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# Intelligent Control of Wind Energy Conversion Systems

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## 1. Introduction

Wind turbines form complex nonlinear mechanical systems exposed to uncontrolled wind profiles. This makes turbine controller design a challenging task (Athanasius & Zhu, 2009). As such, control of wind energy conversion systems (WECS) is difficult due to the lack of systematic methods to identify requisite robust and sufficiently stable conditions, to guarantee performance. The problem becomes more complex when plant parameters become uncertain. Fuzzy control is one of the techniques which deal with this class of systems. The stability of fuzzy systems formed by a fuzzy plant model and a fuzzy controller has recently been investigated. Various stability conditions have been obtained through the employment of Lyapunov stability theory (Schegner & La Seta, 2004; Tripathy, 1997), fuzzy gain- scheduling controllers (Billy, 2011a, 2011b; Iescher et al., 2005), switching controllers (Lescher et al., 2006) and by other methods (Chen & Hu, 2003; Kamal et al., 2008; Muljadi & Edward, 2002). Nonlinear controllers (Boukhezzar & Siguerdidjane, 2009; Chedid et al., 2000; Hee-Sang et al., 2008) have also been proposed for the control of WECS represented by fuzzy models.

In addition to stability, robustness is also an important requirement to be considered in the study of uncertain nonlinear WECS control systems. Robustness in fuzzy-model-based control has been extensively studied, such as stability robustness versus modelling errors and other various control techniques for Takagi-Sugeno (TS) fuzzy models (Kamal et al., 2010; Uhlen et al., 1994).

In order to overcome nonlinearity and uncertainties, various schemes have been developed in the past two decades (Battista & Mantz, 2004; Boukhezzar & Siguerdidjane, 2010; Prats et al., 2000; Sloth et al., 2009). (Battista & Mantz, 2004) addressing problems of output power regulation in fixed-pitch variable-speed wind energy conversion systems with parameter uncertainties. The design of LMI-based robust controllers to control variable-speed, variable-pitch wind turbines, while taking into account parametric uncertainties in the aerodynamic model has been presented (Sloth et al., 2009). (Boukhezzar & Siguerdidjane, 2010) comparing several linear and nonlinear control strategies, with the aim of improving wind energy conversion systems. (Prats et al., 2000) have also investigated fuzzy logic controls to reduce uncertainties faced by classical control methods.

Furthermore, although the problem of control in the maximization of power generation in variable-speed wind energy conversion systems (VS-WECS) has been greatly studied, such

control still remains an active research area (Abo-Khalil & Dong-Choon, 2008; Aggarwal *et al.*, 2010; Barakati *et al.*, 2009; Camblong *et al.*, 2006; Datta & Ranganathan, 2003; Galdi *et al.*, 2009; Hussien *et al.*, 2009; Iyasere *et al.*, 2008; Koutroulis & Kalaitzakis, 2006; Mohamed *et al.*, 2001; Prats *et al.*, 2002; Whei-Min. & Chih-Ming, 2010). (Abo-Khalil & Dong-Choon, 2008; Aggarwal *et al.*, 2010; Camblong *et al.*, 2006; Datta & Ranganathan, 2003; Whei-Min. & Chih-Ming, 2010) maximum power point tracking (MPPT) algorithms for wind turbine systems have been presented (Galdi *et al.*, 2009) as well as design methodology for TS fuzzy models. This design methodology is based on fuzzy clustering methods for partitioning the input-output space, combined with genetic algorithms (GA), and recursive least-squares (LS) optimization methods for model parameter adaptation. A maximum power tracking algorithm for wind turbine systems, including a matrix converter (MC) has been presented (Barakati *et al.*, 2009). A wind-generator (WG) maximum-power-point tracking (MPPT) system has also been presented (Koutroulis & Kalaitzakis, 2006), consisting of a high efficiency buck-type dc/dc converter and a microcontroller-based control unit running the MPPT function. An advanced maximum power-tracking controller of WECS (Mohamed *et al.*, 2001), achieved through the implementation of fuzzy logic control techniques, also appears promising. The input to the controller consists in the difference between the maximum output power from the WES and the output power from the asynchronous link and, the derivative of this difference. The output of the controller is thus the firing angle of the line-commutated inverter, which transfers the maximum tracked power to the utility grid. Fuzzy controllers also permit the increase of captured wind energy under low and high wind speeds (Prats *et al.*, 2002; Hussien *et al.*, 2009). The fuzzy controller is employed to regulate, indirectly, the power flow in the grid connected WECS by regulating the DC current flows in the interconnected DC link. Sufficiently stable conditions are expressed in terms of Linear Matrix inequalities (LMI). (Iyasere *et al.*, 2008) to maximize the energy captured by the wind turbine under low to medium wind speeds by tracking the desired pitch angle and rotor speed, when the wind turbine system nonlinearities structurally uncertain.

Concerning other studies, due to the strong requirements of the Wind Energy Field, fault tolerant control of variable speed wind turbine systems has received significant attention in recent years (Bennouna *et al.*, 2009; Gaillard *et al.*, 2007; Odgaard *et al.*, 2009; Ribrant, 2006; Wang *et al.*, 2010; Wei *et al.*, 2010). To maintain the function of closed-loop control during faults and system changes, it is necessary to generate information about changes in a supervision scheme. Therefore, the objective of Fault Tolerant Control (FTC) is to maintain current performances close to desirable performances and preserve stability conditions in the presence of component and/or instrument faults. FTC systems must have the ability to adjust off-nominal behaviour, which might occur during sensor, actuator, or other component faults. A residual based scheme has been presented (Wei *et al.*, 2010) to detect and accommodate faults in wind turbines. An observer based scheme (Odgaard *et al.*, 2009) has been proposed to detect and isolate sensor faults in wind turbine drive trains. A study of fault tolerant power converter topology (Gaillard *et al.*, 2007) and fault identification and compensation for a WECS with doubly fed induction generator (DFIG), has also been done. In addition, a survey on failures of wind turbine systems in Sweden, Finland and Germany (Ribrant, 2006), has been carried out, where the data are from real maintenance records over the last two decades. Robust fault tolerant controllers based on the two-frequency loop have also been designed (Wang *et al.*, 2010). The low-frequency-loop adopts a PI steady-state optimization control strategy, and the high-frequency-loop adopts a robust fault tolerant

control approach, thus ensuring the actuator part of the system during failure in normal operation. Fault signature analysis to detect errors in the DFIG of a wind turbine has again been presented (Bennouna *et al.*, 2009).

It is well known that observer based 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 these aspects have received much interest. (Khedher *et al.*, 2009, 2010; Odgaard *et al.*, 2009; Tong & Han-Hiong, 2002; Tong *et al.*, 2009; Wang *et al.*, 2008; Yong-Qi, 2009; Zhang *et al.*, 2009) fuzzy observer designs for TS fuzzy control systems have been studied, and prove that a state feedback controller and observer always result in a stabilizing output feedback controller, provided that the stabilizing property of the control and asymptotic convergence of the observer are guaranteed through the Lyapunov method. However, in the above output feedback fuzzy controllers, the parametric uncertainties for TS fuzzy control systems have not been considered. As such robustness of the closed-loop system may not be guaranteed.

In this chapter, a Robust Fuzzy Fault Tolerant control (RFFTC) algorithm is proposed for hybrid wind-diesel storage systems (HWDSS) with time-varying parameter uncertainties, sensor faults and state variable unavailability, and measurements based on the Takagi-Sugeno (TS) fuzzy model. Sufficient conditions are derived for robust stabilization in the sense of Lyapunov asymptotic stability and are formulated in the form of Linear Matrix Inequalities (LMIs). The proposed algorithm combines the advantages of:

- The capability of dealing with non-linear systems with parametric uncertainties and sensor faults;
- The powerful Linear Matrix Inequalities (LMIs) approach to obtain fuzzy fault tolerant controller gains and observer gains;
- The maximization of the power coefficient for variable pitch variable-speed wind energy conversion systems;
- In addition, reduction of voltage ripple and stabilization of the system over a wide range of sensor faults and parameter uncertainties is achieved.

Also in this chapter, a Fuzzy Proportional Integral Observer (FPIO) design is proposed to achieve fault estimation in TS fuzzy models with sensor faults and parameter uncertainties. Furthermore, based on the information of online fault estimation, an observer-based robust fuzzy fault tolerant controller is designed to compensate for the effects of faults and parameter uncertainties, by stabilizing the closed-loop system. Based on the aforementioned studies, the contributions of this chapter are manifold:

- A new algorithm for the estimation of time-varying process faults and parameter uncertainties in a class of WECS;
- And a composite fault tolerant controller to compensate for the effects of the faults, by stabilizing the closed-loop system in the presence of bounded time-varying sensor faults and parameter uncertainties.

This chapter is organized as follows. In section 2, the dynamic modelling of WECS and system descriptions is introduced. Section 3 describes the fuzzy plant model, the fuzzy observer and the reference model. In section 4, robust fuzzy fault tolerant algorithms are proposed, to close the feedback loop and the stability and robustness conditions for WECS are derived and formulated into nonlinear matrix inequality (general case) and linear matrix inequality (special case) problems. Section 5 presents the TS Fuzzy Description and Control structure for HWDSS. Section 6 summarizes the procedures for finding the robust fuzzy fault tolerant controller and fuzzy observer. In section 7 simulation results illustrate the

effectiveness of the proposed control methods for wind systems. In section 8, a conclusion is drawn.

