Disturbance Compensation by Wind Speed Reconstruction based on a Takagi-Sugeno Wind Turbine Model

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Abstract. In this work, the nonlinear Takagi-Sugeno modelling method is utilised to set up an observer-based feed-forward control scheme for wind turbines, which can compensate for the influence of the disturbing wind variation on the rotational speed. The applied scheme leads to a reduced thrust force acting on the rotor.

1. Introduction
An economical operation of wind turbines (WT) requires load optimised components. One way to achieve this requirement is the development of forward-looking control algorithms. For one sort of these control algorithms, namely disturbance compensation by observer-based feed-forward control, a Takagi-Sugeno (TS) modelling approach according to [1] is presented in this work.

In order to extract a maximum energy yield and to avoid system overload, a power optimised and power restricted operation of a wind turbine - depending on the wind speed - is necessary. The power $P_R$ gained with the WT rotor depends on the rotor radius $R$ as well as on the air density $\rho$ and wind speed $v$.

$$P_R = \frac{1}{2} \cdot \rho \cdot v^3 \cdot \pi \cdot R^2 \cdot c_P(\lambda(v, \omega_R), \beta)$$

Furthermore the rotor power depends on the power coefficient $c_P(\lambda(v, \omega_R), \beta)$, resulting from the inflow condition at the rotor blade, i.e. the tip speed ratio $\lambda(v, \omega_R)$ and pitch angle $\beta$.

The inflow condition is influenced by the two control signals generator torque $T_G$ and pitch angle $\beta$, resulting in a changing WT drive train angular velocity and rotational speed $\dot{\theta}_R = \omega_R$ respectively.

Within the controller design the power coefficients for given design inflow conditions are taken from aero maps $c_P(\lambda, \beta)$. The design inflow conditions assume perfect inflow at each working point, resulting in $c_{P, opt}$ (for power optimisation) and $c_{P, res}$ (for power restriction). Within real WT operation the inflow conditions differ from these perfect design inflow conditions and cannot be determined: Though rotation speed $\omega_R$ and pitch angle $\beta$ can be measured exactly, a precise wind speed measurement for operational control is hardly feasible. Therefore WT are commonly operated by means of rotational speed control without taking the wind speed $v$ as
controller input into account - see [2] and [3].

Due to the rotor and drive train mass moment of inertia, the performance of the rotational speed control suffers from a significant time constants between wind speed variation (as disturbance signal $d$), rotational speed variation (as output signal $y$) and generator torque $T_G$ and pitch angle $\beta$ adaption (as control signal $u$). This may result in elevated rotational speed and loads.

To reduce the elevated rotational speed and loads, two controller concepts seem to be promising: Predictive wind speed measurement (e.g. by LiDAR systems) or observer-based control allow to reject, or at least compensate, the disturbance coming from the turbulent wind excitation. The difference between both approaches is the method of wind speed detection. Predictive measuring techniques detect the upwind wind field acting on the complete rotor swept area far in front of the WT. In observer-based wind speed reconstruction algorithms, the wind speed is calculated from measured control signals $u$ and output signals $y$ using a physical WT model. The Takagi-Sugeno modelling method, which was used in [4] for fault diagnosis and fault-tolerant control, is in this work also utilised for observer-based feedforward control, in order to compensate for the disturbance resulting from wind speed variations. For the compensation, the necessary power coefficient $c_P$ and the corresponding control signals respectively have to be determined from the reconstructed wind speed $\hat{v}$, the measured rotation speed $\omega_R$ and the actual collective pitch angle $\beta$.

In WT research projects, wind speed reconstruction methods have already been introduced, in most based on Kalman Filters [5, 6, 7, 8]. Using the Kalman-filter to estimate the wind speed $v$ from the reconstructed rotor torque $T_R$ requires linearised WT models, i.e. the WT dynamic is approximated linearly at several stationary points in the operation range.

