Revisiting disturbance accommodating control for wind turbines

Michael Sinner and Lucy Y. Pao
Department of Electrical, Computer, and Energy Engineering, University of Colorado, Boulder, CO 80309, USA.
E-mail: michael.sinner@colorado.edu, pao@colorado.edu

Abstract. Disturbance accommodating control has received considerable interest in the wind turbine research community for its ability to explicitly account for disturbances in the incoming wind field. Early work was based around estimating the disturbance from feedback information, while more recent research into disturbance accommodating control (as well as other feedforward control laws) has considered disturbance measurements produced by lidar. This work compares the two methods (estimating and measuring the disturbance) while keeping all other aspects of the controller the same. By doing so, we shed light on the performance improvements that can be attained using preview disturbance measurements of the wind.

1. Introduction
Disturbance accommodating control (DAC) is a long-standing method of multivariable control developed in the 1970s and 1980s to make use of known disturbance structures. Several competing methods exist, but the version that appears most commonly, at least for wind turbine control applications, is the observer-based disturbance-minimization mode [8]. In this mode, an existing feedback control law is augmented with a term that minimizes the effect of an estimated disturbance, the latter being generated by a state observer.

DAC was investigated for wind turbine control in the late 1990s and 2000s with studies focused on the observer-based DAC methodology [12, 1, 23, 5, 27, 28, 14, 29]. The disturbance-minimization mode of DAC is the most commonly used in the literature [23, 5, 27, 28, 14], although several other techniques have been presented [12, 1, 29]. More recently, Wang et al. [26, 25] have considered DAC for wind turbine control using extensions to the disturbance-minimization mode with the aim of addressing some of its downsides.

Interest in DAC for wind turbines has been renewed recently [24, 15], along with other feedforward control methods [18], since lidars were shown to produce useful preview disturbance information about the incoming wind [6]. Lidars are capable of providing characteristic measurements of the oncoming wind by scanning at a location some distance upstream of the turbine for use in feedforward control [7]. Lidar preview measurements are only coherent with the turbine-incident wind field up to a point [19], but can be filtered to produce a good estimate of the low-frequency disturbance [22].

The authors have interest in using feedforward DAC as a point of reference for other advanced feedforward control methods, but prior to doing so, aim to provide DAC (both observer-based and feedforward) a thorough treatment. While there have been several studies of observer-
based and feedforward DAC for wind turbines, to our knowledge, no study has compared the two techniques to each other. With this paper, we aim to fill this gap, and in doing so provide further justification for using feedforward disturbance measurements.

In this work, we will not consider retuning the feedback controller after the feedforward action has been added—rather, we will assume that the feedback control law has already been designed and should not be altered. For work that considers retuning after the addition of a feedforward controller, refer to Haizmann et al. [4]. We also point out that a similar study to the present work was carried out recently by Khaniki et al. [13], where observer-based DAC was compared to a nonlinear feedforward control law based on a static curve for the appropriate blade pitch angle [17]. Our study differs by considering various formulations for DAC and looking at both idealized and realistic cases for feedforward DAC.

This paper is organized as follows. Section 2 briefly overviews standard wind turbine controls. Section 3 presents the disturbance accommodating control technique, discusses differences based on whether or not a preview measurement is available, and applies DAC to wind turbines. Sections 4 and 5 present our testing methodology and results, respectively, before Section 6 concludes this paper.

2. Background on wind turbine control

Standard wind turbine controllers utilize generator torque and blade pitch actuation. Generally, operation is split into two regions: below-rated wind speed, or Region II, operation, where the blade pitch angle is held constant and the generator torque is varied to extract maximum power from the wind; and above-rated wind speed, or Region III, operation, where the winds are too high to continue with maximum power extraction and steps are taken to mitigate structural loading on the turbine components. In the latter, the blades are pitched actively to regulate the rotor speed and produce steady ‘rated’ power, which avoids excessive loading of the turbine drive-train, blades, and tower, while generator torque plays a lesser role. For more information, see Pao & Johnson [16].

Benefits from DAC for wind turbines have mainly been reported in above-rated winds, where DAC is applied to blade pitch control to assist in rotor speed regulation and load mitigation [23, 5, 14, 27]. We therefore consider only above-rated operation in this study.

