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Active Fault Tolerant Control of a Wind Turbine via Fuzzy MPC and Moving Horizon Estimation

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Abstract: This paper proposes an approach to active fault tolerant control (AFTC) of a variable-speed wind turbine subject to actuator faults. The actuator faults in the turbine pitch system and generator system are considered in this work. Takagi-Sugeno (T-S) fuzzy modeling of the combined driver train, pitch and generator systems is proposed to account for nonlinearities in the dynamics. Moving horizon estimation (MHE) based on T-S fuzzy modeling is proposed as the actuator fault estimation unit. Model predictive control (MPC) based on T-S fuzzy modeling is used in the design of the AFTC unit in which the predictive controller compensates the actuator faults and takes into account the model nonlinearity and turbine system constraints. A T-S fuzzy observer is used to estimate system states and thus an output feedback strategy of an observer-based predictive controller is formed.

Keywords: Fault tolerant control, Fault estimation, T-S fuzzy model, Moving horizon estimation, Predictive control, Wind turbine control

1. INTRODUCTION

Variable-speed wind turbines can achieve maximum wind energy conversion efficiency in a wide range of wind speeds. The goal of turbine control in the below rated wind speed region is to maximize the wind turbine energy conversion efficiency by regulating the turbine rotor angular speed at the optimal speed and maintaining the turbine pitch angle at an optimal angle. The turbine control problem in the above rated wind speed region is to regulate the produced power at the rated generator power and keep the generator speed below the maximum speed to avoid overload and damage. In highly fluctuating wind conditions the control system may frequently switch between these two operating regions (Wu et al., 2011).

The two turbine actuators are the pitch system for controlling the turbine pitch angle and power converter for controlling the generator torque. The actuators can be faulty due to electrical or mechanical causes. Hence, it is important to consider the potential actuator faults in the design of the control system so as to mitigate the effect of faults on the control performance and have sustainable turbine operation in the presence of loss of actuator effectiveness due to faults. Active fault tolerant control (AFTC) is an advanced approach to controller design by using fault estimation (FE) unit to actively provide the controller the fault information to achieve fault tolerance and sustainable operation. In this paper an AFTC design is proposed for an offshore wind turbine system considering faults in both of the wind turbine actuators. The AFTC design in this work is tested and evaluated on an wind turbine benchmark model (Odgaard et al., 2009).

Moving horizon estimation (MHE) based on Takagi-Sugeno (T-S) fuzzy modeling is proposed in this work as the FE unit for actuator faults. The original nonlinear wind turbine model is reformulated into a nonlinear T-S fuzzy model and used by MHE as the estimation model to estimate faults in the two turbine actuators.

Several control strategies for variable-speed wind turbines based on T-S fuzzy modeling are presented in (Sami and Patton, 2012b, Sami and Patton, 2012c). However, these works only propose the controller design for below the rated wind speed region. A two-controller structure can be designed to take into account the two turbine operating regions with different control goals. Model predictive control (MPC) has the advantage of simplifying the multiple controller design (Maciejowski, 1999). The need for multiple controller design is simplified since only MPC parameter changes are required for different control goals. Another advantage of MPC is that the system constraints can be considered in the MPC formulation. Various studies of the application of MPC to wind turbine control are presented in (Soliman et al., 2011, Yang and Maciejowski, 2012, Mirzaei et al., 2012).

This paper proposes an AFTC approach based on nonlinear T-S fuzzy MPC to compensate for the effect of actuator faults and consider the wind turbine system nonlinearity and constraints. Compared with the multiple-model based MPC approach presented in (Soliman et al., 2011), the proposed T-S fuzzy MPC can achieve continuous model parameter variations rather than the abrupt changes that often accompany multiple-model strategies.

This paper is organized as follows: T-S fuzzy modeling of the wind turbine is described in Section 2. The FE unit based on T-S fuzzy MHE is described in Section 3. The AFTC strategy based on T-S fuzzy MPC is presented in Section 4. Simulation results are presented in Section 5.

2. WIND TURBINE MODELING

2.1 Nonlinear Wind Turbine Model

Modeling of the turbine drive train system, generator system, and pitch system are needed to control the wind turbine. 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.

