Sensor Fault-Tolerant Control of a Drivetrain Test Rig via an Observer-Based Approach within a Wind Turbine Simulation Model

Sören Georg, Stefan Heyde and Horst Schulte
HTW Berlin, School of Engineering I, Control Engineering, Wilhelminenhofstr. 75A, 12459 Berlin, Germany
E-mail: horst.schulte@htw-berlin.de

Abstract. This paper presents the implementation of an observer-based fault reconstruction and fault-tolerant control scheme on a rapid control prototyping system. The observer runs in parallel to a dynamic wind turbine simulation model and a speed controller, where the latter is used to control the shaft speed of a mechanical drivetrain according to the calculated rotor speed obtained from the wind turbine simulation. An incipient offset fault is added on the measured value of one of the two speed sensors and is reconstructed by means of a Takagi-Sugeno sliding-mode observer. The reconstructed fault value is then subtracted from the faulty sensor value to compensate for the fault. The whole experimental set-up corresponds to a sensor-in-the-loop system.

1. Introduction

Due to the growing size and complexity of wind turbines, there is an increasing demand for developing intelligent fault diagnosis and fault-tolerant control strategies to avoid turbine shutdowns that are caused by minor (non-critical) faults. Such strategies are particularly important for offshore wind turbines, which are more difficult and in bad weather conditions even impossible to access, such that a regular maintenance and replacement of faulty system parts is impeded. The fault diagnosis schemes that are nowadays routinely employed in wind turbines are typically on the level of the supervisory control and include sensor comparison, model comparison and thresholding [1]. These strategies enable a safe turbine operation, but no intelligent fault-tolerant control. Typically, the turbines are shut down even in case of faults that are in principle non-critical, like a fault of a redundant sensor. The gains in safety therefore often entail a reduced availability and thus a loss of produced energy.

Several advanced fault diagnosis schemes have been applied in wind turbine simulations in recent years. A good overview can be found in [2], where the results of a wind turbine FDI (fault detection and isolation) competition are summarised. In the presented solutions, all simulations were conducted with a reduced-order benchmark model introduced in [3, 4]. Most of these solutions rely on the evaluation of residuals, a standard technique in FDI methods [5]. The downside of evaluating residuals for FDI is that they yield no estimates of the faults including their magnitude and "direction". This information, however, is important for a full fault analysis and vital for fault-tolerant control.
The competition was later extended to fault-tolerant control (FTC). Of the presented solutions, only few include fault estimation, namely [6], [7] and [8].

The FDI benchmark model from [3], which features only drivetrain degrees of freedom but no blade and tower dynamics, is not a realistic wind turbine simulation model. In a later stage of the FDI/FTC competition [9], the aero-elastic code FAST by NREL [10] was thus used as a simulation model along with the turbine parameters of the NREL 5 MW reference turbine [11]. From among the presented solutions, only [12] includes fault estimation, though only for pitch dynamics parameter faults.

There is therefore still a need for further research on reliable and effective FDI and FTC algorithms that include estimation/reconstruction of faults and are validated in standard wind turbine simulation packages like FAST. The authors of this paper have already published the application of a Takagi-Sugeno sliding mode observer to wind turbine actuator and sensor fault reconstruction and fault-tolerant control [13, 14, 15]. This approach is capable of simultaneously reconstructing several faults (even with significantly differing orders of magnitude) and yields promising results.

What has not yet been conducted, and to the authors’ knowledge has not been published either by other authors, is a validation of FDI/FTC algorithms on a real test rig, let alone on a real wind turbine. In this paper, a first step in this direction is presented in form of a sensor-in-the-loop set-up, where the Takagi-Sugeno sliding mode observer for fault reconstruction is implemented on a dSpace rapid control prototyping system alongside a wind turbine simulation model. The calculated (and scaled) rotor speed from the wind turbine model is then used as the setpoint for a closed-loop controller to control the shaft speed of a mechanical drivetrain. The measured value of the speed sensor on the load side of the drivetrain is then imposed with an additive fault and fed back into the wind turbine model and the observer. The reconstructed fault can then be subtracted from the “faulty” sensor value to achieve a near, though not full, fault-tolerance.

This paper is organised as follows. In Section 2, the combined simulation and experimental set-up is described. In Section 3, the fault reconstruction concept by means of the Takagi-Sugeno sliding mode observer is introduced. In Section 5, results are presented and Section 6 gives a conclusion and outlook.

