi–Sugeno fuzzy system with parametric uncertainties, sensor faults, and actuator faults. The sufficient conditions are formulated in the format of linear matrix inequalities. The effectiveness of the proposed controller design methodology is finally demonstrated through a wind energy system with doubly fed induction generators to illustrate the effectiveness of the proposed method.

1. Introduction

The dynamic behavior of wind turbines varies widely along their operating range. Robust controllers, which are specifically designed to cope with nonlinear dynamics through the use of linearization techniques [1–5], as well as other methods [6,7], have been widely applied to the design of wind turbine control systems. Nonlinearities and system uncertainties are the most important difficulties in designing controllers that ensure stability and acceptable closed-loop performance. Recently, fuzzy control has attracted increasing attention, essentially because it can provide an effective solution to the control of plants that are complex, uncertain, ill-defined, and have available qualitative knowledge from domain experts for their controllers design [8–10].

Recently, the maximum power point tracking (MPPT) control method has been reported in the literature [11–17]. In [11], a wind-speed estimation scheme for the MPPT control of wind-power systems is proposed. In [12], the development of a wind-generator maximum power tracking control system is presented. The development of maximum wind power extraction algorithms for inverter-based variable-speed wind power generation system (WPGS) is given in [13]. In [14], a method to maximize the energy from the wind speed using the proposed fuzzy integral linear inequalities (FILMI) is presented, however it did not take parameter uncertainties into consideration. In [15–18], the authors investigate the robustness and power quality performance of a simple wind-diesel-storage-hybrid system (WDSHS).

Commonly seen in practice, many control systems are subject to faults which can be caused by sensors, actuators, or the system itself. Therefore, it is an important issue in control system design to study how the system is kept stable, with acceptable performance levels maintained, when a failure occurs. In the past few years, fault tolerant control (FTC) problems for systems with actuator faults have been extensively studied by many researchers [19–21], however they did not consider the unmeasured state. Unknown input observer design for general nonlinear systems is still largely an open problem, and thus nonlinear unknown input observer based on fault diagnosis are presented in [35–38]. Afterwards, several FTC methods have been extended to nonlinear systems with sensor faults [23–25]. The problem becomes more complex if a multivariable nonlinear system is subject to parameter uncertainties. In [26], the authors present a fault detection scheme based on a bank of observers and assumed that only one sensor can fail at a given time. After that, the state variables are reconstructed from the output of the healthy sensor and did not take the actuator faults in consideration. The FTC algorithm for variable-speed WES is represented by the Takagi–Sugeno (TS) method in the presence parametric uncertainties and a single faulty sensor. In addition, sufficient robust stabilization conditions are derived (in the sense of Taylor series stability) and are formulated in the form of linear matrix inequalities (LMIs).

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It is well known that the observer design is a very important problem in control systems. Since in many practical nonlinear control systems, state variables are often unavailable, output feedback or observer-based control is necessary and has drawn interest. The authors in [27,28,,30] studied fuzzy observer designs for TS fuzzy control systems and proved that a state feedback controller with an observer always yields a stabilizing output feedback controller provided that the stabilizing property of the control and the asymptotic convergence of the observer are guaranteed by the Lyapunov method. However, in these controllers, the parametric uncertainties for a TS fuzzy control system were not considered. Therefore, the robustness of the closed-loop system cannot be guaranteed.

This approach is an extension of the work proposed in [10,14,26]. This paper addresses the problem of robust fault estimation and robust fuzzy scheduler fault tolerant control (RFSFTC) for a system based on the TS fuzzy model. A fuzzy proportional integral observer (FPIO) design is proposed to estimate faults in TS models with actuator faults, senor faults and parameter uncertainties. Furthermore, based on the information of online fault estimation, RFSFTC is designed to compensate for the effects of faults by stabilizing the closed-loop system. This proposed scheme is based on the fuzzy dedicated observers (FDOS) method using a nonlinear FPIO. Each one of the FDOS is dedicated to each output of the multi-sensors to generate a set of residual signals which, are determined by the difference between the systems measurements and the estimated output of the observers based on [34–36]. By the reconfiguration mechanism (decision and switcher) of the residuals, the sensor faults can be detected and isolated. Utilizing a general distributed compensation (GDC) structure, a method of analyzing the system in terms of LMIs is obtained by applying fuzzy Taylor series expansion and Lyapunov method to fuzzy system sensor faults. Sufficient conditions for the existence of FPIO, FDOS and RFSFTC are given in terms of Linear Matrix Equalities (LMEs) and Lyapunov theory. Simulation results of a WES are presented to illustrate the effectiveness of the proposed method.

Based on the aforementioned works, the contributions of the proposed approach is in the use of the FPIO to estimate actuator faults, sensor fault and unmeasured states in a class of WES. Once the fault is estimated, the FTC controller is implemented as a state feedback controller. Therefore the proposed algorithm combines the merits.