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

$$\begin{bmatrix} \dot{\omega}_r \\ \dot{\omega}_g \\ \dot{\theta}_\Delta \end{bmatrix} = A_{dt} \begin{bmatrix} \omega_r \\ \omega_g \\ \theta_\Delta \end{bmatrix} + B_{dt} \begin{bmatrix} T_a \\ T_g \end{bmatrix}, \tag{1}$$

in which ω_g is the generator rotating speed, ω_r is the turbine rotor speed, and θ_Δ is the torsion angle of the drive train. T_a and T_g are the aerodynamic torque and generator torque separately.

The nonlinear aerodynamic torque T_a resulting from the wind acting on the turbine blades is:

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

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

$$\lambda = \frac{\omega_r R}{v}. \tag{3}$$

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 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.

The generator system model is given as:

$$\frac{T_g(s)}{T_{gr}(s)} = \frac{\alpha}{s+\alpha}, \tag{4}$$

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

The second order turbine hydraulic pitch system model is:

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2+2\zeta\omega_n s+\omega_n^2}, \tag{5}$$

where β_r is the corresponding reference angle.

As shown in (1) to (3), 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), (2), (4) and (5) can be found in the benchmark model (Odgaard et al., 2009).

The measured outputs of the turbine system are generator speed, pitch angle, generator torque, and turbine rotor speed. The turbine rotor speed sensor contains very heavy noise and is only used as a premise variable for fuzzy modelling after being filtered. Therefore, the following nonlinear wind turbine model taking account the actuator faults can be developed by combing (1), (2), (4), and (5) to give:

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

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

2.2 T-S Fuzzy Modeling of Wind Turbine

In this work, T-S fuzzy modeling of the nonlinear wind turbine system is proposed. The three parameters in the nonlinear aerodynamic torque (2) defined in vector form $\eta=[\beta \;\; \omega_r \;\; v]$ are used as the premise variables for building the fuzzy turbine model. To achieve T-S fuzzy modeling, a series of local linear models linearized at different turbine system operating points are needed. Each local model is obtained by first order Taylor series approximation applied to (2) according to the corresponding operating point η and substituting the approximated Taylor series into (6). The following T-S fuzzy wind turbine model considering actuator faults is then obtained:

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

where $A(\eta)=\sum_{i=1}^{L}\sigma_i(\eta)A_i$, $B(\eta)=\sum_{i=1}^{L}\sigma_i(\eta)B_i$, $E(\eta)=\sum_{i=1}^{L}\sigma_i(\eta)E_i$, and $\sum_{i=1}^{L}\sigma_i(\eta)=1$. $A_i\in\Re^{6\times 6}$, $B_i\in\Re^{6\times 2}$, $E_i\in\Re^{6\times 1}$, $i=1,2,\ldots,L$ are system matrices of the local linear models. $f\in\Re^{2\times 1}$ represents the actuator faults. $\sigma_i(\eta)$ is the membership function of a fuzzy system. Several types of membership functions are available in (Feng, 2010).

The following discretized T-S fuzzy turbine model taking account of actuator faults can be acquired from (7) given as:

$$x(k+1) = G(\eta_k)x(k) + H(\eta_k)[u(k) + f(k)] + D(\eta_k)v(k) \\ y(k) = Cx(k) \quad (8)$$

in which $\eta_k = [\beta(k) \quad \omega_r(k) \quad v(k)]$. $G(\eta_k)$, $H(\eta_k)$, and $D(\eta_k)$ are acquired with the same membership function applied to the discretized system matrices of the local linear models.

3. FAULT ESTIMATION

3.1 T-S Fuzzy Observer

A T-S fuzzy observer for the nonlinear wind turbine system is designed to estimate system states. The output feedback turbine controller based on T-S fuzzy MPC also need state estimation from the fuzzy observer.