2. Experimental and Real-Time Simulation Set-Up

A schematics of the combined experimental and simulation set-up highlighting the sensor-in-the-loop structure is depicted in Figure 1.

A reduced-order dynamic wind turbine (WT) model with four degrees of freedom (torsional drivetrain with rotor and generator rotational angles, tower-top and blade-tip deflection) as presented in [16] and [17] was implemented in Simulink and compiled on a dSpace rapid control prototyping system to be run in real-time. In parallel to the wind turbine model, a rotor blade pitch controller [14] was implemented. In Figure 1, the block ”WT Model & Cntrl & Observer” subsumes both the wind turbine model and the pitch controller as well as the observer for fault reconstruction (see Section 3). As wind speed input, a time-series of turbulent wind (at a mean wind speed of 18 m/s), generated with the software TurbSim [18] by NREL, was used. In order to regulate the shaft speed of the drivetrain test rig, a separate controller (state-space with integral action) was implemented (see block ”Motor Cntrl”) and also compiled on the dSpace system. The rotor speed output of the wind turbine model scaled with a factor of 97 (this corresponds to the gearbox ratio of the NREL 5 MW turbine) was set as demanded speed for the shaft speed controller. The output of the speed controller is a demanded torque ($T_M$ in Figure 1) for the motor of the servo drive, which is itself internally controlled via a Beckhoff industrial PC and frequency converter (not explicitly depicted in Figure 1). The mechanical drivetrain (see Figure 2) consists of a shaft with a flat steel spring in the middle to obtain a torsional-flexible shaft, and an inertia disc at the end. This drivetrain test rig was initially developed.
Figure 1: Schematics of the sensor-in-the-loop set-up with wind turbine model, controller and observer running on a dSpace rapid control prototyping system (left side) and the mechanical drivetrain test rig (right side). $\omega_r$: calculated (and scaled) rotor speed from the wind turbine model. $T_M$: demanded motor torque. $\omega_M$, $\omega_L$: measured shaft speed sensor values at motor and load side, respectively. The right block 'Test Rig' consists of the mechanical drivetrain and a Beckhoff servo-motor controlled with a Beckhoff industrial PC and frequency converter. The signal line for the averaged motor speed $\omega_{M,av}$ is drawn dashed since this signal is not utilised further in the wind turbine model.

Figure 2: Mechanical drivetrain test rig - Control Engineering Laboratory of HTW Berlin
for designing a controller to reduce torsional vibrations, not with the intention to use it as a simulator for a wind turbine drivetrain (see also the outlook in Section 6). Two incremental encoders by Pepperl+Fuchs are used to measure the shaft speed at both the motor ($\omega_M$) and the inertia/load side ($\omega_L$) of the flat steel spring. To calculate both angular speeds, the standard method of counting the number of passing increments per cycle time (set to 0.001 s) was applied in this work. Even though the resolution of the encoders is quite high (1024 increments), at the angular speeds tested in the experiments around 120 rad/s, the measured/calculated speed values may still differ by +/- 6 rad/s. These differences occur if one increment more or less is counted per cycle, which easily happens due to the drivetrain vibrations. Ideally, a separate counter module, running at an independent high frequency (several MHz), should be used to measure the time between two increments. In this way, it would be possible to obtain a smoother speed measurement. However, such a configuration was not feasible in the presented system set-up. Therefore, the two speed measurements were filtered using a standard mean value calculation (over the last 20 timesteps) before they were fed back into the wind turbine simulation model (although the averaged motor speed $\omega_{M,av}$ was not utilised further in the wind turbine model).

3. Sliding Mode Observer Based Fault Reconstruction
In this section, the fault reconstruction method applied in this work is presented. Edwards and Spurgeon have shown that sliding mode observers can be effectively employed for direct fault reconstruction [19, 20, 21]. The way this works is by evaluating the so-called equivalent output injection signal, which corresponds to the average behaviour of the nonlinear switching term used to establish and maintain the sliding motion.

In this work, a Takagi-Sugeno sliding mode observer (TS SMO), which is a nonlinear multiple-model extension of the Edwards-Spurgeon observer, is used. The methods for fault reconstruction can thus be employed in a similar way. For an introduction to Takagi-Sugeno (TS) models [22] see for example [23]. The TS SMO was first introduced in [24, 25]. In [13], an extension was presented, which involves a weighted switching action that allows a simultaneous reconstruction of faults of significantly differing orders of magnitude, for example pitch angle and generator torque actuator faults in wind turbines. The reason for using a nonlinear TS sliding mode observer is that the wind turbine model itself is nonlinear. By modelling the system nonlinearities within the TS structure, the switching term is solely needed for reconstructing faults, not for compensating deviations between the underlying nonlinear and a linearised model.