## 2. WECS model and systems descriptions

### 2.1 The wind turbine characteristics

Variable Speed wind turbine has three main regions of operation as shown in Fig.1. (Galdi et al., 2009). The use of modern control strategies are not usually critical in region I, where the monitoring of the wind speed is performed to determine whether it lies within the specifications for turbine operation and if so, the routines necessary to start up the turbine are performed. Region II is the operational mode in which the goal is to capture as much power as possible from the wind. Region III is called rated wind speed. The control objectives on the full load area are based on the idea that the control system has to maintain the output power value to the nominal value of the generator. The torque at the turbine shaft neglecting losses in the drive train is given by (Iyasere et al., 2008):

$$T_G = 0.5\pi C_t(\lambda, \beta) R^3 \rho v^2 \quad (1)$$

where  $T_G$  is the turbine mechanical torque, Where  $\rho$  is the air density ( $\text{kg}/\text{m}^3$ ),  $R$  is the turbine radius (m),  $v$  is the wind velocity (m/s), and  $C_t(\lambda, \beta)$  is the turbine torque coefficient. The power extracted from the wind can be expressed as (Galdi et al., 2009) :

$$P_a = \omega_t T_G = 0.5 C_p(\lambda, \beta) \rho \pi R^2 v^3 \quad (2)$$

where  $C_p(\lambda, \beta)$  is the rotor power coefficient defined by the following relation,

$$C_p(\lambda, \beta) = \lambda C_t(\lambda, \beta)$$

$$C_p(\lambda, \beta) = (0.44 - 0.0167\beta) \sin[\pi(\lambda - 3)/15 - 0.3\beta] - 0.00184(\lambda - 3)\beta \quad (3)$$

$\beta$  is the pitch angle of rotor blades (rad) ( $\beta$  is constant for fixed pitch wind turbines),  $\lambda$  is the tip speed ratio (TSR) and is given by:

$$\lambda = R\omega_t / v \quad (4)$$

where  $\omega_t$  is the rotor speed (rad/sec). It is seen that if the rotor speed is kept constant, then any change in the wind speed will change the tip-speed ratio, leading to the change of power coefficient  $C_p$  as well as the generated power out of the wind turbine. If, however, the rotor speed is adjusted according to the wind speed variation, then the tip-speed ratio can be maintained at an optimal point, which could yield maximum power output from the system. Referring to (3) optimal TSR  $\lambda_{opt}$  can be obtained as follow:

$$\lambda_{opt} = \left( \frac{15 - 0.3\beta}{\pi} \right) \cos^{-1} \left[ \frac{0.00184\beta(15 - 0.3\beta)}{\pi(0.44 - 0.167\beta)} \right] + 3 \quad (5)$$



From (5) it is clear that  $\lambda_{opt}$  depends on  $\beta$ . The relationship of  $C_p$  versus  $\lambda$ , for different values of the pitch angle  $\beta$ , are shown in Fig 2. The maximum value of  $C_p$  ( $C_{p(max)}= 0.48$ ) is achieved for  $\beta = 0^\circ$  and for  $\lambda= 8$ . This particular value of  $\lambda$  is defined as the optimal value of TSR ( $\lambda_{opt}$ ). Thus the maximum power captured from the wind is given by:

$$P_{a(max)} = 0.5C_{p(max)}(\lambda_{opt}, \beta)\rho \pi R^2 v^3$$

(6)

Normally, a variable speed wind turbine follows the  $C_{p(max)}$  to capture the maximum power up to the rated speed by varying the rotor speed at  $\omega_{opt}$  to keep the TSR at  $\lambda_{opt}$ .

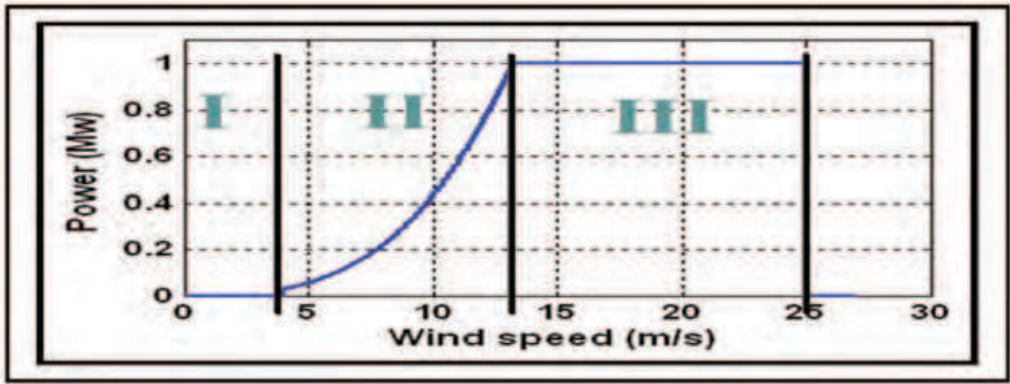


Fig. 1. Power-wind speed characteristics

2.2 WECS system description

A wind-battery hybrid system consists of a wind turbine coupled with a synchronous generator (SG), a diesel-induction generator (IG) and a battery connected with a three-phase thyristor-bridge controlled current source converter. In the given system, the wind turbine drives the synchronous generator that operates in parallel with the storage battery system. When the wind-generator alone provides sufficient power for the load, the diesel engine is disconnected from the induction generator. The Power Electronic Interface (PEI) connecting the load to the main bus is used to fit the frequency of the power supplying the load as well as the voltage. Fig. 3 shows the overall structure of wind-battery system:  $E_{fd}$  is the excitation field voltage,  $f$  is the frequency,  $V_b$  is the bus voltage,  $C_a$  is the capacitor bank,  $V_c$  is the AC side voltage of the converter, and  $I_{ref}$  is the direct-current set point of the converter.

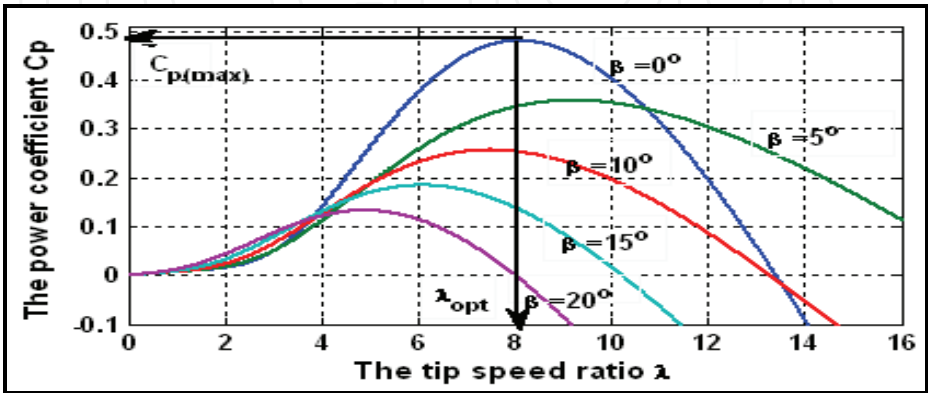


Fig. 2. Power coefficient  $C_p$  versus TSR  $\lambda$

The dynamics of the system can be characterized by the following equations (Kamal et al., 2010):

$$\dot{x} = Ax(t) + Bu(t) , \quad y = Cx(t) \quad , \tag{7}$$

where

$$x(t) = [V_b \quad \omega_s]^T, \quad u(t) = [E_{fd} \quad I_{ref}]^T, \\ A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{L_f}{\tau' \omega_s L_{md}} & \frac{L_f}{\tau' \omega_s L_{md}} (L_d i_{sd} - \frac{r_a i_{sq}}{\omega_s}) \\ \frac{P_{ind} - P_{load}}{J_s \omega V_b} & -\frac{D_s}{J_s} \end{bmatrix} \quad B = \begin{bmatrix} 1 & -\frac{V_c}{\omega_s J_s} \\ 0 & -\frac{V_c}{\omega_s J_s} \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

where  $\omega_s$  is the bus frequency (or angular speed of SG)  $J_s$ ,  $D_s$  are the inertia and frictional damping of SG,  $i_{sd}$ ,  $i_{sq}$  are the direct and quadrature current component of SG,  $L_d$ ,  $L_f$  are the stator d-axis and rotor inductance of SG,  $L_{md}$  is the d-axis field mutual inductance,  $\tau$  is the transient open circuit time constant,  $r_a$  is the rotor resistance of SG,  $P_{ind}$  is the power of the induction generator,  $P_{load}$  is the power of the load. Equation (7) indicates that the matrices  $A$  and  $B$  are not fixed, but change as functions of state variables, thus making the model nonlinear. Also, this model is only used as a tool for controller design purposes.