In contrast to the Kalman Filter, the TS method, using the sector-nonlinearity approach (TS SNL), provides a nonlinear, global system description, with which the wind speed can be directly reconstructed in the complete operating range [9].

This paper is organised as follows: In Section 2, the WT model is presented, i.e. the deduction of the state-space model from the differential equation of motion and its transformation into a TS model. Afterwards, the design of the feedback controller and of the observer is explained in Section 3, followed by the description of the basic idea of a disturbance compensation in Section 4. In Section 5 the simulation model and the results achieved with the TS-observer based feedforward controller are presented. Finally, conclusion and outlook is given in Section 6.

2. Wind turbine model

2.1. Derivation & transformation of the differential equation of motion into a state-space model

In this work, a four degree of freedom (4-DOF) model of a WT, similar to the WT model in [10], is used. The degrees of freedom of the model are the horizontal displacements of rotor blade tip ($y_B$) and tower top ($y_T$) in wind direction and the rotor and generator rotational angles ($\theta_R$, $\theta_G$). The drivetrain is modelled by two rigid bodies joined with a torsionally elastic coupling, as described in [10, 11].

The equations of motion can be deduced using Lagrangian dynamics ([10], which yields four coupled differential equations given in [9].

The coupled differential equations are nonlinear, resulting from the excitation of the thrust force $F_T$ and rotor torque $T_R$, both depending nonlinearly from the wind speed $v$ and the nonlinear thrust coefficients $c_T$ ($\lambda (v, \omega_R), \beta$) and torque coefficient $c_Q$ ($\lambda (v, \omega_R), \beta$):
The coupled differential equations of motion are transformed into matrix form with the generalised coordinates \( q = [ y_T \ y_B \ \theta_R \ \theta_G ]^T \) and the mass matrix \( M \), damping matrix \( D \) and stiffness matrix \( K \)

\[
M \cdot \ddot{q} + D \cdot \dot{q} + K \cdot q = F(z) \quad \text{with} \quad F(z) = F_R(z) + F_G,
\]

given in [11] and the rotor and generator excitation \( F_R(z) \) and \( F_G \):

\[
F_R(z) = [ F_T(z) \ F_T(z) \ T_R(z) \ 0 ]^T
\]

\[
F_G(z) = [ 0 \ 0 \ 0 \ -T_G ]^T
\]

Rearranging (4) to

\[
\ddot{q} = M^{-1} \cdot D \cdot \dot{q} - M^{-1} \cdot K \cdot q + M^{-1} \cdot F_R(z) + M^{-1} \cdot F_G
\]

and introducing the state space vector \( x^{*}_{8x1} = [ q_{1x1} \ \dot{q}_{1x1} ]^T \) leads to the preliminary state-space model:

\[
\begin{bmatrix}
\dot{q}_{1x1} \\
\dot{q}_{1x1}
\end{bmatrix}_{x^{*}} =
\begin{bmatrix}
0_{4x4} \\
\left(-M^{-1} \cdot K\right)_{4x4} \\
\left(-M^{-1} \cdot D\right)_{4x4}
\end{bmatrix}_{x^{*}}
\begin{bmatrix}
q_{1x1} \\
\dot{q}_{1x1}
\end{bmatrix}_{x^{*}} +
\begin{bmatrix}
0_{4x1} \\
\left(-M^{-1} \cdot F_R(z)\right)_{4x1}
\end{bmatrix}_{x^{*}} +
\begin{bmatrix}
0_{4x1} \\
\left(-M^{-1} \cdot F_G\right)_{4x1}
\end{bmatrix}_{x^{*}}
\]