3.1. Takagi-Sugeno Sliding Mode Observer
In the most general form, the TS SMO design is based on a nonlinear TS system subject to external disturbances $\xi$, actuator faults $f_a$ and sensor fault $f_s$, which is essentially the TS modified form of the basic state-space model normally assumed for FDI problems [5]:

$$\dot{x} = \sum_{i=1}^{N_r} h_i(z) \left( A_i x + B_i u + D_i \xi + E_i f_a \right), \quad \dot{y} = y + f_s = C x + f_s,$$ (1)

where $N_r$ denotes the number of distinct nonlinearities. The TS membership functions $h_i$ fulfill the condition $\sum_{i=1}^{N_r} h_i = 1$ and the premise variables $z$ may depend on system states, inputs, and external variables [23].
Transformed Form of the TS SMO The TS SMO is designed in a transformed system, where the measurable system states $y$ and the non-measurable system states $x_1$ are separated. This separation is achieved via a transformation $T_c = [N_c \ C]^T$, where $N_c$ denotes the null-space of $C$. With a series of transformations $T_i = T_L,i \ T_D,i T_c$ (see [20, 24, 25] for a description of the transformation matrices and the transformed system matrices), the TS system is brought into a structure where the uncertainties and faults only act on the measurable system states [24]:

$$\dot{x}_1 = \sum_{i=1}^{N_r} h_i(z) \left( A_{11,i} x_1 + A_{12,i} y + B_{1,i} u \right),$$  \hspace{1cm} (2)$$

$$\dot{y} = \sum_{i=1}^{N_r} h_i(z) \left( A_{21,i} x_1 + A_{22,i} y + B_{2,i} u + D_{2,i} \xi + F_{2,i} f_a \right) + f_s,$$  \hspace{1cm} (3)$$

The structure of the transformed system matrices is as follows: $A_i = T_i A_i T_i^{-1} = [A_{11,i} \ A_{12,i} \ A_{21,i} \ A_{22,i}]$, $B_i = T_i B_i = [B_{1,i}^T \ B_{2,i}^T]^T$, $D_i = T_i D_i = [0^T \ D_{2,i}^T]^T$, $F_i = T_i F_i = [0^T \ F_{2,i}^T]^T$. For a stable observer to exist, the following three existence conditions have to be fulfilled [20, 24, 25]:

**Condition 1.** The disturbances and actuator faults are unknown but bounded: $\| \xi(t) \|_T \leq \Xi$. Furthermore, individual bounds exist: $\| \xi(t) \|_T \leq \Xi_\xi$ and $f_a(t) \leq \Xi_{f_a}$. The sensor faults and their derivatives are assumed to be bounded, too: $\| f_s \| \leq \Psi$, $\| \dot{f}_s \| \leq \Psi_d$. Moreover, the system states and inputs are assumed to be bounded.

**Condition 2.** Let $q$ be defined as the number of columns of $[D_i \ F_i]$. Then, the condition $q = \text{rank}([C \ D_i \ F_i]) = \text{rank}[D_i \ F_i]$ must be fulfilled. Furthermore, it must hold that $p > q$, where $p$ is the number of measurable system states.

**Condition 3.** All invariant zeros of $(A_i, [D_i \ F_i], C)$ must lie in $\mathbb{C}_-$. The TS sliding mode observer in transformed form is given by

$$\dot{x}_1 = \sum_{i=1}^{N_r} h_i(z) \left( A_{11,i} x_1 + A_{12,i} \dot{y} + B_{1,i} u - A_{12,i} e_y \right),$$  \hspace{1cm} (4)$$

$$\dot{y} = \sum_{i=1}^{N_r} h_i(z) \left( A_{21,i} x_1 + A_{22,i} \dot{y} + B_{2,i} u - (A_{22,i} - A_{22,i}^s) \dot{e}_y + \nu \right),$$  \hspace{1cm} (5)$$

where $\dot{e}_y := \dot{y} - (y + f_s)$ denotes the output error including sensor faults and $A_{22,i}^s$ is a stable design matrix. In this work, the discontinuous switching term necessary to establish and maintain a sliding motion is given by

$$\nu = -\rho \frac{P_2 \ W \ \dot{e}_y}{\| P_2 \ W \ \dot{e}_y \|}, \quad (\dot{e}_y \neq 0).$$  \hspace{1cm} (6)$$