3. Disturbance accommodating control

Disturbance accommodating control is generally formulated around a state-space plant model. In the present work we will focus on a discrete-time plant

\[
\begin{align*}
    x(k + 1) &= Ax(k) + Bu(k) + B_d d(k) \\
    y(k) &= C x(k) + D u(k) + D_d d(k)
\end{align*}
\]

where \( x \in \mathbb{R}^{n_x} \), \( u \in \mathbb{R}^{n_u} \), \( d \in \mathbb{R}^{n_d} \), and \( y \in \mathbb{R}^{n_y} \) are the system state, control input, disturbance (or exogenous) input, and measured output, respectively; and \( A \), \( B \), \( B_d \), \( C \), \( D \), and \( D_d \) are the discrete-time system, input, disturbance input, output, feedthrough, and disturbance feedthrough matrices.

In the commonly-used disturbance-minimization mode of DAC, hereafter referred to simply as DAC, the control input \( u \) is constructed as the sum of two terms, i.e.

\[
    u = u_1 + u_2.
\]

\( u_1 \) is a traditional feedback term that is used to perform the main control task such as stabilization, regulation, or reference tracking, which is assumed to have been already designed. \( u_2 \) is a term that is dedicated to minimizing the impact of the disturbance \( d \) on the state \( x \).
Substituting (2) into (1a), we have system dynamics

\[ x(k+1) = Ax(k) + Bu_1(k) + Bu_2(k) + B_d d(k). \]  

(3)

Assuming that \( u_1 \) has been designed to drive the state to zero in the case of zero disturbances \((d \equiv 0)\), the DAC control term \( u_2 \) is designed according to

\[ u_2 = \text{argmin}_\nu (||Bu + B_d d||_{Q_{DAC}}) \]  

where \( || \cdot ||_{Q_{DAC}} \) is the \( Q_{DAC} \)-weighted 2-norm (i.e., \( ||v||_{Q_{DAC}} = \sqrt{v^\top Q_{DAC}v} \)). Most commonly, \( Q_{DAC} \) is chosen as the identity and \( u_2 \) minimizes the standard 2-norm in (4). This is the choice for \( Q_{DAC} \) that we use in this work. In this case (and assuming that \( n_u \leq n_x \) for uniqueness), the disturbance-minimizing control law is

\[ u_2 = -B^\top B_d \]  

(5)

where \( B^\top = (B^\top B)^{-1} B^\top \) is the left Moore-Penrose pseudo-inverse. To ensure that \( u_2 \neq 0 \), it is necessary that the intersection of the range spaces (column spaces) of \( B \) and \( B_d \) is non-empty. This method cannot handle a pitch actuator model (since the \( \mathcal{R}(B) \cap \mathcal{R}(B_d) = \emptyset \) in this case) nor guarantee complete disturbance rejection at the output unless there exists a \( u_2 \) such that \( Bu_2 = B_d d \forall d \) [25]; however, we choose to use a simple DAC method that has provided reasonable results in rotor speed regulation [27, 14] and load mitigation [5, 23] in the literature.

### 3.1. Observer-based disturbance accommodating control

In most DAC applications the disturbance \( d \) is unknown and must be estimated online. However, a linear model for the general wave-form structure of \( d \) is assumed to be known [8]. We therefore model \( d \) as the output of an uncontrolled state-space system

\[ x_d(k+1) = A_d x_d(k) \]  

(6a)

\[ d(k) = C_d x_d(k) \]  

(6b)

with known dynamics \((A_d, C_d)\) but unknown initial condition \( x_d(0) \in \mathbb{R}^{n_x} \), and design an observer around the disturbance model (6) to produce a disturbance estimate \( \hat{d}(k) \).

To do this, we create an augmented system with state \( x'(k) \triangleq [x(k)^\top x_d(k)^\top]^\top \) and dynamics (combining (1) and (6))

\[ x'(k+1) = A' x'(k) + B' u(k) \]  

(7a)

\[ y(k) = C' x'(k) + Du(k) \]  

(7b)

where

\[ A' \triangleq \begin{bmatrix} A & B_d C_d \\ 0 & A_d \end{bmatrix}, \quad B' \triangleq \begin{bmatrix} B \\ 0 \end{bmatrix}, \quad \text{and} \quad C' \triangleq \begin{bmatrix} C & D_d C_d \end{bmatrix}. \]

