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Sensor Fault Tolerant Control of a Wind Turbine via Takagi-Sugeno Fuzzy Observer and Model Predictive Control

Xiaoran Feng, Ron Patton, Zhihuo Wang
Department of Engineering
University of Hull
Hull, UK
x.feng@2011.hull.ac.uk; r.j.patton@hull.ac.uk; zhihuo.wang@2012.hull.ac.uk

Abstract— **This paper proposes an approach to fault tolerant control (FTC) of a wind turbine subject to sensor faults. Both analytical and hardware redundancies are utilized in this approach. A residual generator based on a Takagi-Sugeno (T-S) fuzzy observer is proposed as the fault detection and isolation (FDI) unit. A T-S fuzzy observer design method via online eigenvalue assignment is proposed. It is shown that single residual can be utilized to identify different sensor faults by analyzing the characteristics of the residual. Model predictive control (MPC) based on T-S fuzzy modeling is proposed as the wind turbine controller to take into account the turbine system nonlinearity and physical constraints of the turbine actuators.**

Keywords— Fault tolerant control; Fault detection; Wind turbine control; T-S fuzzy modelling; Model predictive control

I. INTRODUCTION

Today, more and more installed modern wind turbines are variable-speed due to their high energy conversion efficiency. The variable-speed wind turbine can achieve maximum wind energy conversion efficiency over a wide range of wind speeds in two ranges of operation, (i) below rated wind speed and (ii) above the rated wind speed [1], with different outputs regulated in each region through switched control action. The wind turbine operates below the rated value required to maximize the conversion efficiency from wind power to electrical power. At low speed the turbine rotor angular speed is regulated at an optimal value, whilst maintaining the turbine pitch at zero degrees. For wind speeds above the rated speed the goal of the wind turbine operation is to keep the generator speed below its maximum value and regulate the produced power at its rated level to guarantee safe generator operation.

The reliable operation of wind turbines becomes more challenging as the size and power capacities of newly installed turbines increase and as these large rotor wind turbines are operated off-shore. However, the sensors installed on offshore wind turbines are subject to potential "weathering" faults, such as icing, lightning and even salt corrosion. These faults can cause offsets or gain factor sensor errors. It is thus important to improve the reliability of turbine operation by considering sensor faults in the controller design.

Fault tolerant control (FTC) combined with a fault detection and isolation (FDI) unit is an advanced approach to controller design to provide the controller with both the information of faults and with this the ability to tolerate faults. Typical approaches of FDI/FTC design are based on utilizing the *analytical redundancy* in which the redundant information is estimated from the inputs and measured outputs of the controlled system. However, the sensors in the wind turbine are often installed in duplex redundant configuration (i.e. hardware redundancy). This hardware redundancy can be used to design the FTC system. Furthermore, the combination of analytical and hardware redundancy can simplify the design of FTC and FDI system.

In this study, an FTC system for wind turbine sensor faults is proposed utilizing both analytical and hardware redundancy. Sensor faults in the turbine generator speed sensor, pitch angle sensor and torque sensor are considered. The redundant counterparts of these sensors are utilized in the FTC design.

An FTC system design based on residual signals generated from a Takagi-Sugeno (T-S) fuzzy observer and sensor outputs is proposed in [2], based on the concept of the generalized observer. However, the design of the T-S fuzzy observer requires a feasible solution for a set of LMIs and the eigenvalues of the T-S fuzzy observer gain cannot be assigned in this standard approach [3]. A method for assigning eigenvalues of a T-S fuzzy observer to a certain region in the z-plane has been proposed [2]. However, this approach requires solving more LMIs and thus a feasible solution may be difficult to achieve. In this paper, a T-S fuzzy observer design method is proposed based on online eigenvalue assignment obviating the need for LMI solutions. Furthermore, the eigenvalues of the fuzzy observer can be assigned to specified points rather than within certain regions.