Here, $P_2$ is the symmetric, positive definite solution of the Lyapunov equation $P_2 A_{22,i}^s + A_{22,i}^{s T} P_2 = -Q_2$, where $Q_2$ is a symmetric positive definite design matrix. Expression (6) differs from the discontinuous switching terms in [20] and [24, 25] in that the output
error vector \( \hat{e}_y \) is modified with a diagonal weighting matrix \( W \) and that a diagonal gain matrix \( \rho = \text{diag}(\rho_1 \cdots \rho_p) \) is used instead of a scalar gain factor. The elements of the weighting matrix are the reciprocal values of the estimated maximum values of the output vector:

\[
W = \text{diag}(W_1 \cdots W_p) = \text{diag}(1/|y_{\text{max},1}| \cdots 1/|y_{\text{max},p}|).
\]

The modified switching function (6) was introduced in [13] to enable a simultaneous reconstruction of both pitch angle and generator torque actuator faults, which have significantly differing orders of magnitude.

**Equivalent Output Injection Signal** Similarly to the equivalent control action in sliding mode control structures, for sliding mode observers the so-called equivalent output injection signal describes the average behaviour of the discontinuous component \( \nu \) [21].

The equivalent output injection signal is a measure for the effort to maintain the sliding motion [21] and can be approximated to arbitrary precision by introducing a small enough positive scalar \( \delta \) into the discontinuous component (6):

\[
\nu_{\text{eq}} = -\rho \frac{P_2 W \hat{e}_y}{\|P_2 W \hat{e}_y\| + \delta},
\]  

(7)

### 3.2. Fault Reconstruction

If faults occur in the system, a higher effort needs to be exerted to maintain the sliding motion, which is then reflected in the equivalent output injection signal \( \nu_{\text{eq}} \). In [20, 21], direct fault reconstruction methods for actuator as well as sensor faults are described based on evaluating this signal. For a TS sliding mode observer, these methods can be adapted and used in a similar fashion [24, 25]. If no sensor faults are present and neglecting disturbances, actuator faults can be reconstructed using the relation

\[
\hat{f}_a = \left( \sum_{i=1}^{N_r} h_i(z) \mathcal{F}_{2,i} \right) \nu_{\text{eq}},
\]  

(8)

where \((\cdot)^+\) denotes the left pseudo-inverse.

For sensor fault reconstruction, the method introduced by Tan and Edwards [26], where sensor faults can be treated as actuator faults within an augmented system, is adapted for TS systems and the fault reconstruction then works analogously to (8). The basic idea is to filter the system outputs and then to augment the system with the filtered outputs. Consider a system with sensor faults \( f_s \) in \( r \) selected output channels:

\[
\begin{align*}
\dot{x} &= \sum_{i=1}^{N_r} h_i(z) (A_i x + B_i u), \\
\hat{y} &= C x + N f_s,
\end{align*}
\]  

(9)

where the matrix \( N \in \mathbb{R}^{p \times r} (n \geq p \geq r) \) (with \( n \) the number of system states and \( p \) the number of outputs) is used to sort the components of \( f_s \) into the channels of the respective output vector. Introducing a delay matrix \( A_f = \text{diag}\left(-\frac{1}{\tau_1} \cdots -\frac{1}{\tau_p}\right) \), with the individual delay time constants \( \tau_i \ (i \in \{1, \ldots, p\}) \) for each output, the dynamics of the filtered output vector \( y_f \) is given by:

\[
\begin{align*}
\dot{y}_f &= -A_f y_f + A_f \hat{y} \\
&= -A_f y_f + A_f C x + A_f N f_s.
\end{align*}
\]  

(10)
Both systems (9) and (10) can be combined into an augmented system with system vector $x_a$, where the sensor faults now appear as actuator faults:

$$\begin{align*}
\dot{x} &= \sum_{i=1}^{N_r} h_i(z) \left( \begin{bmatrix} A_i & 0 \\ A_f C & -A_f \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \end{bmatrix} u \right) + \begin{bmatrix} 0 \\ A_f N \end{bmatrix} f_s \\
y_f &= \begin{bmatrix} 0 & I_{p \times p} \end{bmatrix} x_f.
\end{align*}$$

