Load reduction based on a stochastic disturbance observer for a 5 MW IPC wind turbine

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Abstract. Control and operation systems of wind turbines must primarily ensure the fully automatic operation of wind turbines in a constantly changing environment. Economic efficiency charges the control system to ensure that the highest possible efficiency is achieved and the mechanical loads caused by disturbances are minimized. The ability of an observer, in this case a Kalman filter (Kf), to estimate non-measurable states from a set of measurements using a model of the plant suggests the idea of extending the model of the plant by a model of the disturbance. Disturbance states thus can be reconstructed and an easy-to-determine quasi-disturbance-feedforward controller can be used to reject them. This method is called Disturbance-Accommodating Control (DAC). In this paper, Dryden’s turbulence model - which shapes a white noise signal via a form filter to meet spectrum conditions - and an inverse notch filter to model the rotational sampling effect are used for each blade, in contrary to the hitherto used deterministic disturbance models or the simple random walk models for stochastic turbulence. Measurement- and model-uncertainties are described as uncorrelated white noise. With this approach, the requirements of the Kf derivation are met and quantitative measures for the Kf process noise covariance matrix are available especially for the disturbance. The simplified tuning process and the high potential for load reduction are demonstrated for the NREL 5 MW Wind turbine. The reduction by a factor of 4.4 of the standard deviation of the flapwise root bending moment shows the high potential of this stochastic DAC approach. A parameter study to determine the influence of the turbulence spectrum bandwidth and to identify the dependency of the stochastic DAC approach on uncertainties of the process noise covariance matrix was performed. The study shows that the Kf is robust against a wide spectrum of parameter variations. Only if the time constant of the Dryden filter is significantly reduced, the performance is decreased.

1. Introduction

Advanced control algorithm become more important in modern wind turbines. Due to the increasing size of modern wind turbines, load reduction by active devices to increase the life time or to reduce the components weight is an important technology. Disturbance Accommodating Control (DAC) which utilizes the ability of observer to estimate non-measurable plant and disturbance states from a set of measurements using a model of the plant extended by a model of the disturbance is such an advanced control algorithm. The reconstructed states of the disturbance and an easy-to-determine quasi-disturbance-feedforward controller can then be used to reject the disturbances. The theory of disturbance observers is well developed and made its way into textbooks, e.g. [1] or [2]. In addition,
[3] and [4] provide a good overview on this topic. Balas was the first who used the DAC method for rejection of deterministic disturbances on a wind turbine [5]. Stol [6] examined Disturbance Tracking Control (DTC) for a two-bladed 600 kW turbine and used a step as disturbance waveform. The emphasis in [7] by Stol and Balas was to tune a DAC especially to handle periodic blade root loads. They used a step as disturbance model. Solutions for the quasi-disturbance-feedforward controller and solvability conditions for different control objectives within the DAC framework where discussed in [8]. These conditions encompass DAC controllers solved via the Moore-Penrose pseudoinverse, via the Kronecker product, or based on the inversion of the feed-through term. A combination of a 1P sinusoidal and a step waveform to model the wind disturbance are used in [8]. A comparable approach was used in [9] and an independent blade pitch controller design for a three-bladed turbine using DAC was discussed. The so far described approaches have in common that the considered disturbances and therefore the models are deterministic. Some approaches were tested in stochastic/turbulent environment where the used disturbance models are not derived for. In [10], the DAC method was adapted for stochastic disturbances, in this case Dryden’s turbulence model - which shapes a white noise signal via a form filter to meet spectrum conditions - and the potential for disturbance rejection was demonstrated within a nonlinear motor glider simulation. This approach is called Stochastic Disturbance Accommodation Control (SDAC) and was demonstrated for wind turbines e.g. in [11] and [12]. Both used a simple to implement random walk process, without special spectral properties, triggered by white noise, as disturbance model. Selvam et al. [13] propose the use of an identified filter model that has (approximately) the same spectrum as the wind signals. As such models are typically triggered by white noise sources as input, the boundary conditions for the Kf derivation are met. Nevertheless, for the SDAC design they used a simpler approach and modelled the stochastic wind disturbance as a random walk process.

