Preprints of the 7th IFAC Symposium on
Fault Detection, Supervision and Safety of Technical Processes
Barcelona, Spain, June 30 - July 3, 2009

Unknown Input Observer Based Scheme for Detecting Faults in a Wind Turbine Converter

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Abstract: In order to improve reliability of wind turbines, it is important to detect faults in the turbine as fast as possible to handle them in an optimal way. An important component in modern wind turbines is the converter, which for a wind turbine control point-of-view normally provides the torque acting on the wind turbine generator, as well as measurement of this torque. In this paper an unknown input observer is presented to estimate these faults in the converter and isolate them either to be an actuator fault or a sensor fault. The unknown input observer is used since the speed of wind acting on the wind turbine is assumed unknown, since measurement of it is influenced by the turbulence around the rotor plane. A detection scheme is formed based on these fault estimates. A detail simulation model is used to simulate a wind turbine in which both types of faults are present during the simulation. The detection scheme detects and isolates both faults with in 2 samples of its beginning.

1. INTRODUCTION

As wind turbines increase in sizes and more wind turbine turbines are installed offshore, the need for fast fault detection and accommodation increases. In much industrial manufactured wind turbines only rather simplistic schemes are used to detect and accommodate faults.

A wind turbine converts wind energy to electrical energy. In this example a three blade horizontal axis turbine is considered. The blades are facing the wind direction; these blades are connected to the rotor shaft. The wind is moving the blades and thereby rotating the shaft. A gear box is used to upscale the rotational speed for the rotor in the generator and converter. In terms of control the turbine is working in two regions, partial and full power. In the partial power region the turbine is controlled to generate as much power as possible. This is obtained if a certain ratio between the tip speed of the blade and the wind speed is achieved. In this mode the converter torque is normally used to control the rotational speed of the rotor. In the second control mode the aerodynamics of the blades are controlled by pitching the blades.

Faults in the wind turbine's converter are quite critical for the performance of the wind turbine. In addition to internal supervision in the converter it could be helpful for the wind turbine controller to introduce fault detection and isolation on a wind turbine level. The fault could originate from the electronics or from the converter control system.

Some examples can be found of fault detection and accommodation of wind turbines. An observer based scheme for detection of sensor faults for blade root torque sensors is presented in [Wei et al. 2008]. A residual based scheme is presented in [Dobrila and Stefansen 2007] to detect and accommodate faults in wind turbines. Fault detection for electrical conversion systems can be found in [Rothenhagen and Fuchs 2007, Rothenhagen et al. 2007] and [Poure et al. 2007]. In [Odgaard et al. 2009] an observer based scheme was proposed to detect and isolate sensor faults in the wind turbine drive train. An unknown input observer was used, to design an observer independent on the wind speed and thereby the aerodynamic torque acting on the wind turbine.

In this paper an unknown input observer is used as well, see [Chen and Patton 1999]. The faults are considered as unknown inputs which should be estimated this can be done by introducing internal fault models. Other examples on this usage of the unknown input observer can be seen in [Odgaard and Mataji 2008, Odgaard et al. 2008] where the former reports this scheme applied on fault detection of power plant coal mills and the latter estimates power coefficients for wind turbines. Frequency separation between faults and changes in the wind speed is exploited, such that an uncertain input can be used to represent uncertainties regarding the wind speed measurement.

In the next section the wind turbine system is described and the relevant parts are modelled. This is followed by the method description and a design of the detection scheme. The proposed scheme is subsequently validated by simulations, and finally a conclusion is drawn.

2. WIND TURBINE SYSTEM DESCRIPTION

The three blade horizontal axis turbine which is considered in this paper, works by the principle that the wind is acting on the blades and thereby moving the rotor shaft. In order to upscale the rotational speed to the needed one at the generator a gear box is introduced. The rotational speed and consequently the generated power can be controlled by two controls: the converter torque and the pitch angle of the turbine blades. In partial load of the wind turbine it is controlled to generate as much power as possible. This is achieved by keeping a specific ratio between the tip speed of the blades and the wind speed, which in turn is achieved by controlling the rotational speed by adjusting the converter torque. In the full power region the converter torque is kept constant and the rotational speed is adjusted by controlling the pitch angle of the blades which changes the aero-dynamical power transfer from wind to blades. This part of the wind turbine is illustrated in Fig. 1.