In analogy to (4) and (5), the TS sliding mode observer in transformed form for the augmented system (11)-(12) is given by

$$\begin{align*}
\dot{\hat{x}}_{a,1} &= \sum_{i=1}^{N_r} h_i(z) \left( (A_{a,11,i} \hat{x}_{a,1} + A_{a,12,i} \hat{y}_f + \mathcal{B}_{a,1,i} u - A_{a,12,i} \bar{e}_y) \right), \\
\dot{\hat{y}}_f &= \sum_{i=1}^{N_r} h_i(z) \left( (A_{a,21,i} \hat{x}_{a,1} + A_{a,22,i} \hat{y}_f + \mathcal{B}_{a,2,i} u - (A_{a,22,i} - \mathcal{A}_{22}^s) \bar{e}_y + \nu) \right),
\end{align*}$$

where $\bar{e}_y = \hat{y}_f - y_f$ denotes the error vector, which is now calculated from the filtered output components of the TS SMO and the sensor faults can then be reconstructed like actuator faults using the pseudo-inverse of the TS sum of the transformed form of the augmented matrices $\mathcal{F}_{a,2,i}$:

$$\hat{f}_s = \left( \sum_{i=1}^{N_r} h_i(z) \mathcal{F}_{a,2,i} \right)^+ \nu_{eq}. $$

### 3.3. Design of the TS Sliding Mode Observer

The TS SMO design in this work was based on a further reduction of the 4-DOF wind turbine model containing only the drivetrain degrees of freedom [13, 14]. This proved a suitable choice for achieving good fault reconstruction results.

### 4. Fault-Tolerant Control

By subtracting the reconstructed sensor faults $\hat{f}_s$ from the faulty outputs, a fault-tolerance can (in principle) be achieved, depending on the quality of the fault reconstruction:

$$y_{corr} = y_{F,s} - \hat{f}_s = C x + \left( f_s - \hat{f}_s \right).$$

For a stability analysis of this structure in the case of wind turbine simulations, please refer to [15]. As will be seen in the next section, even in the case with no speed sensor fault, the TS SMO reconstructs small fault magnitudes. To avoid feeding back these erroneous reconstructions, a threshold was applied, such that only reconstructed magnitudes greater than this threshold were considered for the fault compensation calculation (16).
5. Results

Five measurements over a 120 s period were conducted:

1. Fault-free case
2. Load side ($\omega_L$) sensor fault with a final fault value of ...
   2.1 ... 0.2 rad/s - no fault compensation
   2.2 ... 0.2 rad/s - with active fault compensation
   2.3 ... 0.8 rad/s - no fault compensation
   2.4 ... 0.8 rad/s - with active compensation

The faults were initially fixed to 0 and then gradually increased with a linear ramp to the final fault values of 0.2 respectively 0.8 rad/s. These values are in relation to the magnitude of the calculated rotor speed within the wind turbine simulation model. In relation to the measured angular speed of the drivetrain, the fault values would be $0.2 \text{ rad/s} \cdot 97 = 19.4 \text{ rad/s}$ respectively $0.8 \text{ rad/s} \cdot 97 = 77.6 \text{ rad/s}$.

The results are shown in Figures 3 and 4, where the three cases (fault-free (blue lines), fault without compensation (green lines), fault with active compensation (red lines)) are depicted together to see the effect of the faults and the fault compensation. There are small time offsets between the three cases, because the measurements were started manually.

![Figure 3: Simulation and measurement results for an incipient additive fault on the load side speed sensor (final fault value: 0.2 rad/s). Blue lines: fault-free case; green lines: faulty case without fault compensation; red lines: faulty case with active fault compensation. In the central subfigure, the black line shows the actual fault value for the two faulty measurements.](image)

The results of the measurements with the smaller fault value of 0.2 rad/s are shown in Figure 3. The central middle subfigure shows the true fault value (black line) and the reconstructed fault values in the case without (green) and with (red) fault compensation. One can see that even with a true fault value of 0, the TS SMO reconstructs (erroneous) fault values with absolute values...
up to 0.07 rad/s. For this reason, a threshold value of 0.05 rad/s was defined, such that in the case with active fault compensation, only reconstructed fault values with absolute values greater than this threshold were considered to be fed back via the fault-tolerant control algorithm (16). Even though the largest values of the erroneous reconstructions are greater than this threshold, the value of 0.05 rad/s was chosen to achieve a compromise between a reasonably quick fault compensation and the avoidance of erroneous compensations.