The following T-S fuzzy observer is designed for wind turbine system (8):

$$\hat{x}(k+1) = G(\eta_k)\hat{x}(k) + H(\eta_k)u(k) \\ + F(\eta_k)[y(k) - \hat{y}(k)] + D(\eta_k)v(k), \\ \hat{y}(k) = C\hat{x}(k) \quad (9)$$

where $\hat{x}(k)$ is the estimate of $x(k)$. $F(\eta) \in \Re^{6\times3}$ is the fuzzy observer gain given as:

$$F(\eta_k) = \sum_{i=1}^{L} \sigma_i(\eta_k)F_i \\ F_i = P^{-1}Q_i \\ i = 1,2,...,L \quad (10)$$

in which $\sigma_i(\eta_k)$ is the same membership function for the turbine system model (8). PQ_i is the local fuzzy gain obtained by solving the following LMIs (Feng, 2010):

$$\begin{bmatrix} -P & G_i^{\mathrm{T}}P + C^{\mathrm{T}}Q_i^{\mathrm{T}} \\ PG_i + Q_iC & -P \end{bmatrix} < 0, \\ i = 1,2,...,L \quad (11)$$

where G_i is the system matrix of each local linear models of (8).

The problem of estimation of the EWS is beyond the scope of this work and thus it is assumed that $v(k)$ is known. Some methods of EWS estimation can be found in (Xu et al., 2012, Østergaard et al., 2007, Sami and Patton, 2012a).

3.2 Fault Estimation based on MHE

The fuzzy observer error dynamics is given as:

$$e(k) = x(k) - \hat{x}(k). \quad (12)$$

$e(k)$ approaches zero when there is no actuator fault. However, the actuator faults are not considered in the fuzzy observer and thus $e(k)$ will not approach zero when actuator faults are present. Therefore, there is an error between the estimated output $\hat{y}(k)$ and the sensor output $y(k)$. This error information is used by the MHE to estimate the actuator faults.

MHE can be considered to be the dual problem of MPC (Rao et al., 2003) and has a similar mathematical formulation with that of MPC. It is proposed for solving constrained state estimation problems (Rao et al., 2003). However, its capability of parameter estimation can be utilized for fault estimation (Izadi et al., 2011).

In this work, we propose an MHE based on T-S fuzzy modeling to solve the fault estimation problem of the nonlinear turbine system.

The system (8) can be reformulated as the following system when the estimated states from the fuzzy observer are used:

$$\hat{x}(k+1) = G(\eta_k)\hat{x}(k) + H(\eta_k)[u(k) + f(k)] + D(\eta_k)v(k) \\ \hat{\hat{y}}(k) = C\hat{x}(k) \quad (13)$$

in which $\hat{\hat{y}}(k)$ is the estimated output when faults are considered.

In order to estimate actuator faults, MHE is formulated by online minimizing the following cost function at every sample time*:*

$$J(f(k-N_M), f(k-N_M+1),..., f(k-1)) = \\ \sum_{i=k-N_M+1}^{k} \left\| \hat{\hat{y}}(i) - y(i) \right\|_S \quad (14)$$

where N_M is the estimation horizon of MHE, *k* is the present sample time, and $\|p\|_S = p^{\mathrm{T}}Sp$. $S \in \Re^{3\times3}$ is a positive define matrix which is a design parameter.

Minimization of (14) can be written as the following optimization problem by using (13):

$$\min_{f(k-N_M), f(k-N_M+1),..., f(k-1)} \sum_{i=k-N_M+1}^{k} \left\| C\hat{x}(i) - y(i) \right\|_S \quad (15)$$

subject to:

$$\hat{x}(i) = G(\eta_{i-1})\hat{x}(i-1) + H(\eta_{i-1})[u(i-1) + f(i-1)] + D(\eta_{i-1})v(i-1) \\ \hat{\hat{y}} = C\hat{x}(i) \quad (16)$$

$$f_{\min} \le f(i-1) \le f_{\max}, \quad (17)$$

$$i = k - N_M + 1, \; k - N_M + 2, \; ..., \; k$$

in which $f_{\min}$ and $f_{\max}$ are the bounds of faults that can be decided from the view of practical hardware. (16) is acquired by using (13) recursively in the past N_M sampling times with $t(i)$ being the second and third term on the right side of the first equation in (13) given as:

Minimization of (14) is reformulated into the optimization problem (15) and solved online at each sample time. (15) is a quadratic programming problem and thus can be solved efficiently.