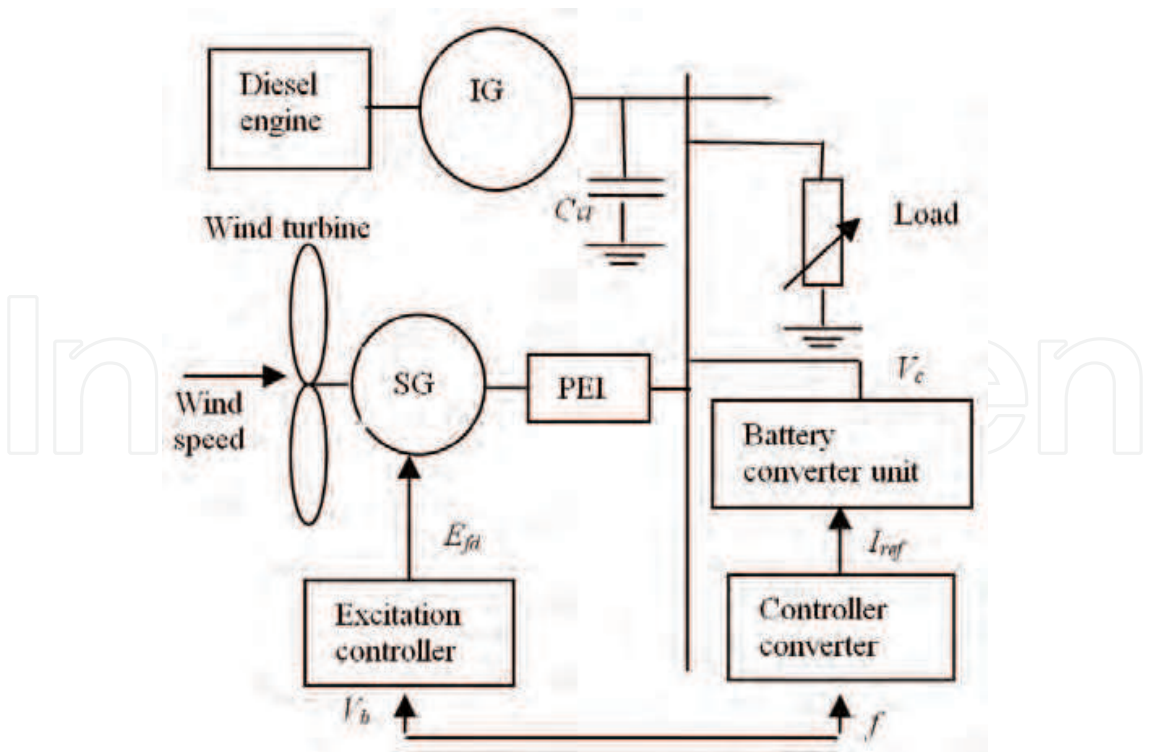


Fig. 3. Structural diagram of hybrid wind-diesel storage system

The used system parameters are shown in Table 1 (Chedid et al., 2000; Kamal et al., 2010).

Rated power	1 [MW]
Blade radius	37.38 [m]
Air density	0.55 [kg /m³]
Rated wind speed	12.35 [m/s]
Blade pitch angle	0°
Rated line ac voltage	230 [V]
AC rated current	138 [A]
DC rated current	239 [A]
Rated Load power	40 [kW]
The inertia of SG	1.11 [kg m²]
Rated power of IG	55 [kW]
The inertia of the IG	1.40 [kg m²]
Torsional damping	0.557 [Nm/ rad]
Rotor resistance of SG	0.96 [ Ω]
Stator d-axis inductance of SG	2.03 [mH]
Rotor inductance of SG	2.07 [mH]
d-axis field mutual inductance	1.704 [mH]
The transient open circuit time constant	2.16 [ms]

Table 1. System parameters

3. Reference model, TS fuzzy plant model and fuzzy proportional-integral observer

3.1 Reference model

A reference model is a stable linear system without faults given by (Khedher et al., 2009, 2010),

$$\dot{\bar{x}}(t) = A_r \bar{x}(t) + B_r r(t) , \quad \bar{y}(t) = C_r \bar{x}(t) \tag{8}$$

where  $\bar{x}(t) \in \kappa^{nx1}$  is the state vector of reference model,  $r(t) \in \kappa^{nx1}$  is the bounded reference input,  $A_r \in \kappa^{nxn}$  is the constant stable system matrix,  $B_r \in \kappa^{nxn}$  is the constant input matrix,  $C_r \in \kappa^{gxnr}$  is the constant output matrix.  $\bar{y}(t) \in \kappa^{gx1}$  is the reference output.

3.2 TS fuzzy plant model with parameter uncertainties and sensor faults

The continuous fuzzy dynamic model, proposed by TS, is described by fuzzy IF-THEN rules, which represent local linear input-output relations of nonlinear systems. Consider an uncertain nonlinear system that can be described by the following TS fuzzy model with parametric uncertainties and sensor faults (Khedher *et al.*, 2009, 2010; Tong & Han-Hiong, 2002). The i-th rule of this fuzzy model is given by:



Plant Rule  $i$ :  $q_1(t)$  is  $N_{i_1}$  AND ... AND  $q_\psi(t)$  is  $N_{i_\psi}$

Then

$$\begin{aligned}\dot{x}(t) &= (A_i + \Delta A_i) x(t) + B_i u(t), \\ y(t) &= C_i x(t) + E_i f(t)\end{aligned}\quad (9)$$

where  $N_{i_\Omega}$  is a fuzzy set of rule  $i$ ,  $\Omega = 1, 2, \dots, \psi$ ,  $i=1, 2, \dots, p$ ,  $x(t) \in \kappa^{n \times 1}$  is the state vector,  $u(t) \in \kappa^{g \times 1}$  is the input vector,  $y(t) \in \kappa^{g \times 1}$  is the output vector,  $f(t) \in \kappa^{m \times 1}$  represents the fault which is assumed to be bounded,  $A_i \in \kappa^{n \times n}$  and  $B_i \in \kappa^{n \times g}$ ,  $C_i \in \kappa^{g \times n}$ ,  $E_i$  are system matrix, input matrix, output matrix and fault matrix, respectively, which are assumed to be known,  $\Delta A_i \in \kappa^{n \times n}$  is the parameter uncertainties of  $A_i$  within known. It is supposed that the matrix  $E_i$  is of full column rank, i.e.  $\text{rank}(E_i) = r$ . It is assumed that the derivative of  $f(t)$  with respect to time is norm bounded, i.e.  $\|\dot{f}(t)\| \leq f_1$  and  $0 \leq f_1 < \infty$  (Zhang *et al.*, 2009),  $p$  is the number of IF-THEN rules, and  $q_1(t), \dots, q_\psi(t)$  are the premise variables assumed measurable variables and do not depend on the sensor faults. The defuzzified output of (9) subject to sensor faults and parameter uncertainty is represented as follows (Khedher *et al.*, 2009, 2010; Tong & Han-Hiong, 2002):

$$\begin{aligned}\dot{x}(t) &= \sum_{i=1}^p \mu_i(q(t)) [(A_i + \Delta A_i) x(t) + B_i U(t)], \\ y(t) &= \sum_{i=1}^p \mu_i(q(t)) [C_i x(t) + E_i f(t)]\end{aligned}\quad (10)$$

where

$$h_i(q(t)) = \prod_{\alpha=1}^{\psi} N_{\alpha}^i(q(t)), \mu_i(q(t)) = h_i(q(t)) / \sum_{i=1}^p h_i(q(t))$$

Some basic properties of

$$\begin{aligned}h_i(q(t)) \text{ are } h_i(q(t)) \geq 0, \quad \sum_{i=1}^p h_i(q(t)) \geq 0 \\ 0 \leq \mu_i(q(t)) \leq 1, \quad \sum_{i=1}^p \mu_i(q(t)) = 1 \quad \forall i = 1, 2, \dots, p\end{aligned}\quad (11)$$

### 3.3 TS Fuzzy Proportional Integral Observer (FPIO)

**Definition 1:** If the pairs  $(A_i, C_i)$ ,  $i=1, 2, \dots, p$ , are observable, the fuzzy system (10) is called locally observable (Xiao-Jun *et al.*, 1998).

For the fuzzy observer design, it is assumed that the fuzzy system (10) is locally observable. First, the local state observers are designed as follows, based on the triplets  $(A_i, B_i, C_i)$ . In order to detect and estimate faults, the following fault estimation observer is constructed (Khedher *et al.*, 2009, 2010; Tong & Han-Hiong, 2002).

Observer Rule  $i$ :  $q_1(t)$  is  $N_{i1}$  AND ... AND  $q_p(t)$  is  $N_{ip}$   
Then

$$\dot{\hat{x}}(t) = A_i \hat{x}(t) + B_i u(t) + K_i (y(t) - \hat{y}(t)) ,$$

$$\dot{\hat{f}}(t) = L_i (y - \hat{y}) = L_i \tilde{y}$$

$$\hat{y}(t) = C_i \hat{x}(t) + E_i \hat{f}(t) \quad i=1, 2, \dots, p \quad (12)$$

where  $K_i$  is the proportional observer gain for the  $i$ -th observer rule and  $L_i$  are their integral gains to be determined,  $y(t)$  and  $\hat{y}(t)$  are the final output of the fuzzy system and the fuzzy observer respectively. The defuzzified output of (12) subject to sensor faults is represented as follows:

$$\dot{\hat{x}}(t) = \sum_{i=1}^p \mu_i(q(t)) [A_i \hat{x}(t) + B_i U(t) + K_i (y(t) - \hat{y}(t))]$$

$$\dot{\hat{f}}(t) = \sum_{i=1}^p \mu_i L_i (y - \hat{y}) = \sum_{i=1}^p \mu_i L_i \tilde{y}$$

$$\hat{y}(t) = \sum_{i=1}^p \mu_i(q(t)) [C_i \hat{x}(t) + E_i \hat{f}(t)] \quad (13)$$

#### 4. Proposed fuzzy fault tolerant algorithm and stability conditions

The goal is to design the control law  $u(t)$  such that the system state  $x(t)$  will follow those of a stable reference model of (8) in the presence of parametric uncertainties and sensor faults.