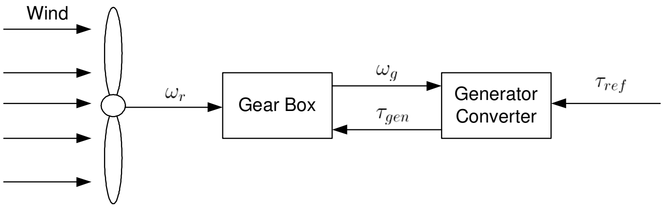

Fig. 1 Illustration of the principles of the wind turbine drive train. For illustrative purposes only two of the three blades are shown.

The wind turbine drive train in question has a number of measurements. $\omega_r[n]$ is a measurement of the rotor speed, $\omega_g[n]$ is a measurement of the generator speed, $\tau_{gen}[n]$ is the torque of the generator controlled by the converter which is provided with the torque reference, $\tau_{ref}[n]$. The estimated aerodynamic torque is defined as $\tau_{aero}[n]$. This estimate clearly depends on the wind speed, which unfortunately is very difficult to measure correctly. A very uncertain measurement is normally provided which is used to provide 10 minutes mean values, since this measurement is heavily influenced by measurement noises. In this example a sample frequency at 100 Hz is used in general.

2.1 Model

The model is first defined in continuous time and subsequently transferred to discrete time.

The aerodynamic model is defined as in (1)

$$\tau_{\mathrm{aero}}(t) = \frac{\rho A C_{\mathrm{p}}(\theta(t), \lambda(t)) v^3(t)}{2\omega_{\mathrm{r}}(t)}, \tag{1}$$

where ρ is the density of the air, A is the area covered by the turbine blades in its rotation, $\theta(t)$ is the pitch angle of the blades, $\lambda(t)$ is the tip speed ratio of the blade. (1) is used to estimate $\tau_{\mathrm{aero}}(t)$ based on an assumed estimated $v(t)$ and measured $\theta(t)$ and $\omega_{\mathrm{r}}(t)$. Due to the uncertainty of the estimate this could be considered as being unknown.

A simple one body model is used to represent the drive train, see (2).

$$\dot{\omega}_r(t) = \frac{1}{J}(\tau_{\mathrm{aero}}(t) - \tau_{\mathrm{gen}}(t)), \tag{2}$$

where

$$\dot{\tau}_{gen}(t) = p_{gen}(\tau_{\mathrm{ref}}(t) - \tau_{\mathrm{gen}}(t)), \tag{3}$$

The generator torque and reference respectively $\tau_{gen}(t)$ and $\tau_{ref}(t)$ are in this context transformed to the low speed side of the drive train (rotor side).

This gives a simple state space model of the system, see (4)-(5).

$$\begin{bmatrix} \dot{\omega}_{\mathrm{r}}(t) \\ \dot{\tau}_{\mathrm{gen}}(t) \end{bmatrix} = \begin{bmatrix} 0 & -\frac{1}{J} \\ 0 & -p_{\mathrm{gen}} \end{bmatrix} \begin{bmatrix} \omega_{\mathrm{r}}(t) \\ \tau_{\mathrm{gen}}(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{J} \\ 0 \end{bmatrix} \tau_{\mathrm{aero}}(t) + \begin{bmatrix} 0 \\ p_{\mathrm{gen}} \end{bmatrix} \tau_{\mathrm{ref}}(t), \tag{4}$$

$$\begin{bmatrix} \omega_r(t) \\ \tau_{\mathrm{gen}}(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \omega_r(t) \\ \tau_{gen}(t) \end{bmatrix}, \tag{5}$$

The parameters are chosen such that they represent a realistic turbine but not a specific one. The following parameters are used:

$\rho = 1.225\frac{\mathrm{kg}}{\mathrm{m}^3}$, $A = 6647.6\mathrm{m}^2$, $J = 7.794 \cdot 10^6 \mathrm{kg} \cdot \mathrm{m}^2$, $p_{\mathrm{gen}} = 100\frac{1}{\mathrm{s}}$, $N_r = 95$,
and the C_p table is chosen such that it represents an industrial turbine with blade diameter at 92 m.