Control strategies for wind turbine systems based on T-S fuzzy modeling are presented in [4, 5]. However, these studies only consider operation below the rated wind speed. The requirement for frequent switching between these two operating regions suggests that duplex control can be useful. As shown in [6], model predictive control (MPC) has the advantage of simplifying multiple controller design. The need for multiple controller designs is obviated since only MPC parameter changes are required for different control goals. Besides, the system constraints are considered externally in the MPC formulation. Several MPC results for wind turbine control are presented in [7-9]. This paper proposes an MPC based on nonlinear T-S fuzzy modeling to consider the system nonlinearity and constraints. Compared with the multiple-model based MPC approach presented in [7], the proposed T-S fuzzy MPC can achieve continuous model parameter change rather than jumping among multiple models.

The paper is organized as follows: The T-S fuzzy modeling of the wind turbine is described in Section II. The design of the FDI unit is explained in Section III. FTC via T-S fuzzy MPC is described in Section IV. Simulation results are presented in Section V.

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II. T-S Fuzzy Modelling of Wind Turbine

A. Nonlinear Wind Turbine Model

The model used in this work is based on a benchmark model for a realistic large variable-speed wind turbine with rated power of 4.8 MW and the blade radius of 57.5m [10]. A wind turbine model comprises of sub-models of the turbine pitch, the generator and the drive train systems.

The second order turbine pitch system model is given as:

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}, \tag{1}$$

where β is the turbine blade pitch angle in degree and β_r is the corresponding reference angle.

The generator dynamic model is given as:

$$\frac{T_g(s)}{T_{gr}(s)} = \frac{\alpha}{s+\alpha}, \tag{2}$$

in which T_g is the generator torque and T_{gr} is the reference torque.

The wind turbine drive train system is a non-linear two-mass model given as:

$$\begin{bmatrix} \dot{\omega}_r \\ \dot{\omega}_g \\ \dot{\theta}_\Delta \end{bmatrix} = A_{dt} \begin{bmatrix} \omega_r \\ \omega_g \\ \theta_\Delta \end{bmatrix} + B_{dt} \begin{bmatrix} T_a \\ T_g \end{bmatrix}, \tag{3}$$

in which T_a is the nonlinear aerodynamic torque resulting from the wind acting on the turbine:

$$T_a = \frac{1}{2}\rho\pi R^3 C_q(\lambda, \beta) v^2, \tag{4}$$

where ρ and R are the air density and radius of the turbine blades which are given constants. v is the wind speed and C_q is the nonlinear torque coefficient as a function of β and the tip-speed-ratio λ computed by:

$$\lambda = \frac{\omega_r R}{v}. \tag{5}$$

The system state space matrices are:

$$A_{dt} = \begin{bmatrix} \frac{-S_{dt} - B_r}{J_r} & \frac{S_{dt}}{N_g J_r} & -\frac{K_{dt}}{J_r} \\ \frac{\eta_{dt} S_{dt}}{N_g J_g} & \frac{-\eta_{dt} S_{dt} - B_g N_g^2}{N_g^2 J_g} & \frac{\eta_{dt} K_{dt}}{N_g J_g} \\ 1 & -\frac{1}{N_g} & 0 \end{bmatrix},$$

$$B_{dt} = \begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & -\frac{1}{J_g} \\ 0 & 0 \end{bmatrix},$$

where J_r J_r and J_g are the rotor and generator moments of inertia. B_r and B_g are the rotor and generator external damping coefficients, S_{dt} is the torsion damping coefficient, N_g and η_{dt} are the gear ratio and drive train efficiency, and K_{dt} is the torsion stiffness. ω_g is the generator rotating speed, ω_r is the turbine rotor speed and θ_Δ is the drive train torsion angle.

As shown in (3) and (4), the drive train model nonlinearity comes from T_a which is a highly nonlinear function of β, ω_r and v. Numerical values of the parameters in (1) to (5) can be found in [10].