##### 4.1 PDC technique

The concept of PDC in (Wang et al., 1996) is utilized to design fuzzy controllers to stabilize fuzzy system (10). For each rule, we can use linear control design techniques. The resulting overall fuzzy controller, which is nonlinear in general, is a fuzzy blending of each individual linear controller. The fuzzy controller shares the same fuzzy sets with the fuzzy system (10).

##### 4.2 Proposed RFFTC controller

**Definition 2:** If the pairs  $(A_i, B_i)$ ,  $i=1, 2, \dots, p$ , are controllable, the fuzzy system (10) is called locally controllable (Xiao-Jun et al., 1998).

For the fuzzy controller design, it is assumed that the fuzzy system (10) is locally controllable. First, the local state feedback controllers are designed as follows, based on the pairs  $(A_i, B_i)$ . Using PDC the  $i$ -th rule of the fuzzy controller is of the following format:

Controller Rule  $i$ :  $q_1(t)$  is  $N_{i1}$  AND ... AND  $q_p(t)$  is  $N_{ip}$

Then

$$u(t)=u_i(t) \quad (14)$$

where  $u_i(t) \in \mathcal{K}^{n \times 1}$  is the output of the  $i$ -th rule controller that will be defined in the next subsection. The global output of the fuzzy controller is given by

$$U(t) = \sum_{i=1}^p \mu_i(q(t)) u_i(t) \quad (15)$$

From (10), (11) and (15), writing  $\mu_i(q(t))$  as  $\mu_i$ , we obtain

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^p \mu_i (A_i + \Delta A_i) x(t) + B u_i \\ y(t) &= \sum_{i=1}^p \mu_i [C_i x(t) + E f(t)] \end{aligned} \quad (16)$$

where

$$B = \sum_{i=1}^p \mu_i B_i \text{ and } E = \sum_{i=1}^p \mu_i E_i \quad (17)$$

Note that  $B$  and  $E$  are known. Also from (11), (12) and (15), we have

$$\begin{aligned} \dot{\hat{x}}(t) &= \sum_{i=1}^p \mu_i [A_i \hat{x}(t) + B u_i(t) + K_i (y(t) - \hat{y}(t))] \\ \dot{\hat{f}}(t) &= \sum_{i=1}^p \mu_i L_i (y - \hat{y}) = \sum_{i=1}^p \mu_i L_i \tilde{y} \\ \hat{y}(t) &= \sum_{i=1}^p \mu_i [C_i \hat{x}(t) + E \hat{f}(t)] \end{aligned} \quad (18)$$

#### 4.3 Stability and robustness analyses for the proposed algorithm

We derived the stability and robustness conditions for a generalized class of WECS with sensor faults and parameter uncertainties described by (16). The main result is summarized in the following lemma 1 and theorem.

**Lemma 1:** The fuzzy control system of (16) subject to plant sensors faults and parameter uncertainties is guaranteed to be asymptotically stable, and its states will follow those of a stable reference model of (8) in the presence of bounded sensor faults and parameter uncertainties, if the following two conditions satisfy;

- $Z$  is nonsingular. One sufficient condition to guarantee the nonsingularity of  $Z$  is that there exists  $P$  such that,

$$Z_i^T P + P Z_i < 0 \quad \forall i \quad (19)$$

- The control laws of fuzzy controller of (15) are designed as, If  $e_1(t) \neq 0$ ; When  $B$  is an invertible square matrix, the control law is given by

$$u_i(t) = Z_{ui}^{-1} Z \quad (20)$$

When  $B$  is not a square matrix, the control law is given by

$$u_i(t) = B^T Z^{-1} Z_{ui} \quad (21)$$

Where  $Z_{ui}$  is given by

$$Z_{ui} = \left\{ \begin{aligned} & [H e_1(t) + A_r \bar{x}(t) + B_r r(t) - \frac{e_1(t) \|e_1(t)\| \|P_1\| \|\Delta A_i\|_{\max} \|x(t)\|}{e_1(t)^T P_1 e_1(t)} \\ & - \frac{e_1(t) \|x(t)\| \|D\|_{\max} \|x(t)\|}{e_1(t)^T P_1 e_1(t)} - A_i x(t) - \frac{1}{2} \frac{e_1(t) \|\hat{f}(t)\| \|S_E\|_{\max} \|\hat{f}(t)\|}{e_1(t)^T P_1 e_1(t)} + S \hat{f}(t) \end{aligned} \right\} \quad (22)$$

If  $e_1(t) = 0$

$$u_i(t) = Z^{-1} \left\{ A_r \bar{x}(t) + B_r r(t) - A_i x(t) + S \hat{f}(t) \right\}; \quad u_i(t) = B^T Z^{-1} \left\{ A_r \bar{x}(t) + B_r r(t) - A_i x(t) + S \hat{f}(t) \right\} \quad (23)$$

where  $Z = B$  if  $B$  is an invertible square matrix or  $Z = BB^T$  if  $B$  is not a square matrix,  $\|\cdot\|$  denotes the  $l_2$  norm for vectors and  $l_2$  induced norm for matrices,  $\|S_E\| \leq \|S_E\|_{\max}$ ,  $\|\Delta A_i\| \leq \|\Delta A_i\|_{\max}$  and  $\|D\| \leq \|D\|_{\max}$ ,  $H \in \mathbb{R}^{n \times n}$  is a stable matrix to be designed and choosing  $S$  so that  $S = E$  and  $S_E = S^T S$ ,  $D = B_{ai}^T B_{ai}$ .

**Theorem:** If there exist symmetric and positive definite matrices  $P_{11}$ ,  $P_{22}$ , some matrices  $K_i$  and  $L_i$ , and matrices  $X_i$ ,  $Y_i$ , such that the following LMIs are satisfied, then the TS fuzzy system (16) is asymptotically stabilizable via the TS fuzzy model based output-feedback controller (15), (20) and (21)

$$A_{i11}^T P_{11} + P_{11} A_{i11} - (Y_i C_i)^T - Y_i C_i + P_{11} P_{11} < -\delta I \quad (24)$$

$$(X_i E)^T + X_i E + P_{22} P_{22} < -\delta I \quad (25)$$

**Proof.** Before proceeding, we recall the following matrix inequality, which will be needed throughout the proof.

**Lemma 2**(Xie, 1996): Given constant matrices  $W$  and  $O$  appropriate dimensions for  $\forall \varepsilon > 0$ , the following inequality holds:

$$W^T O + O^T W \leq \varepsilon W^T W + \varepsilon^{-1} O^T O$$

Let

$$e_1(t) = x(t) - \bar{x}(t) \quad (26)$$

$$e_2(t) = x(t) - \hat{x}(t), \quad \tilde{f}(t) = f(t) - \hat{f}(t) \quad (27)$$

The dynamic of  $e_1(t)$  is given by  $\dot{e}_1(t) = \dot{x}(t) - \dot{\bar{x}}(t)$

$$\dot{e}_1(t) = \sum_{i=1}^p \mu_i [(A_i + \Delta A_i) x(t) + B u_i(t) - A_r \bar{x}(t) - B_r r(t)] \quad (28)$$

The dynamic of  $e_2(t)$  is expressed as follow:

$$\dot{e}_2(t) = \sum_{i=1}^p \mu_i [(A_i - K_i C_i) e_2(t) - K_i E \tilde{f}(t) + \Delta A_i x(t)] \quad (29)$$

The dynamics of the fault error estimation can be written:  $\dot{\tilde{f}}(t) = \dot{f}(t) - \dot{\hat{f}}(t)$ . The assumption that the fault signal is constant over the time is restrictive, but in many practical situations where the faults are time-varying signals. So, we consider time-varying faults rather than constants faults; then the derivative of  $\tilde{f}(t)$  with respect to time is

$$\dot{\tilde{f}}(t) = \dot{f}(t) - \dot{\hat{f}}(t) = \dot{f}(t) - \sum_{i=1}^p \mu_i [L_i C_i e_2(t) + L_i E \tilde{f}(t)] \quad (30)$$

From (29) and (30), one can obtain:

$$\dot{\phi} = A_o \phi + B_o \dot{f}(t) + B_a x(t) \quad (31)$$

$$\text{with } \phi = \begin{bmatrix} e_2(t) \\ \tilde{f}(t) \end{bmatrix}, B_o = \begin{bmatrix} 0 \\ I \end{bmatrix}, A_o = \sum_{i=1}^p \mu_i A_{oi}, B_a = \sum_{i=1}^p \mu_i B_{ai}, \text{ where}$$

$$A_{oi} = \begin{bmatrix} A_i - K_i C_i & -K_i E \\ -L_i C_i & -L_i E \end{bmatrix}, B_{ai} = \begin{bmatrix} \Delta A_i \\ 0 \end{bmatrix}$$



Consider the Lyapunov function candidate

$$V(e_1(t), \phi(t)) = \frac{1}{2} e_1^T(t) P_1 e_1(t) + \frac{1}{2} \phi^T(t) P_2 \phi(t) \quad (32)$$

where  $P_1$  and  $P_2$  are time-invariant, symmetric and positive definite matrices. Let

$$V_1(e_1) = \frac{1}{2} e_1^T(t) P_1 e_1(t), \quad V_2(\phi) = \frac{1}{2} \phi^T(t) P_2 \phi(t) \quad (33)$$

The time derivative of  $V_1(e_1(t))$  is

$$\dot{V}_1(e_1(t)) = \frac{1}{2} \dot{e}_1^T(t) P_1 e_1(t) + \frac{1}{2} e_1^T(t) P_1 \dot{e}_1(t) \quad (34)$$