The measured sensor values and their average values are shown in the last 4 subfigures (denoted $\omega_M$, $\omega_{M,\text{av}}$, $\omega_L$ and $\omega_{L,\text{av}}$). The fault was added on the averaged measurement $\omega_{L,\text{av}}$ of the load side speed of the drivetrain and then used in the wind turbine simulation model ($\omega_{g,F}$: 3rd subfigure). One can see that in the faulty case without fault compensation, this value remains the same (neglecting the small time-offset) as the in the fault-free case, because the pitch controller within the WT model adjusts the pitch angle such as to control the generator speed around its setpoint. Due to this, the physical shaft speed of the drivetrain decreases (see green line in 2nd subfigure).

By contrast, in the case with active fault compensation, the fault-free behaviour is nearly recovered, though not perfectly, because the fault reconstruction is not perfect. The rising fault ramp and the mean fault value are quite well reconstructed by the TS sliding mode observer. However, there is quite a large variation around the mean fault value of 0.2 rad/s. Compared to the results in simulation-only studies presented in [15], the reconstruction quality is thus decreased. Still, it is sufficient to achieve a fairly well working fault-tolerant control.

![Simulation and measurement results for an incipient additive fault on the load side speed sensor (final fault value: 0.8 rad/s). Blue lines: fault-free case; green lines: faulty case without fault compensation; red lines: faulty case with active fault compensation. In the central subfigure, the black line shows the actual fault value for the two faulty measurements.](image)

Figure 4: Simulation and measurement results for an incipient additive fault on the load side speed sensor (final fault value: 0.8 rad/s). Blue lines: fault-free case; green lines: faulty case without fault compensation; red lines: faulty case with active fault compensation. In the central subfigure, the black line shows the actual fault value for the two faulty measurements.

The results of the measurements with the larger fault value of 0.8 rad/s are shown in Figure 4. This fault value corresponds to more than 60% of the demanded rotor speed 1.267 rad/s within the wind turbine simulation model and thus constitutes a very significant fault magnitude. From
the central subfigure it can be seen that in this case, there is a discrepancy of about 0.1 rad/s between the actual final fault value of 0.8 rad/s and the mean of the reconstructed value. Due to this discrepancy, the physical shaft speed in the faulty case with active fault compensation is also slightly decreased compared to the fault-free case. When comparing this result to the case without fault compensation, however, one can see that a significant improvement can be achieved with the fault-tolerant control scheme.

6. Conclusion and Outlook
The investigations presented in this paper are a first step to a practical validation of the TS sliding mode observer for fault reconstruction, with focus on the wind turbine application. It could be shown that the fault-tolerant control strategy achieves a significant improvement of the controlled behaviour of the sensor-in-the-loop set-up in the presence of faults.

For future work, a modification of the drivetrain test rig is planned, for the following reasons. The system set-up with the shaft speed controller in between the wind turbine simulation model and the drivetrain is still somewhat cumbersome. Moreover, it leads to an additional time-lag within the system caused by the transient behaviour (rise time) of the shaft speed controller. Instead of the inertia disc at the one end of the drivetrain, it would be better to install a generator (with the same power as the driving motor). In such a set-up, the motor torque could be adjusted directly from the calculated (and scaled) aerodynamic rotor torque within the wind turbine model. The calculated generator torque from the torque controller within the wind turbine model would then be set as a demanded counteracting torque for the generator. In this way, not only sensor but also generator torque actuator faults could be modelled and reconstructed. Furthermore, the time-lag introduced by the shaft speed controller would not be present, such that the fault reconstruction quality should also be improved. The modified drivetrain with motor and generator would constitute a more realistic scenario for a drivetrain of a real wind turbine.

Acknowledgments
This work was conducted within a research project funded by the German Federal Ministry of Education and Research under grant no. 17N1411.