The measured outputs of the turbine system are generator speed, pitch angle and generator torque. Therefore, the following nonlinear wind turbine model can be developed by combing (1), (2), (3) and (4) to give:

$$\begin{aligned} \dot{x} &= f(x, u, v) \\ y &= Cx \end{aligned}, \tag{6}$$

in which $x = [\omega_r \quad \omega_g \quad \theta_\Delta \quad \dot{\beta} \quad \beta \quad T_g]^{\mathrm{T}}$, $y = [\omega_g \quad \beta \quad T_g]^{\mathrm{T}}$, $u = [T_{gr} \quad \beta_r]^{\mathrm{T}}$, $C \in \Re^{3\times 6}$ is the constant output matrix.

B. T-S Fuzzy Wind Turbine Model

T-S fuzzy model of the nonlinear wind turbine system is proposed in this work and used by both the T-S fuzzy observer and predictive controller. The three parameters in the nonlinear aerodynamic torque (4) are defined in vector form as $\eta = [\beta \quad \omega_r \quad v]$ and are used as the premise variables for designing the fuzzy turbine model. To achieve T-S fuzzy modeling, a series of locally linear models linearized at different turbine system operating points are needed. Each local model is obtained by first order Taylor series approximation applied to (4) according to the corresponding operating point η and substituting the approximated Taylor series into (6). The following nonlinear T-S fuzzy wind turbine model is then obtained:

$$\begin{aligned} \dot{x} &= A(\eta)x + B(\eta)u + E(\eta)v \\ y &= Cx \end{aligned}, \tag{7}$$

where $A(\eta) = \sum_{i=1}^{M} \sigma_i(\eta) A_i$, $B(\eta) = \sum_{i=1}^{M} \sigma_i(\eta) B_i$, $E(\eta) = \sum_{i=1}^{M} \sigma_i(\eta) E_i$, and $\sum_{i=1}^{M} \sigma_i(\eta) = 1$. $A_i \in \Re^{6\times 6}$, $B_i \in \Re^{6\times 2}$, $E_i \in \Re^{6\times 1}$ are system matrices of the local linear models. $\sigma_i(\eta)$ is the membership function of a fuzzy system and M is the number of local models. Several types of membership functions are available in [3].

Based on (7), the following discretized T-S fuzzy turbine model can be achieved:

$$\begin{aligned} x(k+1) &= G(\eta_k)x(k) + H(\eta_k)u(k) + D(\eta_k)v(k) \\ y(k) &= Cx(k) \end{aligned}, \tag{8}$$

in which $\eta_k = [\beta(k) \quad \omega_r(k) \quad v(k)]$, $G(\eta_k) = \sum_{i=1}^{M} \sigma_i(\eta_k) G_i$, $H(\eta_k) = \sum_{i=1}^{M} \sigma_i(\eta_k) H_i$, $D(\eta_k) = \sum_{i=1}^{M} \sigma_i(\eta_k) D_i$. G_i, H_i, and D_i correspond to the system matrices in (7) acquired with the same membership function applied to the discretized system matrices of the local linear models.

III. Fault Detection and Isolation

A. T-S Fuzzy Observer with Online Eigenvalue Assignment

The following standard nonlinear T-S fuzzy observer can be designed for the fuzzy model of the wind turbine system (8):

$$\begin{aligned}\hat{x}(k+1) &= G(\eta_k)\hat{x}(k) + H(\eta_k)u(k) \\ &+ F(\eta_k)[y(k) - \hat{y}(k)] + D(\eta_k)d(k)\end{aligned}, \tag{9}$$

where $\hat{x}(k)$ is the estimated state vector of $x(k)$. $F(\eta_k) \in \Re^{3\times1}$ is the fuzzy observer gain given as:

$$\begin{aligned}F(\eta_k) &= \sum_{i=1}^{M} \sigma_i(\eta_k) F_i \\ F_i &= P^{-1} Q_i \\ i &= 1,2,3,\ldots,M\end{aligned}, \tag{10}$$

in which P and Q_i forms the local fuzzy gains which are obtained by solving the following LMIs [3]:

$$\begin{bmatrix} -P & G_i^{\mathrm{T}}P + C_2^{\mathrm{T}}Q_i^{\mathrm{T}} \\ PG_i + Q_iC & -P \end{bmatrix} < 0. \tag{11}$$
$$i = 1,2,3,\ldots,M$$

It is shown from (10) to (11) that the standard approach for designing the T-S fuzzy observer depends on the existence of feasible solutions of a series of LMIs. Furthermore, many local models are needed for a system with complex nonlinear behaviour and therefore many LMI constraints must be satisfied to design the observer. However, feasible solutions satisfying so many LMI constraints may not exist.