By substituting (28) into (34) yields

$$\begin{aligned} \dot{V}_1 = \frac{1}{2} \left\{ \sum_{i=1}^p \mu_i [(A_i + \Delta A_i) x(t) + B u_i(t) - A_r \bar{x}(t) - B_r r(t)] \right\}^T P_1 e_1(t) \\ + \frac{1}{2} e_1^T(t) P_1 \left\{ \sum_{i=1}^p \mu_i [(A_i + \Delta A_i) x(t) + B u_i(t) - A_r \bar{x}(t) - B_r r(t)] \right\} \end{aligned} \quad (35)$$

we design  $u_i(t)$ ,  $i=1,2,\dots,p$  as follows,

- When  $B$  is an invertible square matrix, the control law is given by

$$u_i(t) = Z^{-1} Z_{ui} \quad (36)$$

- When  $B$  is not a square matrix, the control law is given by

$$u_i(t) = B^T Z^{-1} Z_{ui} \quad (37)$$

where  $Z_{ui}$  is given from (22). A block diagram of the closed-loop system is shown in Fig.4. It is assumed that  $Z^{-1}$  exists ( $Z$  is nonsingular). In the latter part of this section, we shall provide a way to check if the assumption is valid. From (35), (36) or (37) and assuming that  $e_1(t) \neq 0$  and using Lemma 2, one obtain

$$\begin{aligned} \dot{V}_1 = \frac{1}{2} e_1^T(t) (H^T P_1 + P_1 H + P_1 P_1) e_1(t) + \frac{1}{2} \sum_{i=1}^p \mu_i \|e_1(t)\| \|P_1\| (\|\Delta A_i\| - \|\Delta A_i\|_{\max}) \|x(t)\| \\ + \frac{1}{2} (\|\hat{f}(t)\| (\|S_E\| - \|S_E\|_{\max}) \|\hat{f}(t)\| - \|x(t)\| \|D\|_{\max} \|x(t)\|) \end{aligned} \quad (38)$$

The time derivative of  $V_2(\phi(t))$  is

$$\dot{V}_2(\phi(t)) = \frac{1}{2} \dot{\phi}(t)^T P_2 \phi(t) + \frac{1}{2} \phi(t)^T P_2 \dot{\phi}(t) \quad (39)$$

By substituting (31) into (39) yields

$$\begin{aligned} \dot{V}_2(\phi(t)) = & \frac{1}{2} \sum_{i=1}^p \mu_i \phi(t)^T (A_{oi}^T P_2 + P_2 A_{oi}) \phi(t) + \frac{1}{2} \sum_{i=1}^p \mu_i [\dot{f}(t)^T B_o^T P_2 \phi(t) + \phi(t)^T P_2 B_o \dot{f}(t)] \\ & + \frac{1}{2} \sum_{i=1}^p \mu_i [x(t)^T B_{ai}^T P_2 \phi(t) + \phi(t)^T P_2 B_{ai} x(t)] \end{aligned} \quad (40)$$

Using Lemma 2 and the definition (Billy, E. (2011))  $\dot{f}(t)^T B_o^T B_o \dot{f}(t) = f_1^2 \lambda_{\max}(B_o^T B_o)$ , one obtain

$$\dot{V}_2(\phi(t)) = \frac{1}{2} \sum_{i=1}^p \mu_i \phi(t)^T (A_{oi}^T P_2 + P_2 A_{oi} + P_2 P_2) \phi(t) + \frac{1}{2} f_1^2 \lambda_{\max}(B_o^T B_o) + \frac{1}{2} x(t)^T D x(t) \quad (41)$$

where  $\lambda_{\max}(\cdot)$  denotes the largest eigen value. Combining (38) with (41), the time derivative of  $V$  can be expressed as

$$\begin{aligned} \dot{V}(e_1(t), \phi(t)) \leq & -\frac{1}{2} e_1(t)^T Q_1 e_1(t) - \phi(t)^T Q_2 \phi(t) + \frac{1}{2} \|\hat{f}(t)\| (\|S_E\| - \|S_E\|_{\max}) \|\hat{f}(t)\| \\ & + \sum_{i=1}^p \mu_i \|e_1(t)\| \|P_1\| (\|\Delta A_i\| - \|\Delta A_i\|_{\max}) \|x(t)\| + \|x(t)\| (\|D\| - \|D\|_{\max}) \|x(t)\| \end{aligned} \quad (42)$$

where  $Q_2 = -(A_{oi}^T P_2 + P_2 A_{oi} + P_2 P_2 + \delta)$ ,  $Q_1 = -(H_1^T P_1 + P_1 H_1 + P_1 P_1)$  are a symmetric positive definite matrix, where  $\delta = 0.5 f_1^2 \lambda_{\max}(B_o^T B_o)$ , as  $\|S_E\| - \|S_E\|_{\max} \leq 0$ ,  $\|\Delta A_i\| \leq \|\Delta A_i\|_{\max}$ ,  $\|D\| \leq \|D\|_{\max}$ , from (42), we have

$$\dot{V}(e_1(t), \phi(t)) \leq -\frac{1}{2} e_1(t)^T Q_1 e_1(t) - \phi(t)^T Q_2 \phi(t) \quad (43)$$

$e_1$  and  $\phi$  converges to zero if  $\dot{V} < 0$ .  $\dot{V} < 0$  if there exists a common positive definite matrix  $P_1$  and  $P_2$  such that

$$H_1^T P_1 + P_1 H_1 + P_1 P_1 < 0 \quad (44)$$

$$A_{oi}^T P_2 + P_2 A_{oi} + P_2 P_2 < -\delta I \quad i=1,2,\dots,p \quad (45)$$

From (43) , (44) and (45)

$$\dot{V} \leq -\frac{1}{2} e_1(t)^T Q_1 e_1(t) - \phi(t)^T Q_2 \phi(t) \leq 0 \quad (46)$$

If the time derivative of (32) is negative uniformly for all  $e_1(t), \phi(t)$  and for all  $t \geq 0$  except at  $e_1(t) = 0, \phi(t) = 0$  then the controlled fuzzy system (16) is asymptotically stable about its zero equilibrium. Since each sum of the equation in (46) is negative definite, respectively, then the controlled TS fuzzy system is asymptotically stable. According to the (45), the most important step in designing the fuzzy observer based fuzzy controller is the solution of (45) for a common  $P_2 = P_2^T$ , a suitable set of observer gains  $K_i$  and  $L_i$  ( $i = 1, 2, \dots, p$ ). Equation (45) forms a set of bilinear matrix inequalities (BMI's). The BMI in (45) should be transformed into pure LMI as follows:

1. For the convenience of design, assume  $P_2 = \text{diag}(P_{11}, P_{22})$
2. This choice is suitable for simplifying the design of fuzzy observer. Define  $M$  as in (47) and apply congruence transformation (i.e. multiply both side of inequality (45) by  $M$  (Tuan et al., 2001).

$$M = \begin{bmatrix} M_{11} & 0 \\ 0 & I \end{bmatrix} = \begin{bmatrix} P_{11}^{-1} & 0 \\ 0 & I \end{bmatrix} \quad (47)$$

where  $M_{11} = P_{11}^{-1}$

3. With  $Y_i = P_{11}K_i$  and  $X_i = -P_{22}L_i$ , apply the change of variables. Since four parameters  $P_{11}, P_{22}, K_i$  and  $L_i$  should be determined from (45) after applying the above mentioned procedures which results in the LMI's conditions (24) and (25).

The inequalities in (24) and (25) are linear matrix inequality feasibility problems (LMIP's) in  $P_{11}, P_{22}, Y_j$  and  $X_i$  which can be solved very efficiently by the convex optimization technique such as interior point algorithm (Boyd et al., 1994). Software packages such as LMI optimization toolbox in Matlab (Gahinet et al., 1995) have been developed for this purpose and can be employed to easily solve the LMIP. By solving (24) and (25) the observer gain ( $K_i$  and  $L_i$ ) can be easily determined.

In the following, we shall derive a sufficient condition to check the existence of  $Z^{-1}$ . From (17), and considering the following dynamics system,

$$\dot{\theta}(t) = Z\theta(t) = \sum_{i=1}^p \mu_i Z_i \theta(t) \quad (48)$$

Consider the following Lyapunov function

$$V_z = \theta(t)^T P \theta(t) \quad (49)$$

where  $P \in \kappa^{n \times n}$  is a symmetric positive definite matrix. The time derivative of  $V_z$  is

$$\dot{V}_z = \dot{\theta}(t)^T P \theta(t) + \theta(t)^T P \dot{\theta}(t) \quad (50)$$

By substituting (48) into (50) yields

$$\dot{V}_z = - \sum_{i=1}^p \mu_i \theta(t)^T Q_{zi} \theta(t) \quad (51)$$

where  $Q_{zi} = -(Z_i^T P + P Z_i)$ . If  $Z_i^T P + P Z_i < 0 \quad \forall i$ , then from (51), we have,

$$\dot{V}_z = - \frac{1}{2} \sum_{i=1}^p \mu_i \theta(t)^T Q_{zi} \theta(t) \leq 0 \quad (52)$$

From (52), the nonlinear system of (48) is then asymptotically stable and  $Z^{-1}$  exists if there exist  $Z_i^T P + P Z_i < 0 \quad \forall i$