References
[1] Johnson K E and Fleming P A 2011 Mechatronics 21 728–736
[2] Odgaard P F and Stoustrup J 2012 Results of a Wind Turbine FDI Competition IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (Mexico City, Mexico) pp 102–107
[3] Odgaard P F, Stoustrup J and Kinnaert M 2009 Fault Tolerant Control of Wind Turbines - a benchmark model IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (Barcelona, Spain) pp 155–160
[4] Odgaard P F, Stoustrup J and Kinnaert M 2013 IEEE Transactions on Control Systems Technology 21 1168–1182
[5] Chen J and Patton R J 1999 Robust Model-Based Fault Diagnosis for Dynamic Systems (Kluwer Academic Publishers)
[6] Yang X and Maciejowski J M 2012 Fault-tolerant model predictive control of a wind turbine benchmark IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (Mexico City, Mexico) pp 337–342
[7] Rotondo D, Nejjari F, Puig V and Blesa J 2012 Fault Tolerant Control of the Wind Turbine Benchmark using Virtual Sensors/Actuators IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (Mexico City, Mexico) pp 114–119
[8] Sami M and Patton R J 2012 An FTC Approach to Wind Turbine Power Maximisation via T-S Fuzzy Modelling and Control IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes (Mexico City, Mexico) pp 349–354
[9] Odgaard P F and Johnson K E 2013 Wind turbine fault detection and fault tolerant control - an enhanced benchmark challenge American Control Conference (Washington, D.C., USA) pp 4447–4452
[10] Jonkman J M and Buhl Jr M L 2005 FAST User’s Guide Tech. rep. NREL/EL-500-38230, National Renewable Energy Laboratory, Golden, Colorado

[11] Jonkman J, Butterfield S, Musial W and Scott G 2009 Definition of a 5-MW Reference Wind Turbine for Offshore System Development Tech. rep. NREL/TP-500-38060, National Renewable Energy Laboratory, Golden, Colorado

[12] Sheibat-Othman N, Othman S, Benlahrache M and Odgaard P F 2013 Fault detection and isolation in wind turbines using support vector machines and observers American Control Conference (Washington, D.C., USA) pp 4459–4464

[13] Georg S and Schulte H 2014 Takagi-Sugeno Sliding Mode Observer with a Weighted Switching Action and Application to Fault Diagnosis for Wind Turbines Intelligent Systems in Technical and Medical Diagnostics (Advances in Intelligent Systems and Computing vol 230) ed Korbič J and Kowal M (Springer-Verlag Berlin Heidelberg) pp 41–52

[14] Georg S and Schulte H 2013 Actuator Fault Diagnosis and Fault-Tolerant Control of Wind Turbines using a Takagi-Sugeno Sliding Mode Observer International Conference on Control and Fault-Tolerant Systems (Nice, France) pp 516–522

[15] Georg S and Schulte H 2014 Journal of Physics: Conference Series 524 (012053)

[16] Bianchi F D, De Battista H and Mantz R J 2007 Wind Turbine Control Systems - Principles, Modelling and Gain Scheduling Design Advances in Industrial Control (Springer-Verlag London Limited)

[17] Georg S, Schulte H and Aschemann H 2012 Control-Oriented Modelling of Wind Turbines Using a Takagi-Sugeno Model Structure IEEE International Conference on Fuzzy Systems (Brisbane, Australia) pp 1737–1744

[18] Kelley N NWTC Computer-Aided Engineering Tools (TurbSim by Neil Kelley, Bonnie Jonkman). http://wind.nrel.gov/designcodes/preprocessors/turbsim

[19] Edwards C and Spurgeon S K 1994 International Journal of Control 59

[20] Edwards C and Spurgeon S K 1998 Sliding Mode Control: Theory and Applications (Taylor & Francis, Boca Raton)

[21] Edwards C, Spurgeon S K and Patton R J 2000 Automatica 36 541–553

[22] Takagi T and Sugeno M 1985 IEEE Transactions on Systems, Man, and Cybernetics 15 116–132

[23] Tanaka K and Wang H O 2001 Fuzzy Control Systems Design and Analysis: A Linear Matrix Inequality Approach (John Wiley & Sons, Inc)

[24] Gerland P, Groß D, Schulte H and Kroll A 2010 Robust Adaptive Fault Detection Using Global State Information and Application to Mobile Working Machines International Conference on Control and Fault-Tolerant Systems (Nice, France) pp 813–818

[25] Gerland P, Groß D, Schulte H and Kroll A 2010 Design of Sliding Mode Observers for TS Fuzzy Systems with Application to Disturbance and Actuator Fault Estimation IEEE Conference on Decision and Control (Atlanta, USA) pp 4373–4378

[26] Tan C P and Edwards C 2003 International Journal of Robust and Nonlinear Control 13 443–463