In this work, an algorithm for designing T-S fuzzy observes is proposed by online assigning eigenvalues of the fuzzy observer gain, which avoids solving LMIs.

Algorithm 1: *Online Eigenvalue Assigment*

1. Choose eigenvalues of the fuzzy observer gain.
2. Acquire $\hat{x}(k)$ from the T-S fuzzy observer.
3. Update η_k from $\hat{x}(k)$ and wind speed $v(k)$.
4. Update $G(\eta_k)$.
5. Calculate $F(\eta_k)$ from $G(\eta_k)$, C and chosen eigenvalues of the fuzzy observer gain using standard pole placement method.
6. $k = k+1$, go to step 2.

The assumption for algorithm 1 is that each local model should be observable. The eigenvalues of the fuzzy observer gain cannot be assigned and are changing at every sample time by using the LMI method as shown in (9) to (10). On the other hand, the eigenvalues of the fuzzy observer gain can be fixed and assigned to specific points in the Z-plane by using algorithm 1, which allows tuning of the fuzzy observer gain.

B. Fault Detection and Isolation

Sensor faults can be detected by comparing the signals from the sensor and the corresponding redundant sensor. However, it's difficult to identify the faulty sensor without FDI unit. A method of FDI by using residual generated from a series of fuzzy observers was proposed in [2]. Each observer is based on a set of reduced number of outputs. Therefore, a limitation of this method is that each observer based on the reduced number of system outputs must be observable. However, in the case of this wind turbine system, it is not observable if the number of system outputs are reduced.

In this work, a FDI unit based on single fuzzy observer is proposed. It is shown that one residual signal from the fuzzy observer can be utilized to identify faults in different sensors by analyzing the characteristic of the residual signal.

The T-S fuzzy observer designed by algorithm 1 is used to acquire the estimated state vector $\hat{x}(k)$. Sensor faults can be detected by a residual vector generated from the T-S fuzzy observer and the sensor output as follows:

$$\varepsilon(k) = \lfloor r_\omega(k) \quad r_\beta(k) \quad r_T(k) \rfloor, \tag{12}$$

where $r_\omega(k) = \left|\hat{\omega}_g(k) - \omega_g(k)\right|$, $r_\beta(k) = \left|\hat{\beta}(k) - \beta(k)\right|$, $r_T(k) = \left|\hat{T}_g(k) - T_g(k)\right|$. $\hat{\omega}_g(k)$, $\hat{\beta}(k)$ and $\hat{T}_g(k)$ are estimated system states from the fuzzy observer.

Theoretically, $\varepsilon(k)$ should be a zero vector if there is no fault. However, $\varepsilon(k)$ lies within a threshold vector ε_r due to sensor noise and uncertainty. Therefore, the value of $\varepsilon(k)$ will exceed the threshold when the sensor fault is present.

It should be noted that the sensitivity of each element in the residual vector $\varepsilon(k)$ to different sensor fault may be different. The sensitivity of $r_T(k)$ to faults present from 200 seconds to 300 seconds in generator speed sensor and generator torque sensor is shown in Fig. 1. The range of generator speed is 0 to 186 rad/s and the input range of generator torque is 0 to 3.6×10^4 N·m for the wind turbine model. It can be seen from Fig. 1 $r_T(k)$ is very sensitive to generator torque sensor fault since only a subtle sensor offset fault of 3.6×10^2 N·m can result in a great value of $r_T(k)$. On the other hand, $r_T(k)$ is much less sensitive to generator speed sensor fault since a great offset fault value of 10 rad/s results in a very small response of $r_T(k)$. Therefore, two thresholds can be set for $r_T(k)$ to identify both generator torque and generator speed sensor faults.