Under the condition that \((A', C')\) is observable [3], we can then design an observer gain \( L' \in \mathbb{R}^{(n_x+n_z)_d \times n_y} \) (using, for example, a Kalman filter or pole placement method) and implement the observer

\[ \hat{x}'(k+1) = A' \hat{x}'(k) + B' u(k) + L' (y(k) - C' \hat{x}'(k) - D u(k)), \]

where \( y(k) \) is the measured output of the physical system at time step \( k \). The observability condition means that both the plant state \( x \) and disturbance state \( x_d \) can be reconstructed from a history of output measurements \( y \) and control inputs \( u \), and depends strongly on the disturbance model chosen as well as the properties of the plant. However, a necessary condition for the augmented system (7) to be observable is that the plant (1) is observable—see Appendix for details. \( \hat{x}'(k) \) is then broken down into its constituents \( \hat{x}(k) \), which may be used for the feedback control \( u_1 \), and \( \hat{x}_d(k) \), from which \( \hat{d}(k) = C_d \hat{x}_d(k) \) is used to replace \( d(k) \) in (4) and (5) (Figure 1a).
3.2. Adding disturbance measurements

On the other hand, if a direct measurement of $d(k)$ is available online, there is no need to use the disturbance estimator described above. In this case, the DAC control law (5) can be applied directly. Since this case (preview measurement of the disturbance) is less common, we refer to it here as feedforward disturbance accommodating control. In doing so, we stress that observer-based DAC is not a true feedforward law, since it still relies solely on feedback of the measured plant output $y$. The feedforward DAC configuration is represented in Figure 1b.

3.3. Wind turbine application

For wind turbine applications, a lidar is used to sample the wind field upstream of the turbine and (after filtering) produce a measurement of $d$. In our case, we consider $d$ to be the (scalar) rotor-averaged wind velocity perpendicular to the rotor plane.

For this study, we model the rotor rotational and tower fore-aft bending degrees of freedom, so that we can focus on improving rotor speed regulation without increasing tower loading. Thus, $x = \begin{bmatrix} \omega_{\text{rot}} & x_T & \dot{x}_T \end{bmatrix}^T$ where $\omega_{\text{rot}}$, $x_T$, and $\dot{x}_T$ are the rotor speed, tower-top position, and tower-top velocity (in the fore-aft direction), respectively. We consider the measured output $y = \begin{bmatrix} \omega_{\text{gen}} & \ddot{x}_T \end{bmatrix}$, i.e. the generator speed and tower-top fore-aft acceleration. We use a simple constant disturbance model $(A_d, C_d) = (1, 1)$ for observer-based DAC.

The majority of the wind turbine DAC literature focuses on blade pitch control in above-rated operation, where promising results are obtained [5, 14, 15, 25]. We therefore consider $u = \beta$, the collective blade pitch angle. Based on this, we generate a discrete-time linear-time invariant model (1) of the wind turbine by linearizing a FAST nonlinear turbine model [11] at a steady above-rated wind condition. Because we have linearized the wind turbine about a nominal operating point $(x_0, y_0, u_0)$, $x$, $y$, and $u$ in model (1) represent deviations from nominal operation.

4. Test scenario

We carry out tests on the NREL 5MW reference turbine [10] implemented in FAST [11], embedded in a Simulink environment for ease of controller design. Each controller (see Section 4.3) is tested using six turbulent wind fields with mean wind speed 18 m/s, well into above-rated operation for the NREL 5MW, that are constructed using TurbSim [9] with class B turbulence.
4.1. Lidar simulator

Accurate simulation of the measured disturbance signal $d_{\text{meas}}$ is critical to this study. In particular, the wind evolves between the lidar measurement location and the turbine. To account for this, we generate decorrelated upstream wind fields based on Bossanyi & Hassan [2] that we sample to generate lidar measurements.

We also simulate the sampling behavior of the lidar. We include the effects of sequential sampling, probe volume averaging, and line-of-sight limitations for a continuous-wave lidar, as detailed in Simley et al. [20] and sketched in Figure 2. The focus distance of the lidar is set to be one rotor diameter upstream of the turbine. Figure 3 provides an example output from the lidar simulator (denoted Feedforward, see Section 4.3).

Although we keep this section brief, simulating the lidar is crucial and we strongly recommend that researchers follow the literature on lidar simulation [2, 20, among others] when investigating lidar-based feedforward control.

Figure 2: Representation of lidar behavior for a single measurement in the sequential scan pattern. The color strength along the lidar beam represents probe-volume averaging, whereas the cone angle $\theta$ indicates line-of-sight limitations.

Figure 3: Example disturbance estimates. The gray line represents the hub-height incident wind.