In this paper, the Dryden’s turbulence model, which models the spectral properties of turbulence, and an inverse notch filter to model the rotational sampling effect are used for each blade, in contrary to the hitherto used deterministic disturbance models or the simple random walk models. Measurement noise, model-uncertainties, and not explicitly considered dynamics are described as uncorrelated white noise. With this disturbance modelling approach, the requirement of the Kf derivation [14] is met and quantitative measures for the hard to determine Kf tuning matrix, the process noise covariance matrix, are available especially for the disturbance. This enables a simplified Kf tuning. To demonstrate the potential for load reduction, simulations with a model of NREL’s (National Renewable Energy Laboratory) 5 MW wind turbine are performed. To determine the influence of the turbulence spectrum bandwidth and to identify the dependency of the SDAC approach on uncertainties of the process noise covariance matrix, a parameter study is performed.

2. Wind turbine description
As benchmark problem, the virtual 5 MW NREL wind turbine (see [15] for more details) has been chosen. A design summary of this reference wind turbine is given in table 1.

| Description                        | Value              |
|-----------------------------------|--------------------|
| Rated Power (MW)                  | 5.0                |
| Rotor diameter (m)                | 126.0              |
| Hub Height (m)                    | 90.0               |
| Rated Rotor speed (rpm)           | 12.1               |
| Cut-in, Rated, Cut-out speed (m/s)| 3.0, 11.4, 25.0    |

Table 1. NRELs 5 MW 3 bladed reference wind turbine design summary.
As variable-speed variable-pitch (vs-vp) wind turbine, the control objectives depend on the relation (either above or below) of the wind speed to the so-called rated wind speed (rated wind speed = 11.4 m/s). Below rated wind speed, the focus is to maximize the energy capture. This is done via generator torque control. Above rated wind speed, the focus is to prevent the turbine from excessive loads. The set point is controlled by collective blade pitching to keep the moment and the speed and therefore the power constant at rated power. Collective pitch control is good enough to control the set point. To reduce fatigue loads, the blades have to be pitched individually (IPC). An observer-based approach that uses IPC - in the control region above rated wind speed - is described in the next section.

3. Stochastic disturbance accommodating control

According to the "internal model principle", the potential for disturbance rejection is increased the more information is available on the character of the disturbance (turbulence). This principle is directly taken up by the observer-based SDAC. Additionally, this model based approach takes the ability of observer into account to estimate non-measurable states from a set of measurements. In the following paragraphs the used models for disturbance observation, as well as the determination of the quasi-disturbance-feedforward controller to reject them and the Kf tuning process are described.

3.1. Wind turbine model

3.1.1. Nonlinear model. NREL provides a nonlinear aeroelastic model of their 5 MW wind turbine [15] for their CAE (Computer-Aided Engineering) tool FAST (Fatigue Aerodynamics Structure and Turbulence) [16]. The nonlinear aeroelastic model is represented by the following equation:

$$M(q,u,t)\ddot{q} + f(q,\dot{q},u,d,t) = 0$$

(1)

Where $M$ is the mass matrix, $f$ is the nonlinear forcing function vector, $q$ is the vector of DOF, $\dot{q}$ and $\ddot{q}$ are the 1st respectively the 2nd time derivative of the DOF vector, $u$ is the vector of control inputs, $d$ is the vector of wind disturbances, and $t$ is time.

3.1.2. Linearization. The linearization of this model at a certain trim point ($wind\;speed\;V_w = 15 m/s$, $pitch\;angle\;\Theta_{trim} = 10.5^\circ$) can be done by FAST [16]. Due to the spatial and temporal resolution of the turbulence, each blade experiences its own fatigue loads. To reduce blade individual loads, each blade needs as minimum one control device to guarantee controllability and as minimum one measurement value to guarantee observability. For a good and broadband disturbance observation, it is reasonable to use measurements of signals where the disturbance has a direct impact to, like moments and forces (e.g. blade root bending moments) or translational and rotational accelerations (e.g. blade tip flap acceleration). This principle was the keynote of the determination of the state ($x_i$), output ($y_j$) and input ($u_k$) variables shown in Table 2 and Table 3.