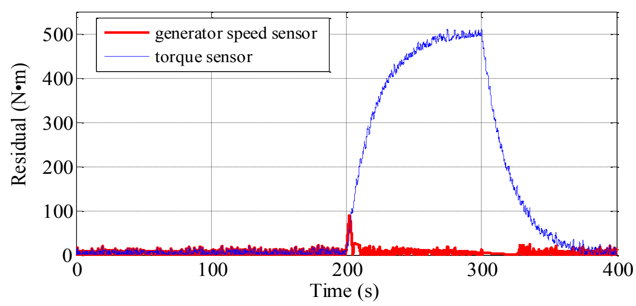

Figure 1. Response of $r_T(k)$ to sensor faults

Some residual signals may not respond to certain kinds of faults and always lie within the threshold. The response of $r_\beta(k)$ to the generator torque sensor offset fault of 3.6×10^2 N·m from 200 seconds to 300 seconds is shown in Fig. 2. It is shown that $r_\beta(k)$ is not sensitive to this sensor fault. Hence, a more suitable residual should be chosen from which the fault can be fully detected and isolated.

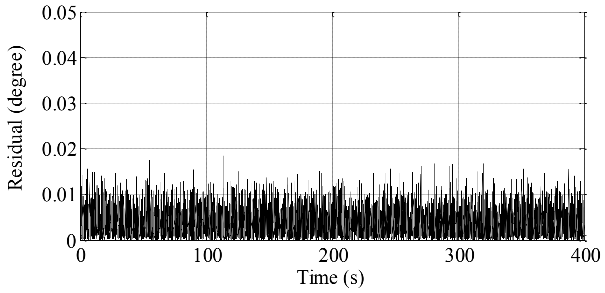

Figure 2. Response of $r_\beta(k)$ to torque sensor fault

The FDI logic based on Table 1 can be acquired by analyzing the response of residual signals to different kinds of sensor faults. × means the residual in the corresponding column is not sensitive to the fault in the corresponding row and √ otherwise.

TABLE I. FDI LOGIC TABLE

	$r_\omega(k)$	$r_\beta(k)$	$r_T(k)$
generator speed sensor fault	×	×	√
pitch angle sensor fault	×	√	
generator torque sensor fault	×	×	√

IV. FTC OF WIND TURBINE

A. Control of Wind Turbine

The goal of wind turbine control in below rated wind speed region is to drive the turbine rotor speed $\omega_r(k)$ to track the optimal rotating speed given as:

$$\omega_{r\_opt}(k)=\frac{v(k)\lambda_{opt}}{R}, \tag{13}$$

where λ_{opt} is the optimal tip-speed ratio which is a given constant. The maximum conversion efficiency from wind power to electrical power can be achieved if the turbine rotor is rotating at the speed of $\omega_{r\_opt}(k)$ and the pitch angle is regulated at the optimal pitch angle $\beta_{opt}=0$. However, in practice the filtered optimal rotor speed $\hat{\omega}_{r\_opt}(k)$ is being tracked to avoid heavy drive train torsion caused by trying to follow the highly fluctuating wind speed precisely.

The goal of wind turbine control in above rated wind speed region is to protect the generator by regulating the generator speed around a reference speed ω_{gr} below the generator safe limit $\omega_{g\_\max}$. The generated power $P_g(k)$ should also be regulated around the rated power P_{gr}. The pitch angle is changing in this region to regulate the power and generator speed rather than being regulated at the optimal pitch angle.

The control inputs for both turbine operation regions are $T_{gr}(k)$ and $\beta_r(k)$. Regulation of $P_g(k)$ is achieved by regulating $T_g(k)$ to track the following value according to the power and torque relation:

$$T_{g\_opt}(k)=\frac{P_{gr}}{\omega_g(k)}. \tag{14}$$

The turbine controller switches between the two operating regions according to the following rules [10]. The operation region is switching to above rated wind speed region if:

$$P_g(k)\ge P_{gr} \quad or \quad \omega_g(k)\ge\omega_{gr}.$$

The operation region is switching to below rated wind speed region if:

$$\omega_g(k)<\omega_{gr}-\Delta\omega,$$

where ω_{gr} satisfies $\omega_{gr}<\omega_{g\_\max}=186$. $\Delta\omega=15$ is an offset for some hysteresis during the switching between the two operation regions. Hence, frequent switching between operating regions is avoided by using this approach.