4.2. Measurement noise and Kalman filter tuning

The performance of observer-based DAC depends heavily on the quality of the wind speed estimate [13]. Most DAC studies either explicitly [12, 23] or implicitly ignore the influence of measurement noise in $y$ when designing the observer gain $L'$ and simulating the system response. In an effort to simulate an accelerometer, we add white Gaussian noise to the tower-top acceleration measurement produced by FAST with a standard deviation of approximately 5% of the peak accelerations observed in simulation. On the other hand, we assume that the generator speed measurement contains very little noise, and simply use the true generator speed (as is used by the NREL 5MW baseline controller [10]).

We design the observer gain $L'$ as the steady-state optimal Kalman filter gain [21] with process noise covariance

$$Q_{\text{KF}} = 0.01 \times \begin{bmatrix} I_{\text{ns}} & 0 \\ 0 & q_{\text{dist}} \end{bmatrix}$$
and measurement noise covariance

\[ R_{KF} = \begin{bmatrix} 1 & 0 \\ 0 & 0.025 \end{bmatrix} . \]

The noise covariance matrix entry \([R_{KF}]_{22} = 0.025\) is the true accelerometer noise covariance, and the generator speed entry \([R_{KF}]_{11} = 1 > 0\) is required for positive-definiteness of \(R_{KF}\) (and represents a signal-to-noise ratio of approximately 100), although no real noise was added to the signal for simulation. We found (via simulation testing and tuning) that \(Q_{KF}\) produced satisfactory state estimation performance, where the disturbance state process noise variance term \(q_{\text{dist}} > 0\) can be varied to tune the ‘aggressiveness’ of the disturbance estimation (see Section 4.3). Smaller values of \(q_{\text{dist}}\) indicate a stronger trust in the disturbance model (6) relative to the measurements \(y\), while larger values of \(q_{\text{dist}}\) indicate a lower trust in the model relative to the measurements.

### 4.3. Controllers tested

The focus of this study is to quantify the improvements gained using feedforward DAC in place of observer-based DAC for above-rated wind turbine operation. To do so, we compare various test cases in simulation, each producing the disturbance measurement \(d\) using a different method:

(i) **Baseline control** (Baseline) Feedback-only control with no DAC. This can be thought of as setting \(u_2 \equiv 0\).

(ii) **Ideal feedforward DAC** (Ideal) Feedforward DAC with an idealized measurement of \(d\) that is noiseless and taken at the rotor plane.

(iii) **Lidar-based feedforward DAC** (Feedback) Feedforward DAC with a realistic upstream lidar measurement (Sections 3.2 & 4.1) that is filtered using a noncausal moving average filter [22] with 1001 samples to remove high-frequency turbulence from the lidar measurement.

(iv) **Observer-based DAC** DAC with disturbances estimated from feedback measurements (Sections 3.1 & 4.2). We test three variations: \(q_{\text{dist}} = 0.1\) (Observer 0.1), \(q_{\text{dist}} = 1\) (Observer 1), and \(q_{\text{dist}} = 10\) (Observer 10).

In all cases, we use the standard NREL 5MW feedback control law for \(u_1\) [10]. The disturbance measurements/estimates for the methods described above are shown in Figure 3. The plot shows that the Feedforward measurement is essentially a smoothed version of the Ideal case, while the Observer-estimated disturbances vary significantly with the choice of \(q_{\text{dist}}\), as expected [13]. In particular, Observer 1 has a similar level of frequency content to the Feedforward measurement, but is slightly delayed because it is based on feedback signals.

### 5. Results

Illustrative results for the Feedforward controller are shown in Figure 4, while full results from this study are shown in Figure 5. Considering Figure 4, which shows the contributions of the feedback and feedforward components of the control signal \((u_1 \text{ and } u_2, \text{ respectively}) for the Feedforward DAC, we see that the feedforward component handles most of the large, low frequency variations, leaving the feedback term to respond to smaller, higher frequency components in the disturbance. This separation may be used to retune the feedback controller to further improve operation [4].

In Figure 5, we see that all DACs are able to reduce the variations in generator speed (left plot) without significant increases in tower loading (middle plot) compared to the Baseline NREL 5MW controller. However, pitch actuator usage varies significantly between the controllers (right plot).
Figure 4: Blade pitch control input signal for 100 s of simulation for the Feedforward DAC controller. The feedforward contribution $u_2$ is shown by the dashed line, whereas the full control input $u$ is shown in the solid line. The shaded difference is the contribution of the feedback component $u_1$.

plot), with Feedforward DAC the only controller that offers a significant reduction in pitch actuator velocity compared to the Baseline. The Feedforward and Observer 1 DACs are in fact able to reduce the tower motions while improving generator speed regulation. Compared to the Baseline, the Feedforward DAC reduces the peak tower base moment over the six simulation cases by 20.6%, while the Observer 1 DAC achieves a 15.6% reduction.