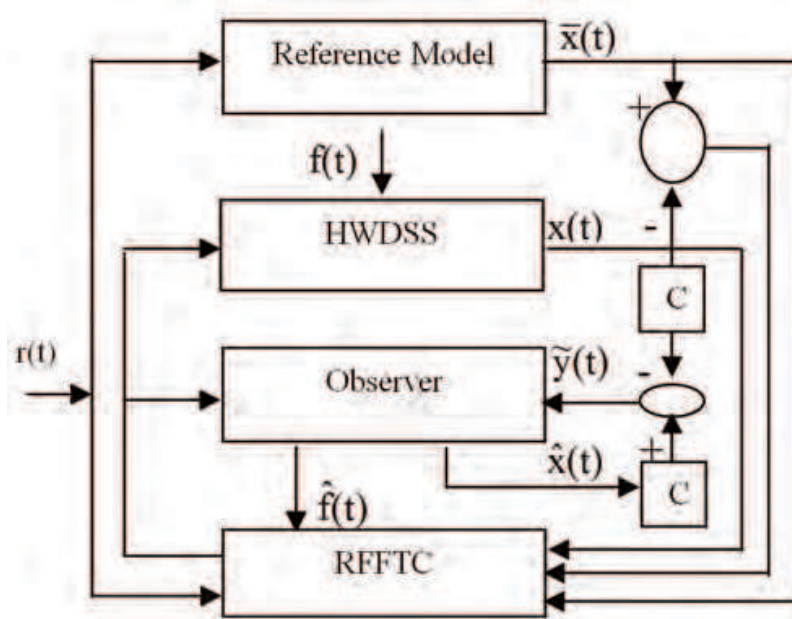


Fig. 4. Block diagram of RFFTC scheme

## 5. TS Fuzzy description and control structure

### 5.1 Control structure

Fig. 5 depicts the input and output relationship of the wind-battery system from the control point of view. The control inputs are the excitation field voltage ( $E_{fd}$ ) of the SG and the direct-current set point ( $I_{ref}$ ) of the converter. The measurements are the voltage amplitude ( $V_b$ ) and the frequency ( $f$ ) of the AC bus. The wind speed ( $v$ ) and the load ( $v_l$ ) are considered

to be disturbances. The wind turbine generator and the battery-converter unit run in parallel, serving the load. From the control point of view, this is a coupled 2×2 multi-input-multi-output nonlinear system.

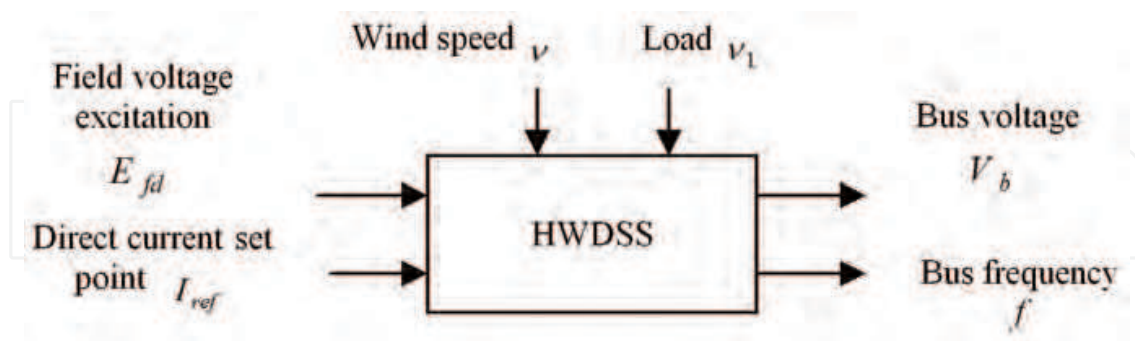


Fig. 5. The HWDSS control system

## 5.2 TS Fuzzy WECS description

To design the fuzzy fault tolerant controller and the fuzzy observer, we must have a fuzzy model that represents the dynamics of the nonlinear plant. The TS fuzzy model that approximates the dynamics of the nonlinear HWDSS plant (7) can be represented by the following four-rule fuzzy model. Referring to (10) the fuzzy plant model given by:

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^4 h_i [(A_i + \Delta A_i) x(t) + B_i u(t)] \\ y(t) &= \sum_{i=1}^4 \mu_i [C_i x(t) + E_i f(t)] \end{aligned} \quad (53)$$

where  $x(t) \in \kappa^{2 \times 1}$ ,  $u(t) \in \kappa^{2 \times 1}$  are the state vectors and the control input, respectively. For each sub-space, different model ( $i = 1, 2, 3, 4$ ) and ( $p = 4$ ) is applied. The degree of membership function for states  $V_b$  and  $\omega_s$  is depicted in Fig.6. Where

$$\begin{aligned} A_g &= \begin{bmatrix} -0.006 & 1.213 \\ 0 & -0.002 \end{bmatrix}, A_j = \begin{bmatrix} -0.0063 & 1.207 \\ 0 & -0.002 \end{bmatrix}, B_g = \begin{bmatrix} 1 & -0.5808 \\ 0 & -0.5808 \end{bmatrix}, \\ B_j &= \begin{bmatrix} 1 & -0.5979 \\ 0 & -0.5979 \end{bmatrix}, E_g = E_j = E = \begin{bmatrix} 10 & 1 \\ 0.1 & 0.01 \end{bmatrix} \quad g=1,2 \text{ and } j=3,4 \end{aligned}$$

$\Delta A_i$  represent the system parameters uncertainties but bounded, the elements of  $\Delta A_i$  randomly achieve the values within 40% of their nominal values corresponding to  $A_i$ ,  $\Delta B_i = 0$  ( $i=1,2,3,4$ ), and the faults  $f(t)$  are modeled as follow:

$$f_1(t) = \begin{cases} 0 & t < 20.75 \text{ sec} \\ 5.9 \sin(\pi t) & t \geq 20.75 \text{ sec} \end{cases}, f_2(t) = \begin{cases} 0 & t \leq 20.75 \text{ sec} \\ 1 & t \geq 20.75 \text{ sec} \end{cases} \quad (54)$$



where  $f_1(t)$  is the bus voltage sensor fault and  $f_2(t)$  is the generator speed sensor fault.

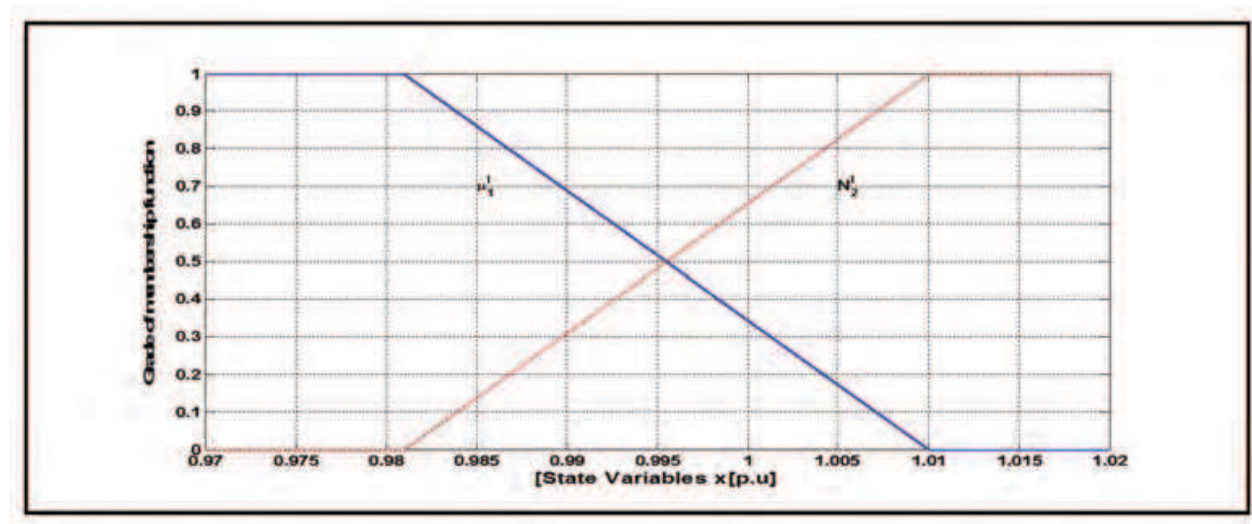


Fig. 6. Membership functions of states  $\omega_s$  and  $V_b$

## 6. Procedures for finding the robust fuzzy fault tolerant controller and fuzzy observer

According to the analysis above, the procedure for finding the proposed fuzzy fault tolerant controller and the fuzzy observer summarized as follows.

1. Obtain the mathematical model of the HWDSS to be controlled.
2. Obtain the fuzzy plant model for the system stated in step (1) by means of a fuzzy modeling method.
3. Check if there exists  $Z^{-1}$  by finding  $P$  according to Lemma 1. If  $P$  cannot be found, the design fails.  $P$  can be found by using some existing LMI tools.
4. Choose a stable reference model.
5. Solve LMIs (24) and (25) to obtain  $X_i$ ,  $Y_i$ ,  $P_{11}$ ,  $P_{22}$ ,  $K_i$  and  $L_i$  thus ( $K_i = P_{11}^{-1} Y_i$  and  $L_i = -P_{22}^{-1} X_i$ ).
6. Construct fuzzy observer (12) according to the theorem and fuzzy controller (14) controller according to the Lemma 1.

## 7. Simulation studies

The simulations are performed on a simulation model of hybrid wind-diesel storage system (7). The proposed Fuzzy Fault Tolerant controller for the HWDSS is tested for two cases. The proposed controller is tested for random variation of wind speed signal as shown in Fig.7 to prove the effectiveness of the proposed algorithm. The reference input ( $r(t) = \omega_{t(opt)} = \nu \lambda_{opt} / R$ ) is applied to the reference model and the controller to obtain the maximum power coefficient from the wind energy.