2.2 Extended Model

Two unknown inputs $d_1(t)$ and $d_2(t)$ are introduced and the fault states are modelled as band pass filters:

$$\dot{\tilde{\tau}}_{\mathrm{aero}}(t) + p_{f1}\tilde{\tau}_{\mathrm{aero}}(t) = \dot{d}_1(t) + z_{f1}d_1(t), \tag{6}$$
$$\dot{\tilde{\tau}}_{\mathrm{gen}}(t) + p_{f2}\tilde{\tau}_{\mathrm{gen}}(t) = \dot{d}_1(t) + z_{f2}d_1(t), \tag{7}$$
$$\dot{\tilde{\tau}}_{\mathrm{gen,m}}(t) + p_{f3}\tilde{\tau}_{\mathrm{gen,m}}(t) = \dot{d}_2(t) + z_{f3}d_2(t), \tag{8}$$

where $\tilde{\tau}_{\mathrm{aero}}(t)$ is the state representing the uncertain aerodynamic component, $\tilde{\tau}_{\mathrm{gen}}(t)$ is the state representing the converter fault and $\tilde{\tau}_{\mathrm{gen,m}}(t)$ is the state representing the converter sensor fault. $p_{f1},\ p_{f2},\ p_{f3}$ are the filter poles, and $z_{f1},\ z_{f2},\ z_{f3}$ are the filter zeros. Requirements are that:

$$z_{f1} > p_{f1} \wedge z_{f2} > p_{f2} \wedge z_{f3} > p_{f3} \tag{9}$$

In terms of detection of the converter faults the 4th and 5th estimated states in the state vector are of interest, ($\hat{x}_4[n]$ and $\hat{x}_5[n]$), since these are the estimates of the converter and converter measurement faults. The 3rd state represents the uncertainty in the wind speed measurements. All three states are driven by unknown inputs, and the observer can only handle two unknown input, since the model only has two measurements, however, wind speed uncertainties and converter faults can be separated in frequencies meaning they can be represented by the same unknown input signal containing two different frequencies regions representing respectively wind speed uncertainties and converter faults.

This state space model is subsequently extended to the following model:

$$\begin{bmatrix} \dot{\omega}_r(t) \\ \dot{\tau}_{\text{gen}}(t) \\ \dot{\tilde{\tau}}_{\text{aero}}(t) \\ \dot{\tilde{\tau}}_{\text{gen}}(t) \\ \dot{\tilde{\tau}}_{\text{gen,m}}(t) \end{bmatrix} = \mathbf{A}_{\text{e}} \begin{bmatrix} \omega_r(t) \\ \tau_{\text{gen}}(t) \\ \tilde{\tau}_{\text{aero}}(t) \\ \tilde{\tau}_{\text{gen}}(t) \\ \tilde{\tau}_{\text{gen,m}}(t) \end{bmatrix} + \mathbf{B}_{\text{e}} \begin{bmatrix} \tau_{\text{ref}}(t) \\ \tau_{\text{aero}}(t) \end{bmatrix} + \mathbf{E}_{\text{e}} \begin{bmatrix} d_1(t) \\ d_2(t) \end{bmatrix}, \tag{10}$$

$$\begin{bmatrix} \omega_{\text{r,m}}(t) \\ \tau_{\text{gen,m}}(t) \end{bmatrix} = \mathbf{C}_{\text{e}} \begin{bmatrix} \omega_r(t) \\ \tau_{\text{gen}}(t) \\ \tilde{\tau}_{\text{aero}}(t) \\ \tilde{\tau}_{\text{gen}}(t) \\ \tilde{\tau}_{\text{gen,m}}(t) \end{bmatrix}, \tag{11}$$

where

$$\mathbf{A}_{\text{e}} = \begin{bmatrix} 0 & -\frac{1}{J} & -\frac{z_{f2}-p_{f2}}{J} & \frac{z_{f1}-p_{f1}}{J} & 0 \\ 0 & -p_{\text{gen}} & 0 & 0 & 0 \\ 0 & 0 & -p_{f2} & 0 & 0 \\ 0 & 0 & 0 & -p_{f1} & 0 \\ 0 & 0 & 0 & 0 & -p_{f3} \end{bmatrix}, \tag{12}$$

$$\mathbf{B}_{\text{e}} = \begin{bmatrix} 0 & \frac{1}{J} \\ p_{\text{gen}} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \tag{13}$$

$$\mathbf{C}_{\text{e}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & z_{f3} - p_{f3} \end{bmatrix}, \tag{14}$$

$$\mathbf{E}_{\text{e}} = \begin{bmatrix} 10^{-5} & 0 \\ 10^{-5} & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \tag{15}$$

Notice that $\mathbf{E}_{\text{e}}$ has non zero elements in the first two elements in the first column; these are introduced to give some robustness toward model uncertainties.