As the wind speed \( v \) shall be reconstructed from a state-space model like (8) and observers are only able to reconstruct states from the state vector, the state-space model is enlarged with an additional wind model, which is essentially taken from [12], yet without the white noise term and modified with a mean wind speed \( \bar{v} \) as described in [9]

\[
\dot{\bar{v}} = \frac{-1}{\tau_v} \cdot (v - \bar{v}),
\]

where \( \tau_v \) denotes the delay time constant. Furthermore, a first-order delay model for the pitch dynamics is added to the state-space model (8) for the controller design and advanced analysis:

\[
\dot{\beta} = \frac{1}{\tau_\beta} \cdot (\beta_d - \beta),
\]

where \( \tau_\beta \) denotes the delay time constant and \( \beta_d \) the desired pitch angle. Both modifications lead to an extension of the state vector from \( x^{*}_{8x1} \) to \( x_{10x1} \) and the following augmented state-space model:
\[
\begin{bmatrix}
\dot{q}_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
= \begin{bmatrix}
0_{4x4} & I_{4x4} & 0_{4x1} & 0_{4x1} \\
-M^{-1} \cdot K_{4x4} & -M^{-1} \cdot D_{4x4} & 0_{4x1} & 0_{4x1} \\
0_{1x4} & 0_{1x4} & -\frac{1}{\tau_\beta} & 0 \\
0_{1x4} & 0_{1x4} & 0 & -\frac{1}{\tau_c}
\end{bmatrix}
\cdot
\begin{bmatrix}
q_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
+ \begin{bmatrix}
0_{4x1} \\
0_{4x1} \\
0_{4x1} \\
0_{4x1}
\end{bmatrix}
\cdot
\begin{bmatrix}
\dot{u}
\end{bmatrix}
\]

Substituting \(F_R (z)\) with a matrix product of the state vector and combining \(F_G\) and \(u^*\) leads to:

\[
\begin{bmatrix}
\dot{q}_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
= \begin{bmatrix}
0_{4x4} & I_{4x4} & 0_{4x1} & 0_{4x1} \\
-M^{-1} \cdot K_{4x4} & -M^{-1} \cdot D_{4x4} & 0_{4x1} & 0_{4x1} \\
0_{1x4} & 0_{1x4} & -\frac{1}{\tau_\beta} & 0 \\
0_{1x4} & 0_{1x4} & 0 & -\frac{1}{\tau_c}
\end{bmatrix}
\cdot
\begin{bmatrix}
q_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
+ \begin{bmatrix}
0_{4x1} \\
0_{4x1} \\
0_{4x1} \\
0_{4x1}
\end{bmatrix}
\cdot
\begin{bmatrix}
\dot{u}^*
\end{bmatrix}
\]

Now the matrices \(A_{\text{lin}}\) and \(A_{\text{non-lin}} (z)\) are combined to the system matrix \(A (z)\), which contains the nonlinear terms from \(F (z)\). Furthermore, \(u^{**}\) is substituted with a matrix product of the constant input matrix \(B\) and the input vector \(u\):

\[
\begin{bmatrix}
\dot{q}_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
= \begin{bmatrix}
0_{4x4} & I_{4x4} & 0_{4x1} & 0_{4x1} \\
-M^{-1} \cdot K_{4x4} & -M^{-1} \cdot D_{4x4} & 0_{4x1} & 0_{4x1} \\
0_{1x4} & 0_{1x4} & -\frac{1}{\tau_\beta} & 0 \\
0_{1x4} & 0_{1x4} & 0 & -\frac{1}{\tau_c}
\end{bmatrix}
\cdot
\begin{bmatrix}
q_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
+ \begin{bmatrix}
0_{4x1} \\
0_{4x1} \\
0_{4x1} \\
0_{4x1}
\end{bmatrix}
\cdot
\begin{bmatrix}
\dot{u}
\end{bmatrix}
\]

\[
\begin{bmatrix}
\dot{q}_{4x1} \\
\dot{q}_{4x1} \\
\beta \\
\dot{v}
\end{bmatrix}
= \begin{bmatrix}
0_{4x1} \\
0_{4x1} \\
0_{4x1} \\
\frac{1}{\tau_G} \cdot \left(-M^{-1} \cdot F_G\right)
\end{bmatrix}
\begin{bmatrix}
\beta_d \\
\beta_d \\
\dot{v} \\
\dot{v}
\end{bmatrix}
\quad \text{and} \quad y = C \cdot x
\]