### 7.1 System responses of the fuzzy control system without and with parameter uncertainties

Fig. 8 shows the HWDSS responses of the fuzzy control system without (solid lines) and with parameter uncertainties (dash lines), and the reference model (dotted lines) under  $r(t)$ .

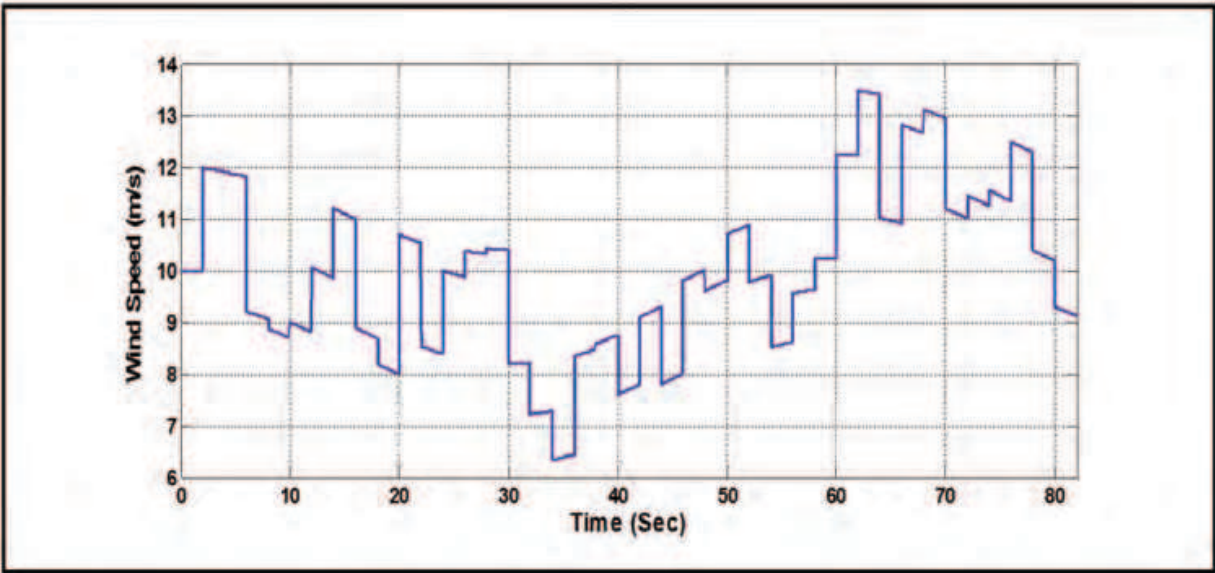


Fig. 7. Wind speed

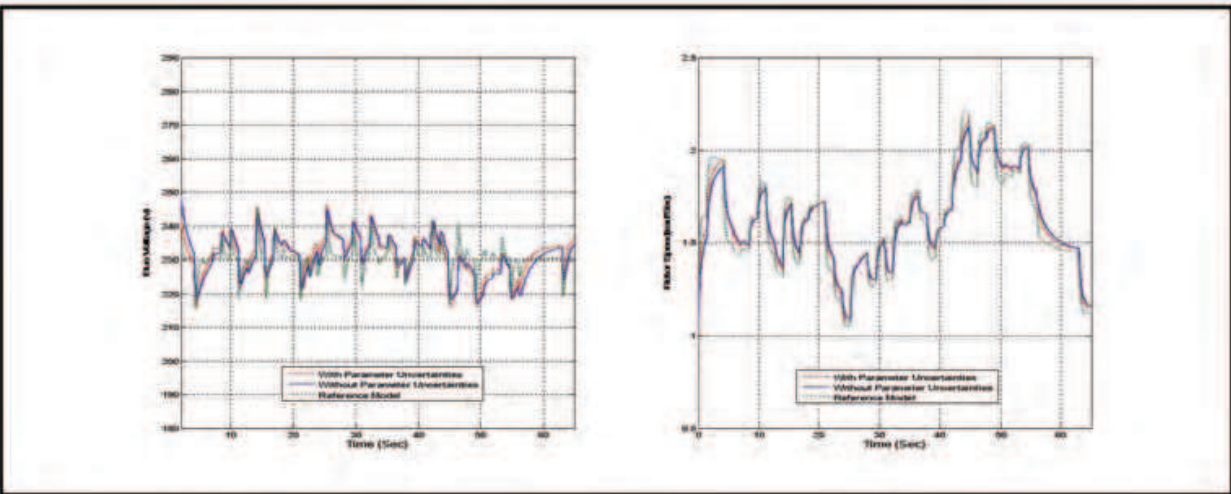


Fig. 8. Responses of bus voltage ( $V_b$ ) and rotor speed ( $\omega_s$ ) of the fuzzy control system without (solid line) and with parameter uncertainties (dash line), and the reference model (dotted line) under  $r(t)$

7.2 System responses of the fuzzy control system with sensor faults and with parameter uncertainties

The Fig.9 (top) shows the time evolution of the sensor fault  $f(t)$  (solid lines) and its estimate  $\hat{f}(t)$  (dash lines) based on (54) while the bottom part shows the fault estimation errors  $\tilde{f}(t)$ . The response of the HWDSS states (solid lines), the states of the observer (dash lines) and reference model states (dotted lines) are given in Fig.10. The state estimation errors ( $V_b - \hat{V}_b, \omega_s - \hat{\omega}_s$ ) are shown in the top of Fig.11, while the bottom part shows the state tracking errors ( $V_b - \bar{V}_b, \omega_s - \bar{\omega}_s$ ). As the wind speed varying as the random variation, the produced power curve takes almost the wind speed curve as shown in Fig. 12, but there is only spike when the fault is detected at 20.75 sec.

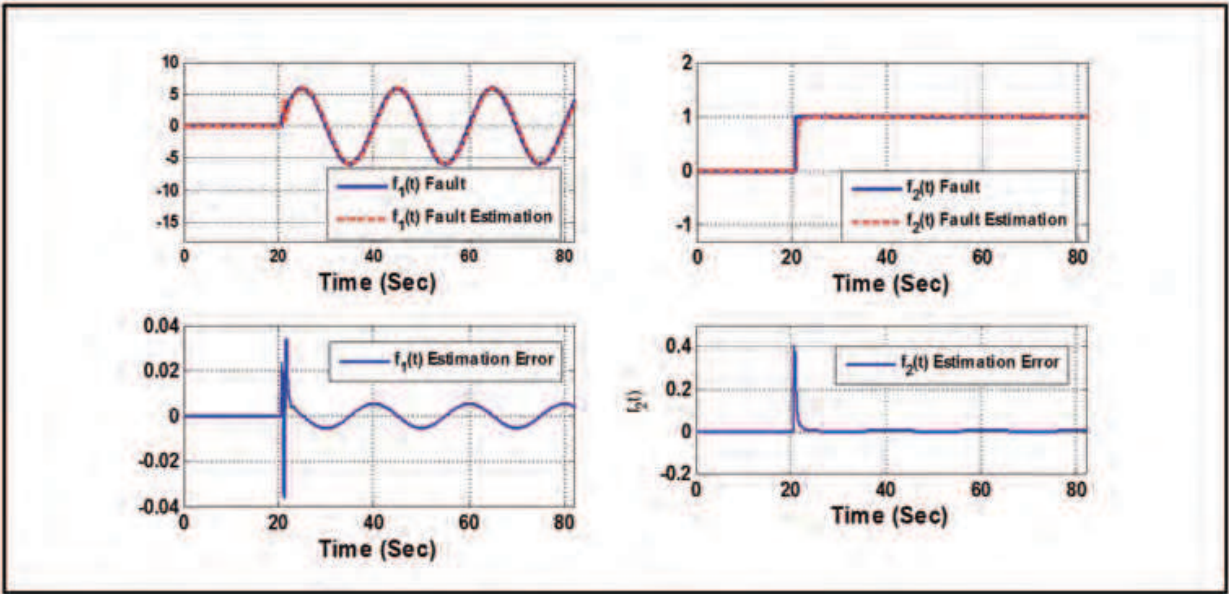


Fig. 9. Faults and their estimations (bus voltage sensor fault  $f_1(t)$  and its estimate and generator speed sensor fault  $f_2(t)$  and its estimate)(top) Fault estimation errors (bottom)