Subsequently the continuous model in (10)-(15) is discretized. This means that in the following an extra subscript d is added to the system matrices and states, inputs and outputs in samples instead of time ($[n]$ instead of (t)) .

3. OBSERVER DESIGN

The basic idea in the fault detection scheme is to use an observer to estimate two states in the models representing the converter fault or converter measurement fault.

Since the system in mind contains some unknown inputs the idea is to use an unknown input observer in its optimal version, see [Chen and Patton 1999]. The structure is:

$$\begin{aligned} \mathbf{z}[n+1] &= \mathbf{F}_{n+1}\mathbf{z}[n] + \mathbf{T}_{n+1}\mathbf{B}_n\mathbf{u}[n] + \mathbf{K}_{n+1}\mathbf{y}[n], \\ \hat{\mathbf{x}}[n+1] &= \mathbf{z}[n+1] + \mathbf{H}_{n+1}\mathbf{y}[n+1], \end{aligned} \tag{16}$$

where $\mathbf{F}_{n+1}$, $\mathbf{T}_{n+1}, \mathbf{K}_{n+1}$ and $\mathbf{H}_{n+1}$ are matrices designed to achieve decoupling from the unknown input and as well obtain an optimal observer. $\hat{\mathbf{x}}[n]$ is a vector of the estimated states in the model. The matrices in the unknown input observer are found using the following equations.

$$\mathbf{E}_n = \mathbf{H}_{n+1}\mathbf{C}_{n+1}\mathbf{E}_{n+1}, \tag{17}$$

$$\mathbf{T}_{n+1} = \mathbf{I} + \mathbf{H}_{n+1}\mathbf{C}_{n+1}, \tag{18}$$

$$\mathbf{F}_{n+1} = \mathbf{A}_n - \mathbf{H}_{n+1}\mathbf{C}_{n+1}\mathbf{A}_n - \mathbf{K}^1_{n+1}\mathbf{C}_n, \tag{19}$$

$$\mathbf{K}^2_{n+1} = \mathbf{F}_{n+1}\mathbf{H}_n, \tag{20}$$

$$\mathbf{K}^1_{n+1} = \mathbf{A}^1_{n+1}\mathbf{P}_n\mathbf{C}^T_{n+1}\left(\mathbf{C}_n\mathbf{P}_n\mathbf{C}^T_n + \mathbf{R}_n\right)^{-1} \tag{21}$$

$$\mathbf{A}^1_{n+1} = \mathbf{A}_n - \mathbf{H}_{n+1}\mathbf{C}_{n+1}\mathbf{A}_n, \tag{22}$$

$$\begin{aligned} \mathbf{P}_{n+1} =& \mathbf{A}^1_{n+1}\mathbf{P}^1_{n+1}\left(\mathbf{A}^1_{n+1}\right)^T + \mathbf{T}_{n+1}\mathbf{Q}_n\mathbf{T}^T_{n+1} \\ &+ \mathbf{H}_{n+1}\mathbf{R}_{n+1}\mathbf{H}^T_{n+1}, \end{aligned} \tag{23}$$

$$\mathbf{P}^1_{n+1} = \mathbf{P}_n - \mathbf{K}^1_{n+1}\mathbf{C}_n\mathbf{P}_n\left(\mathbf{A}^1_{n+1}\right)^T, \tag{24}$$

$$\mathbf{H}_{n+1} = \mathbf{E}_n\left(\mathbf{C}_n\mathbf{E}_n\right)^+, \tag{25}$$

The observer design procedure can be described by the following algorithm:

1) Set Initial values:

$$\begin{aligned} \mathbf{P}_0 =& \mathbf{P}(0), \\ \mathbf{z}[0] =& \mathbf{x}[0] - \mathbf{C}_0\mathbf{E}_0\left(\mathbf{C}_0\mathbf{E}_0\right)^+\mathbf{y}[0], \\ \mathbf{H}_0 =& 0, \\ \mathbf{k} =& 0. \end{aligned}$$

2) Compute $\mathbf{H}_{n+1}$using (25).