| Variable | Description |
|----------|-------------|
| $x_1$    | 1st tower fore-aft bending mode DOF |
| $x_2$    | Variable speed generator DOF |
| $x_{3,4,5}$ | 1st flapwise bending-mode DOF of blade 1,2,3 |
| $x_6$    | 1st time derivative of 1st tower fore-aft bending mode DOF |
| $x_7$    | 1st time derivative of variable speed generator DOF |
| $x_{8,9,10}$ | 1st time derivative of 1st flapwise bending-mode DOF of blade 1,2,3 |
Table 3. Output and input variables

| Variable | Description |
|----------|-------------|
| $y_1$    | Rotational speed of the generator (GenSpeed) |
| $y_{2,3,4}$ | Blade 1,2,3 edgewise moment at the blade root (RootMxb1,2,3) |
| $y_{5,6,7}$ | Blade 1,2,3 flapwise moment at the blade root (RootMyb1,2,3) |
| $y_{8,9,10}$ | Blade 1,2,3 pitching moment at the blade root (RootMzb1,2,3) |
| $y_{11}$ | Side-to-side tower root bending moment (TwrBsMxt) |
| $y_{12}$ | Fore-aft tower root bending moment (TwrBsMyt) |
| $y_{13}$ | Tower yaw moment (TwrBsMzt) |
| $u_{1,2,3}$ | Blade 1,2,3 pitch command |
| $d$ | Horizontal wind speed disturbance input for the whole rotor |

Due to the nonlinear but periodic character of the wind turbine, the steady-state solution and therefore the linearized model is periodic - with a period time $T_p$ equal to the time of one rotor revolution. A possible way to overcome this problem for controller design is to average the model over a whole revolution, as described in [7]. In this paper, the equally-spaced matrices ($\Delta \Psi = 10^\circ$) are averaged over a whole revolution. This leads to the following linear wind turbine model (subscript WT):

$$\Delta x_{WT} = A_{WT} \Delta x_{WT} + B_{WT} \Delta u_{WT} + E_{WT} \Delta d_{WT}$$
$$\Delta y_{WT} = C_{WT} \Delta x_{WT} + D_{WT} \Delta u_{WT} + F_{WT} \Delta d_{WT}$$

The prefix $\Delta$ indicates that the linearized equations are just right in a small region around the trim point and will be neglected in the rest of the paper.

3.1.3. Extension of the linear model. For observability of blade individual disturbances, the above described linear model has to be modified. Until now, only one horizontal wind speed disturbance input $d_{WT}$ for the whole rotor exists. To extend the linear model for blade individual disturbance inputs, the disturbance input vector $E_{WT}$ and the disturbance feed-through vector $F_{WT}$ are transformed via the transformation matrix $T_{i1}$ and $T_{i2}$ to get blade individual disturbance inputs $[d_{WT,Blade1} \ d_{WT,Blade2} \ d_{WT,Blade3}]^T$:

$$E_{WT}^{i1} = E_{WT} T_{i1} \quad \text{with} \quad T_{i1}^T = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1/3 & 1/3 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/3 & 1/3 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/3 & 1/3 & 0 & 0 & 1 \end{bmatrix}$$

$$F_{WT}^{i1} = F_{WT} T_{i1} \quad \text{with} \quad T_{i1}^T = \begin{bmatrix} 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1/3 & 1/3 & 1/3 & 1/3 & 1/3 & 1/3 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}$$

3.2. Disturbance

3.2.1. Dryden Spectrum. Dryden’s turbulence model is a 1-dimensional approximation of real gust Power Spectral Density (PSD). Because of its simplicity, it is often used for aerospace applications. According to [17] the PSD for horizontal turbulence is:
The PSD characteristics depend on height, terrain roughness, and wind speed. For the reference wind speed \( V_w = 15 \, \text{m/s} \) as well as the hub height \( H = 90 \, \text{m} \), and moderate turbulence, the characteristic values of the Dryden spectrum are - according to [17] - in stable atmosphere:

\[
\sigma_{V_w} = 1 \, \text{m/s}, L = 90 \, \text{m}, T = 6 \, \text{s}
\]  