B. FTC based on Fuzzy MPC

MPC based on T-S fuzzy modeling is proposed in this work as the FTC unit to consider the system nonlinearity.

The T-S fuzzy MPC for wind turbine is formulated as:

$$\min_{u(k),u(k+1),,,u(k+N-1)}\sum_{i=1}^{N}\left\|x(k+i)-x_r(k)\right\|_R \tag{15}$$

subject to:

$$x(k)=\hat{x}(k), \tag{16}$$

$$x(k+i+1)=G(\eta_k)x(k+i)+H(\eta_k)u(k+i)+D(\eta_k)v(k), \tag{17}$$

$$\begin{aligned}&\beta_{\min}(k+i)\le\beta_r(k+i)\le\beta_{\max}(k+i)\\&\Delta\beta_{\min}(k+i)\le\beta_r(k+i)-\beta_r(k+i-1)\le\Delta\beta_{\max}(k+i)\\&T_{\min}(k+i)\le T_{gr}(k+i)\le T_{\max}(k+i)\\&\Delta T_{\min}(k+i)\le T_{gr}(k+i)-T_{gr}(k+i-1)\le\Delta T_{\max}(k+i)\end{aligned}, \tag{18}$$

$i=0,1,2,...N-1$

where N is the MPC prediction horizon, $\|p\|_R=p^{\mathrm{T}}Rp$ and $x_r(k)=[\hat{\omega}_{r\_opt}(k)\;\;\omega_{gr}\;\;0\;\;0\;\;\beta_{opt}\;\;\frac{P_{gr}}{\omega_g(k)}]^{\mathrm{T}}$ is the reference signal. Equation (17) is the prediction model of system (8) and $R\in\Re^{6\times6}$ is a weighting matrix that depends on the turbine operating region given as:

$$R=\begin{cases}diag(1\quad0\quad0\quad0\quad1\quad0)\,below\,rated\,wind\,speed\\diag(0\quad1\quad0\quad0\quad0\quad1)\,above\,rated\,wind\,speed\end{cases}. \tag{19}$$

During the turbine operation, the range of control inputs is limited by physical constraints imposed by the turbine actuators due to hardware specifications of the hydraulic system and the power converter. Hence, constraints should be considered in the controller design. The constraints are considered naturally in the MPC and formulated into the nonlinear optimization problem given in (18).

As shown in (19), the multiple controller strategy is realized by only changing the parameter R according to the turbine operation region and thus the multiple controller design is simplified since the need for complete redesign of controllers for different control goals is removed. (17) is a linear time-varying system and thus a linear system at each sample time. Therefore, (15) becomes a quadratic programming problem that can be solved efficiently. The optimization problem (15) is solved online at every sample time to calculate $u(k)$ which is used as the control input. An alternative MPC formulation with $\Delta u(k+i)$ rather than $u(k+i)$ as the decision variable is used to eliminate constant disturbance for linear systems. However, the wind turbine is a nonlinear system and the disturbance is not constant since the wind speed is always changing. Thus the straightforward form of decision variable $u(k+i)$ is used in this work.

Fault tolerance is realized by combing the hardware redundancy and the FDI unit. When a fault is detected and identified by the FDI unit, the fuzzy observer switches to the healthy redundant sensor to provide state estimation for the fuzzy MPC.

The MPC controller and the FDI unit based on the T-S Fuzzy observer form the output feedback FTC strategy, as shown in Fig. 3.