4) Compute $\mathbf{K}^1_{n+1}$ and $\mathbf{P}^1_{n+1}$ using (21) and (24).

5) Compute $\mathbf{T}_{n+1}$, $\mathbf{F}_{n+1}$, $\mathbf{K}^2_{n+1}$ and $\mathbf{K}_{n+1}$ by (18), (19), (20) and $\mathbf{K}_{n+1} = \mathbf{K}^1_{n+1} + \mathbf{K}^2_{n+1}$.

6) Compute the state estimate $\hat{\mathbf{x}}[n+1]$ and $\mathbf{z}[n+1]$ using (16).

7) Compute $\mathbf{P}_{n+1}$ using (23).

8) Set $n = n+1$ and go to step 2).

4. FAULT DETECTION SCHEME DESIGN

Based on these estimates of the converter actuator and sensor faults the detection scheme is based. Unfortunately these signals cannot directly be used for detection of the faults, since the estimate of the sensor fault also reacts on the actuator fault since a wrong sensor value could be due to both sensor or actuator faults, on the other hand the actuator fault signal is decoupled the sensor fault, since the observer uses the rotor speed estimate the fault as well, notice here that a actuator fault would be seen on the generator speed as well.

Detection of faults in the converter can be found using the detection signal $\gamma[n]$, which is defined in

$$\gamma[n] = \|\hat{x}_5[n]\| > \epsilon_s. \tag{26}$$

Now define two isolation signals $\gamma_a[n]$ and $\gamma_s[n]$ which respectively represent detection of actuator and sensor faults. The detection rules for the actuator fault can subsequently be defined as:

$$\gamma_a[n] = \begin{cases} 1, \text{ if } \|\hat{x}_4[n]\| > \epsilon_a \ \wedge \ \|\hat{x}_5[n]\| > \epsilon_s, \\ 0, \text{ else} \end{cases} \tag{27}$$

where ϵ_a and ϵ_s respectively are the actuator and sensor thresholds. The thresholds are found by trail and error such that false positive detections are avoided.

The detection rule for the sensor fault can be defined as:

$$\gamma_s[n] = \begin{cases} 1, \text{ if } \|\hat{x}_4[n]\| \le \epsilon_a \ \wedge \ \|\hat{x}_5[n]\| > \epsilon_s, \\ 0, \text{ else} \end{cases} . \tag{28}$$

5. SIMULATIONS RESULTS

In the simulation test this observer based detection scheme for faults in the converter both as measurement and actuator faults, the inputs to the observer is generated by a nonlinear detail industrial simulation model of wind turbine in with two faults are introduced. In general the controller in this simulation model, runs in two modes: power optimization (speed controlled by converter torque), speed control (speed controlled by pitching blades). The same simulation model was used in [Odgaard et al. 2008]. The simulation of the faulty wind turbine is sampled with 100 Hz as the sample frequency of the designed observer is as well. Between sample 8000 and 8500 an actuator fault is present in terms of 50% converter torque. The sensor fault is present between sample 12000 and sample 12500, this faults results in a torque measurement dropping to 0.

In the simulation a wind speed in the range from approx. 5 m/s to 15 m/s is used, the wind signal can be seen in Fig. 2. This wind speed scenario is used to cover the relevant wind speed region of power optimization including turbulence.

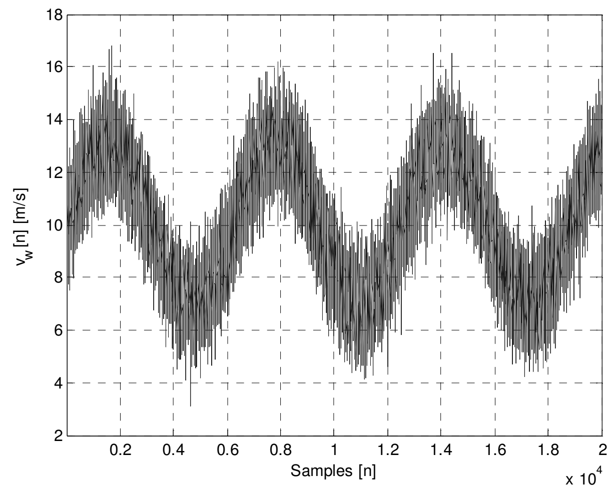

Fig. 2 Plot of the wind speed sequence used in the simulation.