(6)

where \( \sigma_{V_w} \) is the standard deviation (turbulence strength), \( T = L/V_w \) is the characteristic time constant, and \( L \) is the characteristic wave length. To generate turbulence for simulation purpose with these PSD characteristics, zero mean Gaussian white noise \( r \) with a variance of 1 is shaped through a Dryden form filter \( \hat{F}_{V_w} \) [17]. For horizontal turbulence, the transfer function is given by (7). Because of the low-pass characteristic of the filter, high frequency components are attenuated.

\[
S_{V_w}(\omega) = F_{V_w}(j\omega)F_{V_w}(-j\omega) = \hat{F}_{V_w} = \frac{\sigma_{V_w} \sqrt{2T}}{1 + Ts}
\]  

(7)

To model uncorrelated turbulence individually for each of the blades, three independent Dryden filter (subscript Dry) are needed and the seeds of the white noise sources have to be different \( r_i \quad i = 1,2,3 \). Therefore, the linear model is as follows:

\[
\begin{align*}
\ddot{x}_{\text{Dry}} &= A_{\text{Dry}} \dot{x}_{\text{Dry}} + B_{\text{Dry}} \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} \\
\dot{y}_{\text{Dry}} &= C_{\text{Dry}} \dot{x}_{\text{Dry}} \\
A_{\text{Dry}} &= \begin{bmatrix} -1/T & 0 & 0 \\ 0 & -1/T & 0 \\ 0 & 0 & -1/T \end{bmatrix} ; B_{\text{Dry}} = \begin{bmatrix} \sigma_{V_w} \sqrt{1/T} & 0 & 0 \\ 0 & \sigma_{V_w} \sqrt{1/T} & 0 \\ 0 & 0 & \sigma_{V_w} \sqrt{1/T} \end{bmatrix} ; C_{\text{Dry}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\end{align*}
\]  

(8)

3.2.2. Rotational sampling. Usually eddies affect only parts of the rotor but are seen several times by the blades. This "rotational sampling" or "eddy slicing" transforms the wind spectrum seen by the blade to a lumping at the rotor frequency \( \omega_{rot} \) and multiples of this frequency. This effect is modelled with inverted notch filters. A reasonable expression for this is:

\[
\begin{align*}
\ddot{x}_{\text{rot}} &= A_{\text{rot}} \dot{x}_{\text{rot}} + B_{\text{rot}} u_{\text{rot}} \\
\dot{y}_{\text{rot}} &= C_{\text{rot}} \dot{x}_{\text{rot}} + D_{\text{rot}} u_{\text{rot}}
\end{align*}
\]  

(9)
\begin{equation}
A_{\text{rot}} = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 & 0 \\
-\omega_p^2 & -2D\omega_p^2 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & -\omega_p^2 & -2D\omega_p^2 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & -\omega_p^2 & -2D\omega_p^2
\end{bmatrix};
B_{\text{rot}} = \begin{bmatrix}
0 & 0 & 0 \\
1 & 0 & 0 \\
0 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 0 \\
0 & 0 & 1
\end{bmatrix};
C_{\text{rot}} = \begin{bmatrix}
0 & 2\omega_p(1-D) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 2\omega_p(1-D) & 0 \\
0 & 0 & 0 & 0 & 0 & 2\omega_p(1-D)
\end{bmatrix};
D_{\text{rot}} = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}.
\end{equation}

\(\omega_p = 1.27 \text{ rad/s}\) is the rotational speed, which should be constant in the region above rated wind speed and \(D\) is the damping ratio of the inverted notch filter which was chosen to \(D=0.05\) to form the typical spikes in the spectrum. Inverted notch filters to model high frequency rotational sampling effects, higher than \(\omega_p\), are neglected.