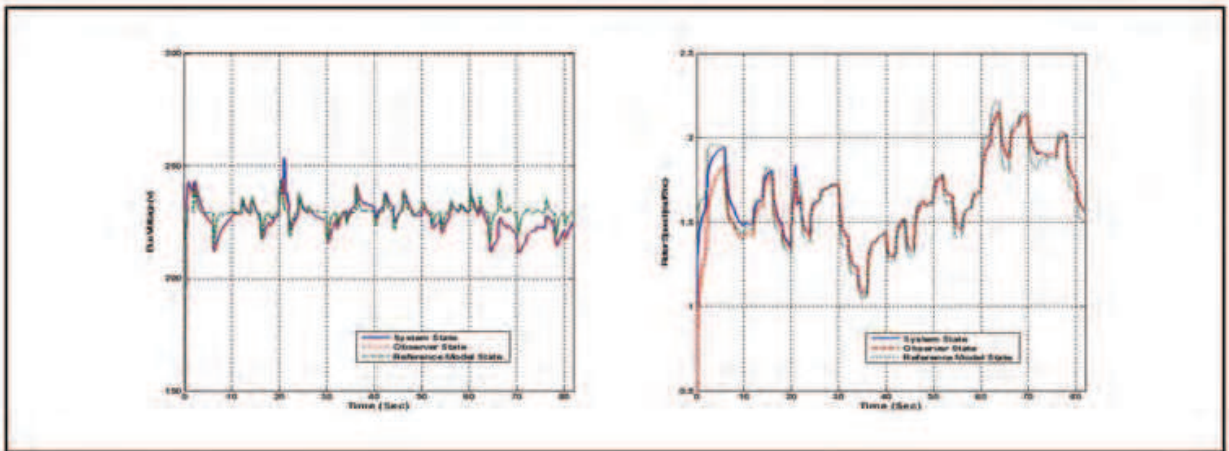


Fig. 10. Responses of bus voltage ( $V_b$ ) and rotor speed ( $\omega_s$ ) of the fuzzy control system (solid line) , observer (dash line) and the reference model (dotted line) with parameter uncertainties and sensor faults based on (54) under the same refence input  $r(t)$

It can be seen from the simulation results that the states of the HWDSS system follow those of the reference model in the presence bounded parametric uncertainties and sensor faults. Fig. 8 shows that the responses of the fuzzy control system with parameter uncertainties are better than that of the fuzzy control system without parameter uncertainties. This is

because an additional control signals, i.e., 
$$\frac{e_1(t)\|e_1(t)\|P_1\|\Delta A_i\|_{\max}\|x(t)\|}{e_1(t)^T P_1 e_1(t)}, \frac{e_1(t)\|x(t)\|D\|_{\max}\|x(t)\|}{e_1(t)^T P_1 e_1(t)}$$
 are used, the reason can also be seen from (42), i.e., 
$$\sum_{i=1}^p \mu_i \|e_1(t)\|P_1(\|\Delta A_i\| - \|\Delta A_i\|_{\max})\|x(t)\| + \|x(t)\|(\|D\| - \|D\|_{\max})\|x(t)\|$$
 makes error  $e(t)$  approach



zero at a faster rate. Figs. 10 shows there is spike when the fault is detected at 20.75 sec and then the HWDSS trajectory follows the trajectory of the reference model, this is because an additional control signals,  $e_1(t) \left\| \hat{f}(t) \right\| \left\| S_E \right\|_{\max} \left\| \hat{f}(t) \right\| / e_1(t)^T P_1 e_1(t)$ .

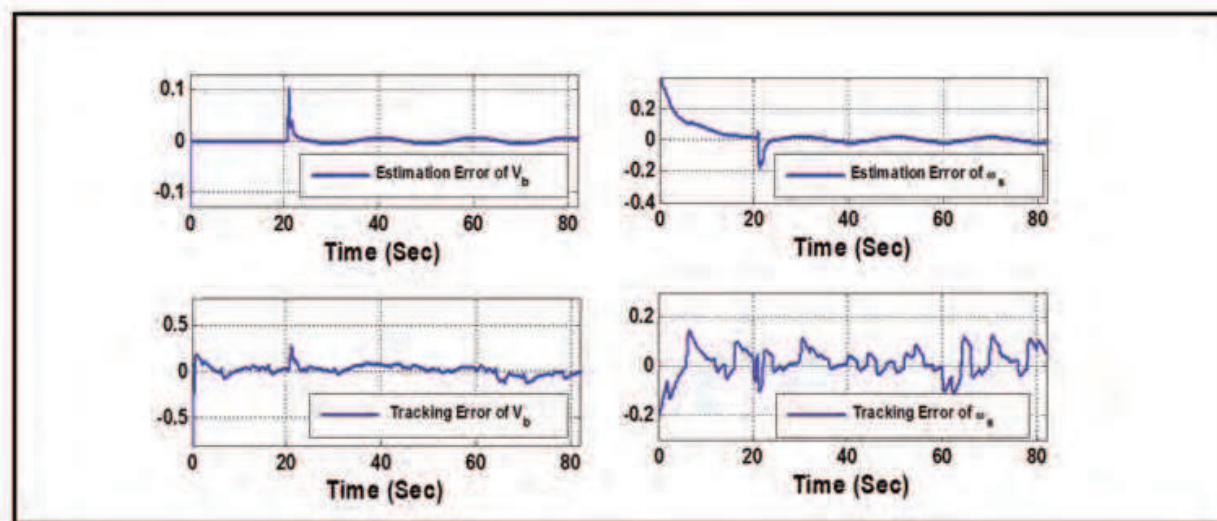


Fig. 11. State estimation errors  $(V_b - \hat{V}_b, \omega_s - \hat{\omega}_s)$ (top) State tracking errors  $(V_b - \bar{V}_b, \omega_s - \bar{\omega}_s)$  (bottom)

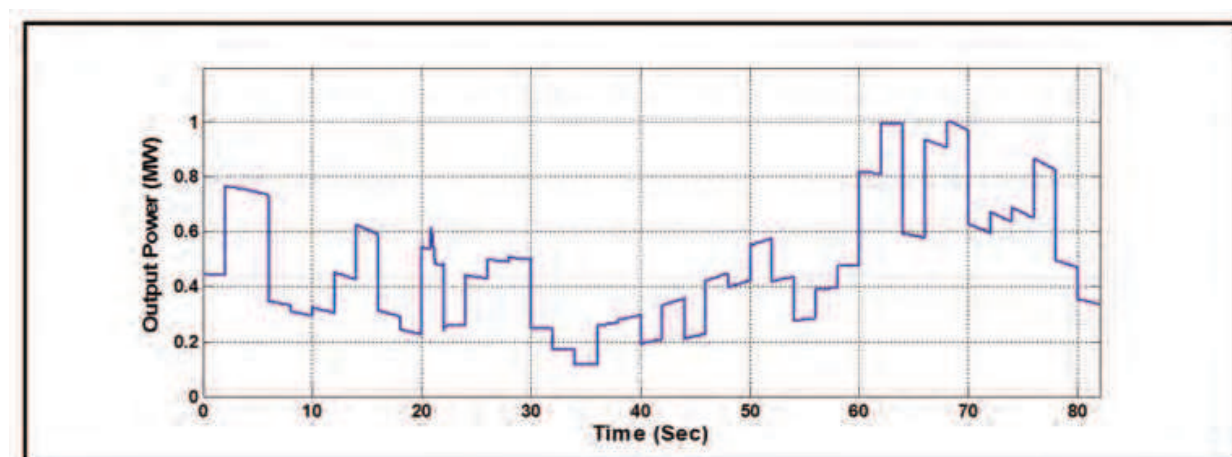


Fig. 12. Per unit wind turbine produced power

In summery results, we can be seen that the system trajectory follows the trajectory of the reference model which represents the trajectory of the HWDSS in the fault free situation. Thus, the TS fuzzy model based controller through fuzzy observer is robust against norm-bounded parametric uncertainties and sensor faults. Comparing the results of the proposed algorithm, with that given in the previous algorithms, we can be seen that the proposed controller has the following advantages:

1. It can control the plant well over a wide range of sensor faults compared with (Wei *et al.*, 2010 ; Odgaard *et al.*, 2009; Gaillard *et al.*, 2007).

2. Is stable over a wide range of uncertainty up to 40% compared with (Uhlen *et al.*, 1994).
3. The generated power is increased up to 45% compared with (Chen & Hu, 2003; Kamal *et al.*, 2010).
4. The algorithm is more robust in the presence of high nonlinearity.
5. Bus voltage is nearly constant and voltage ripple is reduced to 25% compared with (Chedid *et al.*, 2000; Kamal *et al.*, 2010).

## 8. Chapter conclusion

The stability analysis and design of nonlinear HWDSS control systems have been discussed. An improved stability criterion has been derived. In this chapter, we have developed a new robust fuzzy fault tolerant controller to control a HWDSS, while taking into account sensor fault(s) and parametric uncertainties in the aerodynamic model under the conditions that the state variables are unavailable for measurement as well as enabling the system to capture as much wind power as possible. A reference model is used and the proposed control is then designed for guaranteeing the convergence of the states of the HWDSS to the states of a reference model even if sensor fault(s) occurs and with parametric uncertainties. The basic approach is based on the rigorous Lyapunov stability theory and the basic tool is LMI. Some sufficient conditions for robust stabilization of the TS fuzzy model are formulated in the LMIs format. The closed-loop system will behave like a user-defined reference model in the presence of bounded sensor faults and parameter uncertainties. A simulation on HWDSS has been given to show the design procedure and the merits of the proposed fuzzy fault tolerant controller.

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## **Wind Farm - Impact in Power System and Alternatives to Improve the Integration**

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During the last two decades, increase in electricity demand and environmental concern resulted in fast growth of power production from renewable sources. Wind power is one of the most efficient alternatives. Due to rapid development of wind turbine technology and increasing size of wind farms, wind power plays a significant part in the power production in some countries. However, fundamental differences exist between conventional thermal, hydro, and nuclear generation and wind power, such as different generation systems and the difficulty in controlling the primary movement of a wind turbine, due to the wind and its random fluctuations. These differences are reflected in the specific interaction of wind turbines with the power system. This book addresses a wide variety of issues regarding the integration of wind farms in power systems. The book contains 14 chapters divided into three parts. The first part outlines aspects related to the impact of the wind power generation on the electric system. In the second part, alternatives to mitigate problems of the wind farm integration are presented. Finally, the third part covers issues of modeling and simulation of wind power system.

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