The estimate of the $\hat{x}_5[n]$ can be seen in Fig. 3, from which it can be seen that the two faults in the converter can be detected quite well using a threshold, γ_s. Consequently faults in the converter can be detected by using this proposed observer.

The next step would be to isolate the faults to either an actuator fault or a sensor fault. In order to do so the detection scheme requires comparison between $\hat{x}_4[n]$ and the threshold ϵ_a. Fig. 4 shows the estimation of $\hat{x}_4[n]$ compared with ϵ_a. From this figure it is clear that the actuator fault which is present between 8000 and 8500 samples, but the estimated signal is highly influenced by the uncertain wind speed. This is due to the fact the wind speed is assumed totally unknown, a measurement of the wind speed is most often available in turbines, but fare from precise. Consequently is interesting to detect these faults in the wind turbine independent of this wind measurement. In order to remove influence from the unknown wind speed on $\hat{x}_4[n]$ the estimated wind speed multiplied with a gain factor k_1 is subtracted from $\hat{x}_4[n]$.

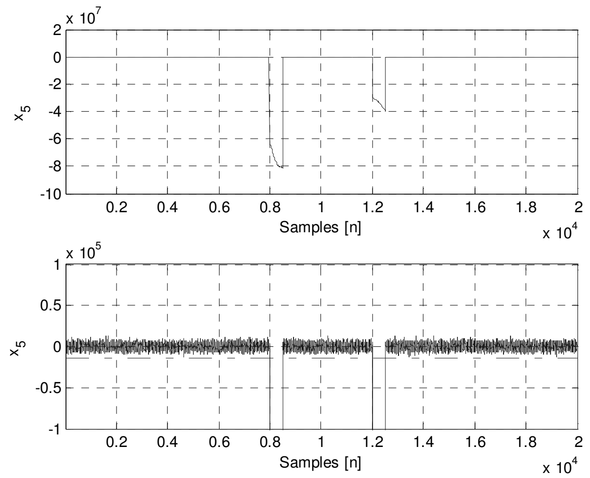

Fig. 3 Plot showing the converter fault estimate, the upper plot showing the entire sequence and the lower plot a zoom to compare the threshold with the fault estimate.

This means that the detection scheme presented in (27) and (28) are modified to the scheme presented in (29) and (30).

$$\gamma_a[n] = \begin{cases} 1, \text{ if } \|\hat{x}_4[n] - k_1 \cdot \hat{x}_3[n]\| > \epsilon_a \ \wedge \ \|\hat{x}_5[n]\| > \epsilon_s, \\ 0, \text{ else} \end{cases} \tag{29}$$

$$\gamma_s[n] = \begin{cases} 1, \text{ if } \|\hat{x}_4[n] - k_1 \cdot \hat{x}_3[n]\| \le \epsilon_a \ \wedge \ \|\hat{x}_5[n]\| > \epsilon_s, \\ 0, \text{ else} \end{cases} \tag{30}$$

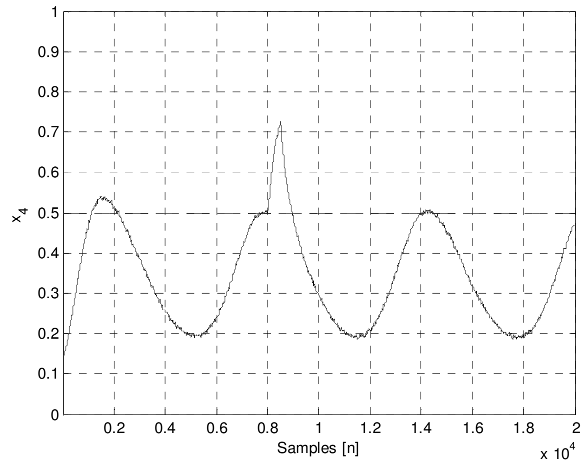

Fig. 4 Plot showing the converter actuator fault estimate.