3.2.3. Effective wind model. To model the effective wind speed for each blade, the Dryden form filter and the inverted notch filter are a series connection, as described by the following equations:

\begin{equation}
\begin{bmatrix}
\dot{\bar{x}}_{\text{rot}} \\
\dot{\bar{x}}_{\text{Dry}} \\
\dot{\bar{x}}_{\text{rot}}
\end{bmatrix} = \begin{bmatrix}
A_{\text{rot}} & B_{\text{rot}} & C_{\text{rot}} \\
0 & A_{\text{Dry}} & 0 \\
0 & 0 & A_{\text{rot}}
\end{bmatrix} \begin{bmatrix}
\bar{x}_{\text{rot}} \\
\bar{x}_{\text{Dry}} \\
\bar{x}_{\text{rot}}
\end{bmatrix} + \begin{bmatrix}
0 \\
0 \\
0
\end{bmatrix} \begin{bmatrix}
\gamma_1 \\
\gamma_2 \\
\gamma_3
\end{bmatrix}
\end{equation}

\(y_{\text{dist}} = \begin{bmatrix}
C_{\text{rot}} \\
0 \\
\bar{y}_{\text{rot}}
\end{bmatrix} \begin{bmatrix}
\bar{x}_{\text{rot}} \\
\bar{x}_{\text{Dry}} \\
\bar{x}_{\text{rot}}
\end{bmatrix} \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}.

This lead to the following effective wind speed spectrum (figure 1) experienced by each blade.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Spectrum of the effective wind speed per blade and its components}
\end{figure}

3.2.4. Process and measurement noise. The noises are assumed to be zero mean Gaussian white noise with variances \(\xi\) and \(\zeta\) for the process noise and measurement noise, respectively. In this paper, uncertainties and not included dynamics are modelled as process noise. The process noise \(\xi\) was
chosen such that the effects on the output variables are proximately 20-30% as they are for moderate turbulence as mentioned in section 3.2.1.

\[
\tilde{\xi}_{WT} = \begin{bmatrix}
0.0125^2 & 0.0125^2 & 0.25^2 & 0.25^2 & 0.0125^2 & 0.25^2 & 0.25^2 & 0.25^2
\end{bmatrix}^T
\]

\[
\tilde{\xi}_{rot} = \begin{bmatrix}
0.1^2 & 0.1^2 & 0.1^2 & 0.1^2 & 0.1^2
\end{bmatrix}^T
\]

\[
\tilde{\xi} = \begin{bmatrix}
\tilde{\xi}_{WT} \\
\tilde{\xi}_{rot}
\end{bmatrix}
\]

(11)

\[
\tilde{\xi} = \begin{bmatrix}(1rpm)^2 & (10kNm)^2 & (10kNm)^2 & (10kNm)^2 & (10kNm)^2 & (10kNm)^2 & (10kNm)^2 & (10kNm)^2 \ldots
\end{bmatrix}^T
\]

(12)

### 3.3. Quasi-disturbance-feedforward control

Using state feedback according to

\[
\begin{bmatrix}
\chi_{WT} \\
\chi_{rot}
\end{bmatrix} = \begin{bmatrix}
A_{WT} & -B_{WT} & R_{WT} \\
0 & A_{rot} & C_{rot}
\end{bmatrix} \begin{bmatrix}
\chi_{WT} \\
\chi_{rot}
\end{bmatrix} + \begin{bmatrix}
B_{WT} \\
0
\end{bmatrix} u_{dist} + \begin{bmatrix}
\text{diag} \left( \tilde{\xi} \right)
\end{bmatrix} \xi.
\]

(13)

All uncorrelated white noise sources, e.g. for turbulence or for process noise are expressed by the row vector \( r \). The influence of the disturbance states \( \chi_{dist} \) on the wind turbine states can be neglected if the quasi-disturbance-feedforward controller \( N \) is selected to:

\[
N = B_{WT}^{+\ast} \begin{bmatrix}
E_{WT}^T & C_{dist}
\end{bmatrix} \Rightarrow 0 \approx \left( \begin{bmatrix}
B_{WT}^T & B_{WT}^T \\
E_{WT}^T & E_{WT}^T
\end{bmatrix} \right)^{-1} \begin{bmatrix}
B_{WT}^T \\
E_{WT}^T
\end{bmatrix} C_{dist}.
\]

(14)

If \( B_{WT} \) cannot be inverted, as in this case, the Moore-Penrose pseudoinverse \( B_{WT}^+ \) is the best approximation by means of least squares.