- The modifications approach is designed such that to handle actuator faults and sensor fault at any time but the authors in [26] assumed only sensor faults, so in [26] If the sensors and actuator are faulty simultaneously, the controller lost performance.
- The problem of Robust Fault Estimation and RFSFTC for system based on TS fuzzy model is addressed.
- A FPIO design is proposed to achieve fault estimation of TS models with actuator faults and parameter uncertainties.
- Based on the information of online fault estimation, an observer-based RFSFTC is designed to compensate the effect of faults by stabilizing the closed-loop system.
- The system state variables are stable in the presence of sensor faults, parametric uncertainties and time varying actuator.
- Sufficient conditions for the existence of FPIO, FDOS and RFSFTC are given in terms of LMIs and Lyapunov theory but in [26] stability conditions are derived for stabilization in the sense of Taylor series stability. Simulation results of a WES are presented to illustrate the effectiveness of the proposed method.
- The algorithm reduces the bus-voltage and bus-frequency ripple and maximization of the output power for a variable-speed wind energy conversion system.
- The use of the LMEs approach which, based on the TS fuzzy model and LMIs [10] is used to obtain control gains and observer gains. This modification leads to simplification of the solution of Riccati type equations.
- The robustness indices (ν,σ,δ) plays a very important role in controlling the system to a high degree of uncertainty and will be viewed in the present simulation.

The paper is organized as follows: TS fuzzy model and fuzzy uncertainty regenerator are given in Section 2. The structure of the fuzzy observers and the proposed scheme RFSFTC are presented in Section 3. Section 4 shows the proposed nonlinear RFSFTC controller. Stability and robustness analysis are given Section 5. In Section 6, the model of the WES with DFIG and its TS fuzzy description are presented. Section 7 presents simulation of the wind turbine with DFIG.

2. TS fuzzy model with parameter uncertainties and faults and fuzzy uncertainty regenerator

Before introduce the RFSFTC, we need to present the TS fuzzy model subject to parameter uncertainties, sensor fault and actuator fault. In addition the fuzzy uncertainty regenerator is presented.

2.1. TS fuzzy plant model with parameter uncertainties, sensor faults and actuator faults

This sub-section is dedicated to a brief presentation of TS models. Consider a nonlinear system described by

$$\begin{cases} \dot{x}(t) = f(x(t), u(t)) \\ y(t) = f(x(t), u(t)) \end{cases} \tag{1}$$

A fuzzy dynamic model proposed by TS [31] is often used to represent a nonlinear system (1) by the interpolation of a set of linear sub-models. The TS fuzzy model is a piecewise interpolation of several linear models through membership functions. The fuzzy model is described by fuzzy If–Then rules and will be employed here to deal with the control design problem for the nonlinear system. The TS fuzzy systems can be classified into three families based on the diversity of their input matrices B_i. Consider the input matrices are defined as follows

$$B_1/\alpha_1 = B_2/\alpha_2 = \cdots = B_p/\alpha_p = B \tag{2}$$

where $\alpha_1, \ldots, \alpha_p$ are positive values and $B \in \kappa^{nxm}$. Let p the number of fuzzy rules. The ith rule of the fuzzy model for the nonlinear system is given by [29]:

Plant Rule i: IF $q_1(x(t))$ is M_{1i} AND $\cdots$ AND $q_\psi(x(t))$ is $M_{\psi i}$

$$\text{Then} \begin{cases} \dot{x}(t) = (A_i + \Delta A_i)x(t) + \alpha_i B u(t) & i = 1,2,\ldots,p \\ y(t) = C_i x(t) & i = 1,2,\ldots,p \end{cases} \tag{3}$$

Here, $M_{\Omega i}$ is the fuzzy set $\Omega = 1, 2, \ldots, \psi$, $x(t) \in \kappa^{nx1}$ is the state vector, $u(t) \in \kappa^{mx1}$ is the input vector, $y_i(t) \in \kappa^{gx1}$ is the output vector, $A_i \in \kappa^{nxn}$ is the system matrix, $C_i \in \kappa^{gxn}$ is the output matrix and $q_1(x(t)), \ldots, q_\psi(x(t))$ are known premise variables. Each linear consequent equation represented by $A_i x(t) + B_i u(t)$ is called a subsystem and $\Delta A_i \in \kappa^{nxn}$ are non time-varying matrices representing parametric uncertainties in the plant model. These uncertainties are admissibly norm-bounded and structured. The main feature of a TS fuzzy model is to express the local dynamics of each fuzzy implication (rule) by a linear system model. The overall fuzzy model of the system is achieved by fuzzy “blending” of the linear system models. In this tutorial, the reader will find, by example in Section 5.3, that almost all nonlinear dynamical systems can be represented by TS fuzzy models to high degree of precision. Each