MHE is generally used for state estimation, which will increase the online computation burden. However, in this FE unit, state estimation is achieved with a T-S fuzzy observer designed offline and thus the online state estimation by MHE is not required. Therefore, MHE is only used to estimate faults and thus the online computation burden due to state estimation is greatly reduced.

4. AFTC OF WIND TURBINE

4.1 Control Principle of Wind Turbine

The goal of wind turbine control in below rated wind speed region is to drive the turbine rotor speed ω_r to track the optimal rotating speed given as:

$$\omega_{r\_opt} = \frac{v\lambda_{opt}}{R}, \tag{18}$$

where λ_{opt} is the optimal tip-speed ratio which is a given constant. The maximum conversion efficiency from wind to electrical power can be achieved if the turbine rotor is rotating at the speed of ω_{r_opt} and the pitch angle is regulated at the optimal pitch angle $\beta_{opt} = 0$. However, in practice the filtered optimal rotor speed $\hat{\omega}_{r\_opt}$ 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 should also be regulated around the rated power P_{gr}. The pitch angle is frequently changing in this region to regulate the generator speed and power rather than being regulated at the optimal pitch angle.

The control inputs for both turbine operation regions are T_{gr} and β_r. Regulation of P_{gr} is achieved by regulating T_g to track the following value according to the power and torque relation:

$$T_{g\_opt} = \frac{P_{gr}}{\omega_g}. \tag{19}$$

The turbine controller switches between the two operating regions according to the following rules. The controller switches to above rated wind speed region if:

$P_g \geq P_{gr}$ or $\omega_g \geq \omega_{gr}$.

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

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

where ω_{gr} satisfies $\omega_{gr} < \omega_{g\_\max} = 186\text{rad/s}$. $\Delta\omega = 15\text{rad/s}$ 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.

4.2 AFTC of Wind Turbine via Fuzzy MPC

The T-S fuzzy MPC is proposed in this work as the AFTC unit to consider the system nonlinearity and compensate for the actuator faults online by including the effects of the faults in the MPC optimization problem. Physical constraints are also considered in the MPC formulation. The fuzzy MPC controller, the T-S Fuzzy observer and the FE unit together form the output feedback AFTC strategy as shown in Fig. 1.

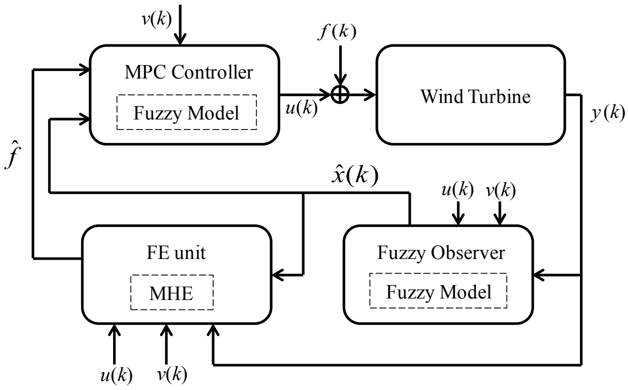

Fig. 1. AFTC control strategy.

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 design of the turbine controller. The constraints are considered naturally in the MPC and formulated into the constraints of the nonlinear optimization problem given in (25).

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

$$\min_{u(k),u(k+1),,,u(k+N-1)} \sum_{i=1}^{N} \left\| x(k+i) - x_r(k) \right\|_R \tag{20}$$

subject to:

$$\hat{f} = f(k-1), \tag{21}$$

$$x(k) = \hat{x}(k), \tag{22}$$

$$x(k+i+1) = G(\eta_k)x(k+i) + H(\eta_k)[u(k+i) + \hat{f}] + D(\eta_k)v(k), \tag{23}$$

$$\begin{array}{l} \beta_{\min}(k+i) \leq \beta_r(k+i) \leq \beta_{\max}(k+i) \\ \Delta\beta_{\min}(k+i) \leq \beta_r(k+i) - \beta_r(k+i-1) \leq \Delta\beta_{\max}(k+i) \\ T_{\min}(k+i) \leq T_{gr}(k+i) \leq T_{\max}(k+i) \\ \Delta T_{\min}(k+i) \leq T_{gr}(k+i) - T_{gr}(k+i-1) \leq \Delta T_{\max}(k+i) \end{array}, \tag{24}$$