### 3.4. Kalman filter

The initial point of the Kf derivation \[14\] is a linear system that is influenced by uncorrelated zero mean Gaussian white process and measurement noise. Due to the disturbance modelling via the Dryden form filter, this requirement of the Kf derivation is met. By a prediction with subsequent correction, the state vector \( \hat{x} = \begin{bmatrix}
\chi_{WT} \\
\chi_{dist}
\end{bmatrix} \) is estimated based on measurements \( \chi_{WT} \), in a way that the estimated error covariance matrix \( P_k \) becomes minimal. The estimated error covariance matrix is defined as \( P_k = E \left( \begin{bmatrix}
\chi_k - \hat{\chi}_k \\
\hat{\chi}_k - \hat{\chi}_k - 1
\end{bmatrix} \right) \), where \( E \) denotes the expectation operator and \( \hat{\chi} \) the estimated state vector. The notation indicates the point in time (subscriber) while the superscript indicates the processing of the set of measurements as follows:

- (…) before the measurement is processed (a priori)
- (…+1) after the processing of the measurement (a posteriori).

Where only one value is calculated for a time step, the superscript is dropped. For this linear, sequential and recursive algorithm the continuous model was, via zero order hold, with the sampling time \( \Delta t = 0.1s \), discretized (subscriber disc).
\[ x_k = A_{\text{dis}} x_{k-1} + B_{\text{dis}} u_k \]
\[ y_k = C_{\text{dis}} x_k + D_{\text{dis}} u_k \]  
(15)

The two phases are described as follows:
\[ \hat{x}_k = A_{\text{dis}}\hat{x}_{k-1} + B_{\text{dis}} u_k \quad \text{with} \quad \hat{x}_0 = 0 \]
Prediction:
\[ \hat{y}_k = C_{\text{dis}}\hat{x}_k + D_{\text{dis}} u_k \]
\[ P_k = A_{\text{dis}} P_k A^{\text{T}}_{\text{dis}} + Q_k \quad \text{with} \quad P_0 = I \]
\[ K_k = P_k C_{\text{dis}}^T (U + C_{\text{dis}} P_k C_{\text{dis}}^T)^{-1} \]
Correction:
\[ \hat{x}_k = (I - K_k C_{\text{dis}}) \hat{x}_k + K_k \hat{y}_k \]
\[ P_k = (I - K_k C_{\text{dis}}) P_k \]  
(17)

The discrete process noise covariance matrix \( Q = \begin{bmatrix} \text{diag} \left( \xi B_{\text{Dry}} \right) \Delta t \end{bmatrix} \), which is, beside the measurement noise covariance matrix \( U = \text{diag} \left( \zeta \right) \), a tuning matrix for the \( Kf \), is hard to determine in the real world. The above described disturbance modelling enables a simplified approach to determine some of the values of \( Q \) because of a good knowledge of the turbulence characteristics via \( B_{\text{Dry}} \).

4. Results
For simulation purpose, the exact process and measurement noise covariance matrices as well as the model of the turbine and the disturbance are known. In reality this will never happen. To examine the influence of the process noise covariance matrix and to determine the influence of the time constant of the Dryden filter, these parameters varied within the \( Kf \) but remained constant in the simulation. The total simulation time is 6000 s with a stepsize of \( \Delta t = 0.1 \) s.

4.1. Disturbance rejection
As representative results, the flapwise root bending moment of blade 1 without control but with estimation is shown in figure 2. The Pearson-correlation coefficient, which is a measure of the linear relationship between two variables, is 1 and therefore as high as possible. To show the potential of SDAC the flapwise root bending moment of blade 1 without control (standard deviation of 1956 kNm) is compared to the case with control (standard deviation of 442.83 kNm) and is therefore 4.4-times higher, see figure 3.