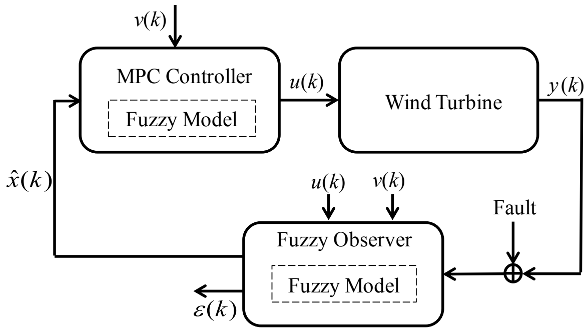

Figure 3. FTC scheme of the wind turbine

V. SIMULATION RESULT

The wind speed data used in the simulation are shown in Fig. 4. The prediction horizons are chosen as $N=6$. The rated power and generator speed are $P_{gr}=4.8\times10^6$ W, $\omega_{gr}=162$ rad/s. The residual thresholds for generator speed, generator torque and pitch angle sensors are set to be $r_T^1=30$ $r_T^2=500$ $r_\beta=0.5$ separately, in which $r_T(k)$ is used to detect both generator speed and generator torque sensor faults. All sensors are subject to zero-mean random noise.

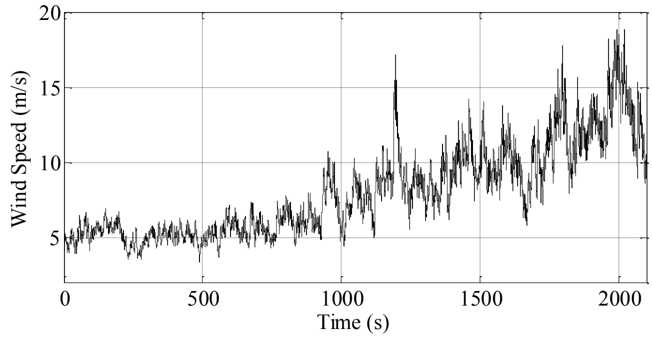

Figure 4. Wind speed data

The performance of the fuzzy MPC without the presence of faults is shown in Fig. 5 to Fig. 7. Fig. 5 corresponds to the filtered optimal rotor speed tracking performance in the below rated wind speed region. Fig. 6 and Fig. 7 correspond to the generator power and speed regulation in the above rated wind speed region. It is shown in Fig. 6 and Fig. 7 that the controller switches between the two operation regions of generator power/speed regulation and optimal rotor speed tracking after 400 seconds since the wind speed in this time scale is highly fluctuating.