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

where N is the MPC prediction horizon, $\hat{f} \in \Re^{2\times1}$ is the estimated fault from the FE unit, $x_r(k) = [\hat{\omega}_{r\_opt}(k) \quad \omega_{gr} \quad 0 \quad 0 \quad \beta_{opt} \quad \frac{P_{gr}}{\omega_g(k)}]^{\mathrm{T}}$ is the reference signal. Equation (23) 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:

$$R = \begin{cases} diag(1 \quad 0 \quad 0 \quad 0 \quad 1 \quad 0)\, below\, rated\, wind\, speed \\ diag(0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 1)\, above rated\, wind\, speed \end{cases}. \tag{25}$$

As shown in (25), 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 operation regions is removed. Faults are compensated in the prediction model (23) which is a linear time-varying system and thus a linear system at each sample time. Therefore, (20) becomes a quadratic programming problem that can be solved efficiently. The optimization problem (20) 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 widely 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 (20).

The future wind speed over the prediction horizon is not known and thus it is approximated by the wind speed of the current instant as shown in (23). The future faults are also not known and considered as constant over the prediction horizon. Therefore, the fault considered in this work is constant or slowly-time-varying fault as shown in (21) and (23).

The AFTC for actuator faults proposed in this work can be extended to the AFTC for system faults and then the term $H(\eta_k)f(k)$ in (8) represents system faults which are estimated by the FE unit and compensated by the T-S fuzzy MPC.

5. SIMULATION RESULT

The wind speed data used in the simulation covering both wind speed regions are shown in Fig. 2. All sensors are subject to random noise as defined in the benchmark model. The prediction and estimation horizons are chosen as $N=6$ and $N_M=6$, respectively. The rated power and generator speed are defined in the benchmark as $P_{gr}=4.8\times10^6\,\mathrm{W}$, $\omega_{gr}=162\mathrm{rad/s}$.

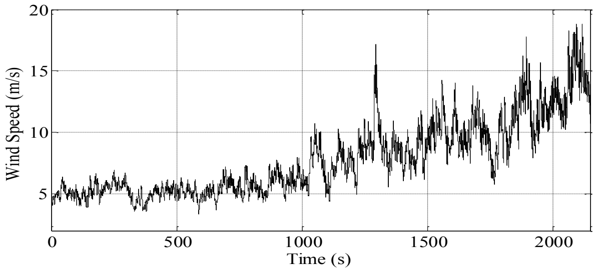

Fig. 2. Wind speed data for simulation.

The performance of the AFTC strategy in the no-fault case is shown in Fig. 3 to Fig. 5. It is shown in Fig. 4 and Fig. 5 that the controller frequently switches between the two control regions when the wind speed is highly fluctuating. The generated power is regulated below the rated power and generator speed is regulated around ω_{gr} and below ω_{g_max}.

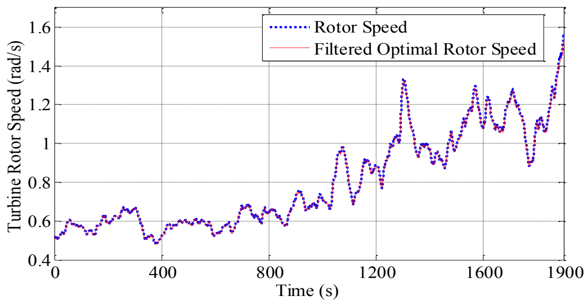

Fig. 3. Tracking performance below the rated wind speed region.

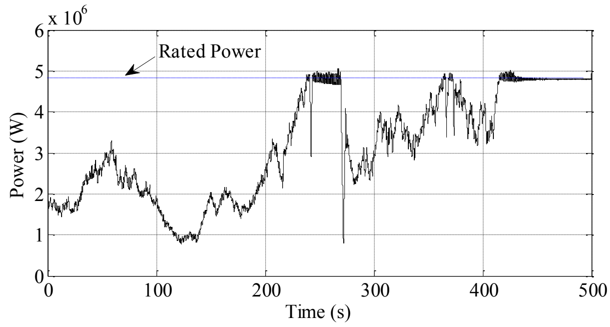

Fig. 4. Power regulation when controller switches between two regions.