Usually, an explicit knowledge of the rotor and generator rotational angles \(\theta_R\) and \(\theta_G\) is not required. It is therefore advantageous to introduce the drive train torsional angle \(\theta_S\) as a combined state like described in [10], whereby the order of the state-space model is reduced.
2.2. Luenberger observer introduction
To reconstruct the unknown wind speed \( v \), a TS Luenberger observer (see Figure 1 b)) is used, which is a nonlinear extension of the classical linear Luenberger observer. The standard Luenberger observer reconstructs the states \( \hat{x} \) of a linear state-space model \( x = A \cdot x + B \cdot u \). The observer is a part of the feedback loop and described by the following differential equation:

\[
\dot{\hat{x}} = A \cdot \hat{x} + B \cdot u + L \cdot (y - \hat{y}) \quad \text{and} \quad \dot{\hat{y}} = C \cdot \hat{x}
\]  

(14)

An observer yields precise reconstruction results of unknown states \( \hat{x} \), if the difference \( e_x \) between the states \( x \) and the reconstructed states \( \hat{x} \) is minimised. As the states \( x \) are not measureable, but the output signals \( y \), the difference \( e_y \) of \( y \) and \( \hat{y} \) is used to evaluate the reconstruction results of the observer, because it is:

\[
e_y = y - \hat{y} = C \cdot x - C \cdot \hat{x} = C \cdot (x - \hat{x}) = C \cdot e_x
\]  

(15)

Therefore in the observer design in section 3.2 the difference of the output signal \( e_y \) is used instead of the difference of the states \( e_x \).

2.3. Transition of the equation of motion into a Takagi-Sugeno model
Before the Luenberger observer can be used, the nonlinear WT state-space model (13) first has to be transformed into a Takagi-Sugeno model (TS) [1]:

\[
\dot{x} = \sum_{i=1}^{2^{NL}} h_i(z) \cdot (A_i \cdot x + B \cdot u).
\]  

(16)

For the derivation of the TS model, which is conducted analogously to [9, 11], the so-called sector-nonlinearity approach (SNL) according to [13, 14] is used, where the nonlinearities are shifted into the membership functions \( h_i(z) \), so that the resulting \( 2^{NL} \) submodels \( (A_i \cdot x + B \cdot u) \) are linear (where \( NL \) represents the number of dissimilar nonlinearities in (13)). I.e. with the TS SNL approach the TS-model (16) is transfered into an identical representation of the nonlinear model\(^1\), as shown in the following.

According to the sector-nonlinearity approach, both nonlinearities of the WT state-space model (2) and (3) - hereinafter denoted with \( f_i(z) \) - are substituted with the sum of their weighted extreme values \( (\bar{f}_i \) and \( \bar{f}_i) \):

\[
f_1(z) = w_{11} \cdot \bar{f}_1 + w_{12} \cdot \bar{f}_1 \quad f_2(z) = w_{21} \cdot \bar{f}_1 + w_{22} \cdot \bar{f}_2,
\]  

(17)

where the so-called weighting functions \( w_{i,j}(z) \) are defined as follows

\[
w_{i,1}(z) = \frac{f_i(z) - \bar{f}_i}{\bar{f}_i - \bar{f}_i} \quad w_{i,2}(z) = \frac{\bar{f}_i - f_i(z)}{\bar{f}_i - \bar{f}_i}.
\]  

(18)

For \( f_i(z) = \bar{f}_i \) and \( f_i(z) = f_i \) the weighting functions are equal to 1 and 0 respectively. The sum of two weighting functions fulfills the convex sum condition \( w_{i,1}(z) + w_{i,2}(z) = 1 \). The product of two weighting functions \( w_{i,j}(z) \cdot w_{i,j}(z) = h_i(z) \) is defined as so-called membership function \( h_i(z) \). The term ”membership function” is derived from the systematic expansion of all \( A(z) \)