![Figure 2. Flapwise root bending moment of blade 1 without SDAC](image-url)
The provoking but still acceptable pitch activity of all three blades as well as the frequency distribution of the pitch activity of blade one is shown.

4.2. Parameter studies

As mentioned above, the influence of uncertainties of the process noise covariance matrix as well as the influence of the Dryden filter time constant and therefore the bandwidth will be discussed in this paragraph with regard to the correlation coefficient and the standard deviation $\sigma$. For simulation purpose, the simulation model, the process noise covariance matrix, and the Dryden filter time constant remain unchanged. The process noise covariance matrix and the time constant are varied according to table 4 (Q-factor; T-factor), in the design process, and the used linear model of the KF and therefore for the controller, because in reality they are never exactly known.

### Table 4. Results parameter studies

| Signal name | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 |
|-------------|--------|--------|--------|--------|--------|--------|
|             | $\sigma$ | cor. coef. | $\sigma$ | cor. coef. | $\sigma$ | cor. coef. | $\sigma$ | cor. coef. | $\sigma$ | cor. coef. | $\sigma$ | cor. coef. |
| GenSpeed (rpm) | 24,00 0,99 | 12,24 0,95 | 12,14 0,95 | 12,47 0,95 | 12,20 0,95 | 12,60 0,95 |
| RootMxb1 (kNm) | 316,00 0,99 | 151,50 0,93 | 158,64 0,93 | 152,50 0,93 | 152,51 0,94 | 147,39 0,92 |
| RootMyb1 (kNm) | 1,956,41 1,00 | 442,83 0,93 | 480,65 0,93 | 467,71 0,93 | 437,29 0,93 | 526,35 0,94 |
| RootMzb1 (kNm) | 28,43 0,93 | 24,16 0,91 | 21,12 0,90 | 24,29 0,90 | 21,14 0,90 | 24,31 0,90 |
| TwrBsMxt (kNm) | 1,204,60 0,99 | 650,66 0,98 | 644,85 0,98 | 664,94 0,98 | 646,69 0,98 | 683,87 0,98 |
| TwrBsMyt (kNm) | 16.332,75 1,00 | 6.243,88 0,99 | 6.236,31 0,99 | 6.478,10 0,99 | 6.217,91 0,99 | 6.490,17 0,99 |
| TwrBsMzt (kNm) | 1.611,51 1,00 | 915,51 1,00 | 907,28 1,00 | 936,08 1,00 | 906,55 1,00 | 987,53 1,00 |

By comparison of case 1 and 2, the standard deviations of the signals are reduced by roughly 40-75%. These results show the high potential of SDAC. A closer look on the correlation coefficients and the standard deviations (case 2-6) show that the estimation by the Kf do not have a significant dependency on uncertainties of the process noise covariance matrix as well as variations of the time constant of the Dryden filter. Only for case 6 - where the time constant is 10 times smaller - the flapwise root bending moment, which is directly influenced by the spectrum, is significantly increased and therefore the Kf performance is slightly decreased. The reason is that especially the low frequent part of the spectrum - which is the high energy part of the turbulence - is damped in the Kf estimation due to the small T.
5. Conclusion
In this paper a SDAC, to reduce loads caused by turbulence, with Dryden’s turbulence model and an inverse notch filter to model the rotational sampling effect individually for each blade was developed. Dryden’s model directly takes frequency properties of the turbulence into account in contrary to the hitherto used deterministic disturbance models or the simple random walk models. The SDAC works well which is shown by the reduction of the standard deviation of the flapwise root bending moment of blade 1. The estimations by the Kf are good and shows no significant dependency on uncertainties of the process noise covariance matrix as well as variations of the time constant. If the time constant is underestimated during the design process no problems are caused in the simulation study. If it is overestimated, the performance is slightly decreased. The robustness and performance of the SDAC will be proven in a nonlinear simulation environment with a 3-dimensional turbulence field and a detailed actuator model.

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