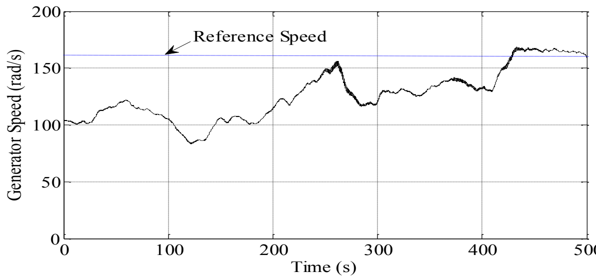

Fig. 5. Generator speed regulation when controller are switching between two regions.

The fault estimation corresponding to the pitch actuator fault and generator torque faults is shown in Fig. 6 and Fig. 7. A 10 degree fault is added to the pitch actuator and a 2000N-m fault is added to the generator torque to reflect a converter malfunction. Estimation of torque fault is more accurate due to the much higher signal-to-noise ratio of the torque sensor.

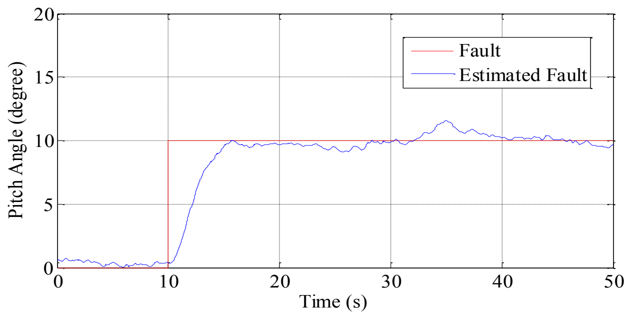

Fig. 6. Estimation of 10 degree pitch actuator fault.

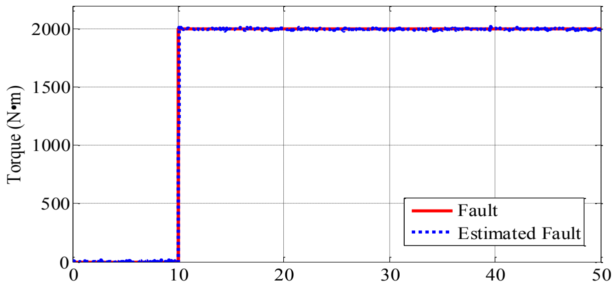

Fig. 7. Estimation of a 2000N-m generator torque fault.

The performance of the AFTC strategy in both operating regions is shown in Fig. 8 to Fig. 9. A 10 degree fault is added to the pitch actuator for 100 seconds in the low wind speed region and a 2000N-m torque offset fault is added to generator torque for 250 seconds. It is shown in Fig. 8 that the tracking error with AFTC is much smaller than that without the action of the AFTC during the fault. Fig. 9 shows that without the action of the AFTC, the generated power can not be regulated around the rated power after 200 seconds in the above rated wind speed region.

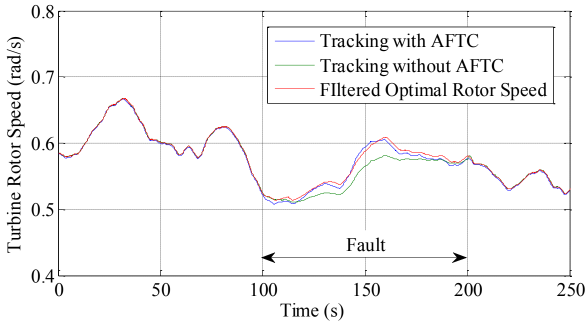

Fig. 8. Tracking performance of AFTC in below rated wind speed region during the pitch actuator fault.