\(^1\) Note: A TS SNL model is a combination of global submodels. I.e. in contrast to the linearised submodels described in section 3.1 to approximate a nonlinear model with local submodels, the TS SNL submodels effect on the global operation range.
elements in (13) with a sum of weighting functions $w_{i,j}(z) + w_{i,j}(z)$. With this expansion the nonlinear system matrix $A(z)$ splits in a sum of linear subsystem matrix $A_i$, each subsystem matrix weighted by $h_i(z)$, as described in [9] for the illustrative example of a simple pendulum. The membership functions also fulfill the relation $\sum_{i=1}^{2^{NL}} h_i(z) = 1$.

The nonlinear model (13) is thus transformed into a sum of $2^{NL}$ weighted linear submodels, where the nonlinearity is shifted to the membership functions $h_i(z)$. Once the state-space model has been transformed into TS structure, the nonlinear TS Luenberger observer is obtained by adding the feedback terms $L_i \cdot (y - \hat{y})$:

$$ \dot{\hat{x}} = \sum_{i=1}^{2^{NL}} h_i(z) \cdot (A_i \cdot \hat{x} + B \cdot u + L_i \cdot (y - \hat{y})) \quad \text{with} \quad \hat{y} = C \cdot \hat{x}, \quad (19) $$

where the feedback matrices $L_i$ can be designed using for example linear matrix inequalities (LMI) techniques [14]. Note: In the TS observer model (19) each submodel consists of a feedback matrix $L_i$ corresponding to the system matrix $A_i$.

3. Feedback controller and observer design

3.1. Feedback controller design

As described in [4] the controller design is based on a reduced WT model consisting of two DOF: The rotational speed $\omega_R$ of a rigid drive train and the pitch angle $\beta$. The nonlinearities result from the rotor torque $T_R$ (3) and the pitch dynamics, i.e. the nonlinear relationship of pitch angle $\beta$ and power coefficient $c_P(\lambda, \beta)$. The nonlinear 2-DOF WT model is linearised at 25 working points covering the complete full load range. Subsequently, the linear submodels are weighted and combined to an approximated nonlinear TS model with linear triangular membership functions $h_i(\beta_i)$, also fulfilling the relation $\sum_{i=1}^{2^{NL}} h_i(\beta_i) = 1$ and each with its peak of $h_i(\beta_i) = 1$ at one of the 25 working points (see figures in [4]). In contrast to the exact TS model in section 2.3, the approximated TS model only yields an exact representation at the stationary points.

The controller design for the approximated TS model is conducted by means of linear LQR design for the local models and its global stability is shown with a Lyapunov approach [4].

3.2. Observer design

For the observer design a reduced WT model consisting of three DOF is used: The horizontal displacement of rotor blade tip $y_B$ and tower top $y_T$ as well as the rotational angle $\theta_R$ of a rigid drive train. For the output vector $y$, the following states are assumed to be measurable:

$$ y = \begin{bmatrix} y_T & y_B & \dot{y}_T & \dot{y}_B & \theta_R & \dot{\theta}_R & \beta \end{bmatrix}^T. $$

To design the observer, the feedback matrices $L_i$ in (19) have to be calculated. Therefor, several methods can be used [14], which all lead to LMI. In this work, the optimal LMI design method from [14] is used, which includes a stability check (by means of a Lyapunov approach) and the calculation of a linear quadratic cost functional [9]. Combining the Lyapunov inequality with the minimised linear quadratic functional $J$, this LMI can be solved using numeric algorithms and results in the feedback matrices $L_i$ as solution. With the calculated feedback matrices also the global stability of the system is proven due to the conditions of the Lyapunov approach.