Using the detection schemes presented in (29) and (30) the detection signals can be found for detecting and isolating the actuator and sensor faults in the converter. In which k_1 is found experimentally such that the fault is isolated and false detections are avoided.

The detection of the converter actuator fault can be seen in Fig. 5, the figure consists of three parts the upper shows the entire signal and the plot in the middle is a zoom on the beginning of the fault and lower plot is a zoom on the end of the fault. From this figure it can be seen that this fault is detected from sample 8002 to sample 8501. This means that the actuator fault is detected 2 samples later than its actual beginning and detects the end 1 sample later than its actual end.

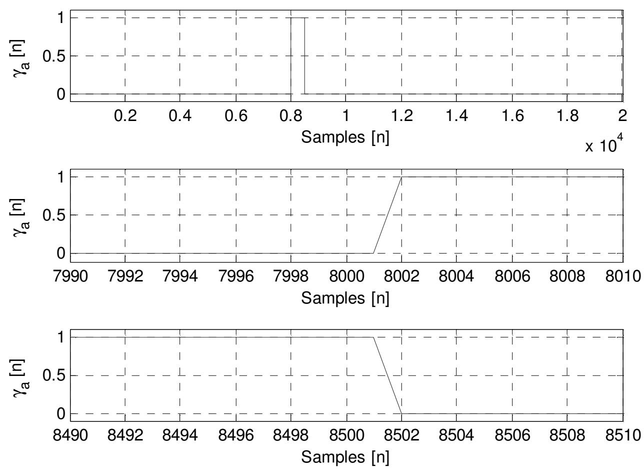

Fig. 5 Plot of the detection signal γ_a for the converter actuator fault, the middle and lower plot zoom on the beginning and end of the detection.

The detection signal of the converter measurement fault, $\gamma_s[n]$, can be seen in Fig. 6. This figure contains the same three subplots as in Fig. 5 are present. The detection and isolation of the converter sensor fault shows detection at sample 12002 to sample 12501. Again the beginning is detected 2 samples later, than its actual beginning, and the end one sample later.

Consequently it can concluded that this detection scheme based on estimation of the present faults using an unknown input observer can detect and isolate sensor and actuator faults in converter using system measurement on a wind turbine, even though that the wind speed is assumed to be entirely unknown.

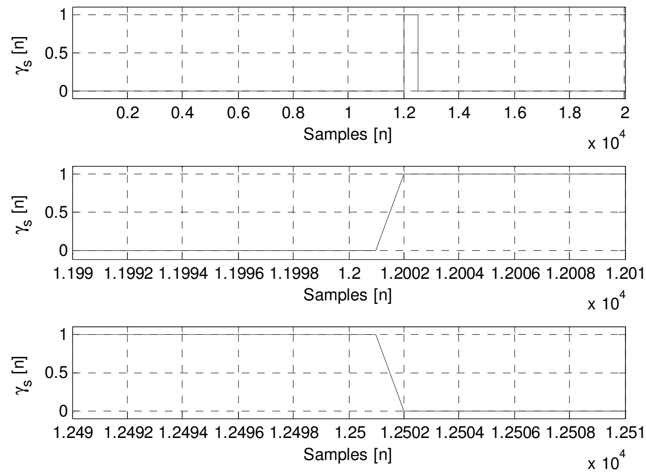

Fig. 6 Plot of the detection signal for converter measurement fault estimate,γ_s , the middle and lower plot shows the zoom on the beginning and end of the detection signal.

6. CONCLUSIONS

This paper deals with a problem of detecting sensor and actuator faults in a wind turbine converter. The detection is based on system view of the wind turbine where the converter is component with known input and measured output. In addition it is assumed that the wind speed is entirely unknown is, available measurements of these normally is not very reliable. An unknown input observer is proposed for estimating the converter sensor and actuator faults. Based on these fault estimates detection signals are formed for fault detection and isolation. Based on estimated signals and detection signals an actuator and a sensor fault is detected in data obtained form a detailed with turbine model. Both faults are detected 2 samples later than their beginning and the end is detected in both cases 1 sample later than the actual end of the fault.

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