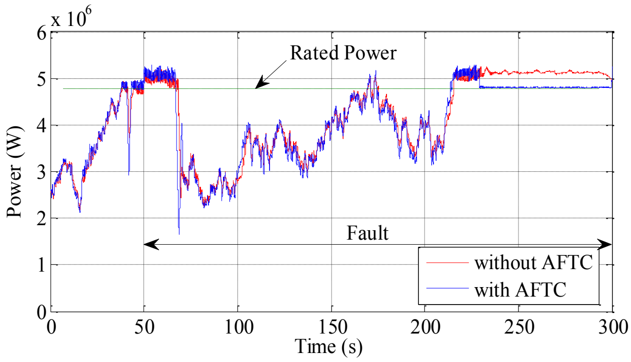

Fig. 9. Power regulation of AFTC when controller switches between two regions.

6. CONCLUSIONS

This paper proposes an AFTC strategy for wind turbine actuator faults. MHE based on T-S fuzzy modelling is proposed as the FE unit to estimate actuator faults. MPC based on T-S fuzzy modelling is proposed as the fault tolerant controller to compensate for the faults and consider the system nonlinearity. The multiple control design for the wind turbine is simplified by the proposed MPC. A future study will consider the robustness issues arising from the use of this AFTC approach.

REFERENCES

Feng, G. (2010). *Analysis and Synthesis of Fuzzy Control Systems: a model-based approach*, CRC Press.

Izadi, H. A., Zhang, Y. & Gordon, B. W. (2011). Fault tolerant model predictive control of quad-rotor helicopters with actuator fault estimation. *Proceedings of the 18th IFAC World Congress*, Milan, pp. 6343-6348.

Maciejowski, J. M. (2002). *Predictive control with constraints*, Prentice Hall, UK.

Mirzaei, M., Pouslen, N. K. & Niemann, H. H. (2012). Robust model predictive control of a wind turbine. *American Control Conference ACC 2012*, Montréal, Canada, pp 4393- 4398

Odgaard, P. F., Stoustrup, J. & Kinnaert, M. (2009). Fault tolerant control of wind turbines: a benchmark model. In *Proc. 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Safeprocess 2009*, Barcelona, pp. 155-160.

Østergaard, K. Z., Brath, P. & Sstoustrup, J. (2007). Estimation of effective wind speed. *Journal of Physics: Conference Series*, IOP Publishing, 012082.

Rao, C. V., Rawlings, J. B. & Mayne, D. Q. (2003). Constrained state estimation for nonlinear discrete-time systems: Stability and moving horizon approximations. *IEEE Transactions on Automatic Control,* 48**,** 246-258.

Sami, M. & Patton, R. J. (2012a). An FTC approach to wind turbine power maximisation via TS fuzzy modelling and control. *Proc. 8th IFAC* Symposium on *Fault Detection, Supervision and Safety of Technical Processes, Safeprocess 2012*, Mexico City, pp. 349-354.

Sami, M. & Patton, R. J. (2012b). Global wind turbine FTC via TS fuzzy modelling and control. *Proc. 8th IFAC* Symposium on *Fault Detection, Supervision and Safety of Technical Processes*, *Safeprocess 2012*, Mexico City, pp. 325-330.

Sami, M. & Patton, R. J. (2012c) Wind turbine power maximisation based on adaptive sensor fault tolerant sliding mode control. 2*0th Mediterranean Conf. on Control & Automation, MED 2012*, pp. 1183-1188.

Soliman, M., Malik, O. & Westwick, D. T. (2011). Multiple model predictive control for wind turbines with doubly fed induction generators. *IEEE Trans. on Sustainable Energy,* 2**,** 215-225

Wu, B., Lang, Y., Zargari, N. & Kouro, S. (2011). *Power Conversion and Control of Wind Energy Systems*, Wiley-IEEE Press.

Xu, Z., Hu, Q. & Ehsani M. (2012). Estimation of effective wind speed for fixed-speed wind turbines based on frequency domain data fusion. *IEEE Trans. on Sustainable Energy,* 3**,** 57-64.

Yang, X. & Maciejowski, J. (2012). Fault-tolerant model predictive control of a wind turbine benchmark. *Proc. 8th IFAC* Symposium on *Fault Detection, Supervision and Safety of Technical Processes*, *Safeprocess 2012*, Mexico City, pp. 337-342.