$^2$ linear quadratic controller, based on a minimised linear quadratic cost functional $J$
4. Feedforward controller design

Once the controller and observer are designed, the feedforward controller can be developed. The objective of a feedforward controller $\text{FF}$ is the rejection or at least compensation of the disturbance $d$. In case of perfect modelling, the disturbance can be rejected completely as shown in the following and in the schematics in Figure 1.

\[ \text{PT} \xrightarrow{dy} = - (\text{FF} \xrightarrow{du_{\text{FF}}} \circ \text{PT} \xrightarrow{uy}) \Leftrightarrow \text{PT} \xrightarrow{dy} + (\text{FF} \xrightarrow{du_{\text{FF}}} \circ \text{PT} \xrightarrow{uy}) = 0 \]

(20)

With (20), the feedforward-transfer behaviour $\text{FF} \xrightarrow{du_{\text{FF}}}$ can be calculated from the inversion of the plant-transfer behaviour $\text{PT} \xrightarrow{uy}$.

\[ \text{FF} \xrightarrow{du_{\text{FF}}} = - \text{PT} \xrightarrow{dy} \circ \text{PT}^{-1} \xrightarrow{uy} \]

(21)

Since an analytical inversion is not possible in most cases, a graphic inversion method is used within this work, as described at the end of this Section.

Assuming perfect modelling of plant dynamics, actuator dynamics and measuring devices, the feedforward-control $\text{FF}$ rejects the disturbance $d$ completely and the feedback-controller is just responsible for command response. Regarding plant modelling, the TS SNL method provides a significant improvement compared to several other modelling methods, especially linear approximations. Regarding actuator modelling especially the pitch dynamics (10) is relevant. In this work the pitch dynamics as well as the measurement device dynamics are omitted to keep the model simple. So the feedback controller faces more than simple command response.

In this work the disturbance compensation with feedforward controller in the full load range (with power restriction to rated power) is examined. For the power restriction, the necessary power coefficient $c_P (\lambda (v, \omega_R), \beta)$ and the corresponding pitch angle $\beta_d (\dot{\theta})$ have to be determined in the feedforward controller, as explained in Section 1 and described in the following.
Once the wind speed is reconstructed, the power coefficient $c_P(\hat{v})$ in the full load range can be calculated from the ratio of rated rotor power $P_{R,r}$ to wind power $P_W(\hat{v})$ with the reconstructed wind speed $\hat{v}$, where $P_{R,r}$ is derived from the rated generator power $P_{G,r}$ by taking the drive train efficiency into account. The power coefficient $c_P$ can also be calculated from a nonlinear approximation of the aero maps $c_P(\lambda(v, \omega_R), \beta)$ with the variables $\lambda(\hat{v}, \omega_R)$ and $\beta$, like described in [11] for the example of the NREL 5MW reference WT. With the reconstructed wind speed $\hat{v}$, the measured rotational speed $\omega_R$ and the calculated power coefficient $c_P$ the necessary pitch angle $\beta_d$ can be determined by inverting the nonlinear approximation $c_P(\lambda(\hat{v}, \omega_R), \beta)$ to $\beta$. However the nonlinear approximation of the aero maps cannot be inverted analytically. Therefore the aero map is "‘inverted’" graphically by calculating the tip speed ratio $\lambda(\hat{v}, \omega_R)$ from the reconstructed wind speed $\hat{v}$ and measured rotational speed $\omega_R$. With $\lambda(\hat{v}, \omega_R)$ and the calculated power coefficient $c_P(\hat{v})$, the pitch angle $\beta$ is determined from the intersection of both values in the pre-tabulated aero map $c_P(\lambda(v, \omega_R), \beta)$. The pitch angle belonging to the characteristic curve cutted at the respective intersection is the desired pitch angle $\beta_d$.