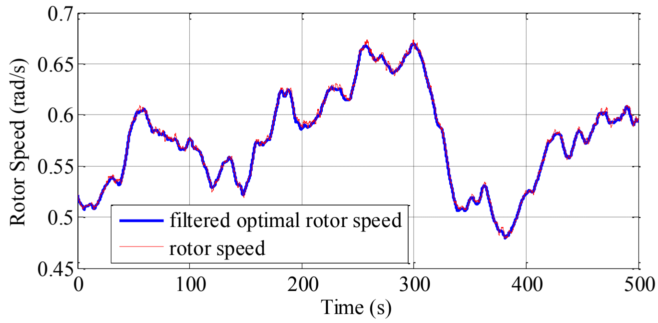

Figure 5. Tracking performance of fuzzy MPC

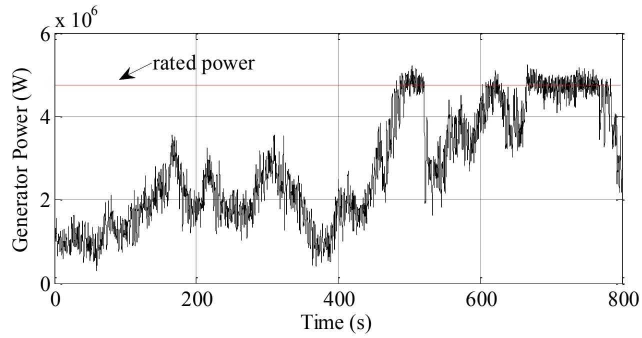

Figure 6. Power regulation by fuzzy MPC

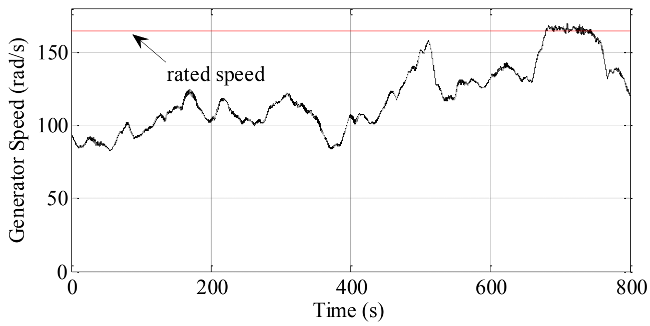

Figure 7. Generator speed regulation by fuzzy MPC

Fig. 8 shows the filtered optimal rotor speed tracking performance of the FTC scheme for a generator speed sensor offset fault of 10 rad/s from 200 seconds to 300 seconds in the below rated wind speed region. The proposed FTC scheme switches to the redundant healthy sensor when the fault is identified by the FDI unit. Fig. 9 shows tracking performance for a 10% gain factor error fault of the generator torque sensor from 200 seconds to 300 seconds. It is shown that the tracking performance is insensitive to the generator torque sensor fault since the FTC tracking error is only slightly smaller than that without FTC.

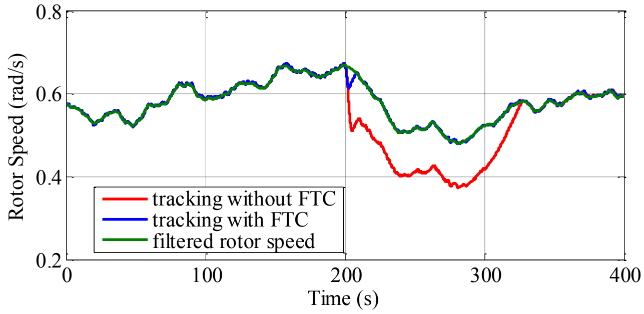

Figure 8. Tracking performance of FTC for generator speed sensor fault

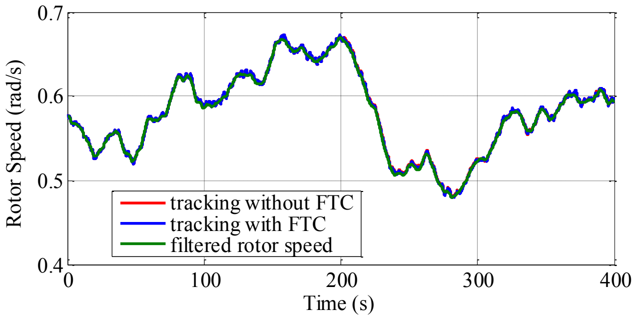

Figure 9. Tracking performance of FTC for torque sensor fault

Fig. 10 shows the FTC performance for a pitch angle sensor fault of 5 degrees from 200 seconds to 300 seconds in the above rated wind speed region. The proposed FTC scheme switches to the redundant healthy sensor when the fault is identified by the FDI unit. As shown in Fig. 10, the generator power exceeds 110% of P_{gr} without FTC around 200 seconds, which is not acceptable for the safe operation of the generator.

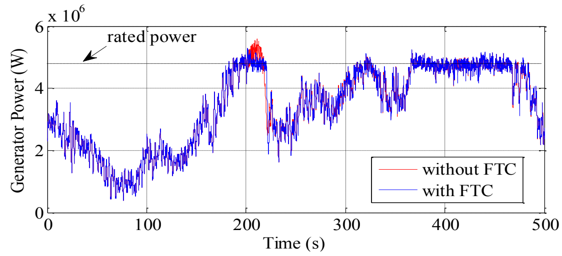

Figure 10. FTC Power regulation for pitch angle sensor fault

VI. Conclusion

This paper proposes an FTC strategy for wind turbine sensor faults. A T-S fuzzy observer design via online eigenvalue assignment is proposed and utilized as the FDI unit. Furthermore, MPC based on T-S fuzzy modelling is proposed as the fault tolerant control scheme taking into account the system nonlinearity and constraints. The multiple control design taking care of both below and above rated wind speed regions is simplified by the proposed fuzzy MPC approach.

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