5. Wind Turbine simulation with feedforward control

Using the derived WT state space model, the influence of a feedforward controller on the variations of the rotational speed and thrust force in full load range was examined in a simulation model developed in MATLAB/Simulink®. The model comprises the TS state-space models (13) and (19) extended by the wind speed model (9). For the WT specification, the data given in [15] were used to simulate the NREL 5MW reference WT, like described in [11]. In the Simulink model the aero maps, i.e. the thrust coefficient $c_T(\lambda, \beta)$ and torque coefficient $c_Q(\lambda, \beta)$, from which the power coefficient $c_P$ can be calculated, are approximated by nonlinear polynomial-exponential functions [11]. In this work only an illustrative gust load case in the full load range (at 18m/s mean, 16m/s minimum und 24m/s maximum wind speed) according to [16] is used to show the applicability of the TS observer based feedforward control.

As shown in Figure 4 (b), the reconstructed wind speed $\hat{v}$ (black line) matches pretty well the given wind speed $v$ (grey line), apart from a short delay time constant. In Figure 2, the times series of pitch angle $\beta$ and rotational speed $\omega_R$ with and without feedforward control are compared. In the subfigures, the influence of the feedforward controller is revealed: The feedforward controller adapts the pitch angle $\beta(FB + FF)$ (blue line in Figure 2 (a) Pitch angle $\beta$ comparison

(b) Rotational speed $\omega$ comparison

Figure 2. Pitch angle $\beta$ and rotational speed $\omega_R$ comparison (with and without FF)
2 (a)) faster and with higher gains to the massive variation of the wind speed.\(^3\) By contrast, the pitch angle adaption without feedforward control \(\beta (FB)\) (red line in Figure 2 (a)) lags according to the rotational speed control performance due to time constant resulting from the acceleration of the drive train.

Correspondingly, the rotational speed variation with feedforward control \(\omega_R (FB + FF)\) (blue line in Figure 2 (b)) is lower than without feedforward control \(\omega_R (FB)\) (red line in Figure 2(b)). Due to the higher gains for the pitch angle \(\beta (FB + FF)\), a pitch angle override occurs, also visible in the thrust force \(F_T\) and rotor torque \(T_R\) series in Figure 3.

![Rotor torque \(T_R\) comparison](image1)

![Thrust force \(F_T\) comparison](image2)

**Figure 3.** Rotor torque \(T_R\) and thrust force \(F_T\) comparison (with and without FF)

A pitch angle override does not so much affect the rotor torque \(T_R\), such that the maximum rotor torque \(T_R\) yield with a feedforward controller \(T_R (FB + FF)\) (blue line in Figure 3 (a)) is lower than without feedforward controller \(T_R (FB)\) (red line in Figure 3 (a)). However, an excess pitch angle leads to a significant negative effect on the maximum thrust force \(F_T\), as maximum \(F_T\) with feedforward controller \((F_T, \text{max} (FB + FF))\) (blue line in Figure 3 (b)) is higher than without feedforward controller \((F_T, \text{max} (FB))\) (red line in Figure 3 (b)). If the feedforward control signal is restricted to 80\%, than also the maximum thrust force \((F_T, \text{max} (FB + FF))\) with feedforward-controller (blue line in Figure 4 (a)) is lower than without feedforward controller \((F_T, \text{max} (FB))\).

6. Conclusion and outlook

As shown in the time-series for rotational speed and loads in Figures 2 to 4, the observer based feedforward control of the Takagi-Sugeno WT model leads to a reduction of the maximum rotational speed as well as the maximum rotor thrust force.

It is shown that the Takagi-Sugeno modelling method, already proven in manifold control engineering applications, can also be used for feedforward control as an alternative to other methods like the wind speed estimation with a Kalman Filter for linearised WT models. The Takagi-Sugeno modelling approach thus combines the features of nonlinear modelling (with the TS SNL approach), the ability to reconstruct all states of a state-space model by means of a TS observer and its manifold applicability in control engineering. In future work, a benchmark comparison between wind speed estimation with a Kalman Filter and a TS observer will be conducted.

\(^3\) The unsteady run of the pitch angle \(\beta (FB + FF)\) results from a low resolution of the aero maps \(c_P (\lambda, \beta)\).
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