Figure 5: Performance results for the various controllers in generator speed regulation (left plot), tower motion (middle plot), and pitch actuator usage (right plot) taken over the six simulation runs. Box plots show range (whiskers), upper and lower quartiles (box), and median (white line) values. The black dashed line in the left plot is the rated generator speed.

Perhaps counterintuitively, the Ideal case (true rotor-average horizontal wind velocity) is not the best performer. Although, compared to Baseline control, generator speed regulation is improved with little change in tower loading, blade pitch actuation is very high. This is due to the high-frequency content present in the ideal disturbance measurement (Figure 3), which
is removed by the moving average filter for the lidar Feedforward case. Thus, when choosing a lidar focus distance, the amount of time available for filtering should be considered [22].

Comparing the three Observer DACs, we see a range of behaviors from ‘not aggressive enough’ (Observer 0.1) to ‘too aggressive’ (Observer 10). This transition can also be seen in Figure 3, where the Observer 1 disturbance estimate has a similar form to the Feedforward measurement, albeit delayed slightly. The aggressive Observer 10 more closely follows the Ideal disturbance measurement, but again injects considerable high-frequency content into the pitch signal (Figure 5, right). On the other extreme, Observer 0.1 produces an estimate that is too slow to be of use, and again produces considerable pitch activity as the feedback control $u_1$ makes up for inaccurate disturbance rejection in $u_2$.

A final point of interest is that all DACs produce a non-zero median error in the generator speed signal of approximately 1%—see Figure 5, left. The reason for this is unclear, especially since we see the error in the Observer DACs as well as the feedforward versions.

6. Conclusions and future work

This work reaffirms the benefits of using lidar for feedforward control of wind turbines by comparing the performance of the same disturbance accommodating control law over various methods for producing a disturbance measurement/estimate. We found that the lidar-based disturbance measurement was the best performer, achieving both tighter generator speed regulation and lower peak tower loading while requiring less pitch actuation than a baseline feedback controller. We also confirm that observer-based DAC can perform well, although tuning is critical—the best-performing observer-based DAC produced a disturbance estimate that contained similar frequency content to the lidar disturbance measurement, although a delay is invariably present since the observer estimate is based only on feedback signals.

We use disturbance accommodating control in this work as a simple way of comparing the performance of controllers based on measured disturbances and estimated ones; however, we do not consider the DAC law that we present to be the state of the art. Much research has been carried out to improve on the simple DAC law we present (see references in Section 1), as well as many other feedforward control laws [18], and investigations into the best way to utilize lidar measurements are ongoing.

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Appendix

We have claimed that observability of the plant (1) is a necessary condition for observability of the augmented system (7). To see this, let

$$O' \overset{\text{def}}{=} \begin{bmatrix} C' \\ C'A' \\ C'A'^2 \\ \vdots \\ C'A'((n_x+n_xd)-1) \end{bmatrix} \in \mathbb{R}^{n_y(n_x+n_xd)\times(n_x+n_xd)}$$

be the observability matrix for the augmented system. The necessary and sufficient condition for $(A', C')$ to be observable is that $O'$ is full rank, i.e., rank $(O') = n_x + n_{xd}$ [3]. By computation,
we break down $\mathcal{O}'$ as

$$
\mathcal{O}' = \begin{bmatrix}
\mathcal{O}'_{11} & \mathcal{O}'_{12} \\
\mathcal{O}'_{21} & \mathcal{O}'_{22}
\end{bmatrix} = \begin{bmatrix}
C & C \mathcal{A} \\
\vdots & \vdots \\
C \mathcal{A}^{(n_x-1)} & C \mathcal{A}^{n_x} \\
\vdots & \vdots \\
C \mathcal{A}^{(n_x+n_xd-1)} & C \mathcal{A}^{n_x} \\
\mathcal{O}'_{12} & \mathcal{O}'_{21}
\end{bmatrix}.
$$

The upper left block element of $\mathcal{O}'$ is, by definition, the observability matrix $\mathcal{O}$ of the original plant (1), for which $\text{rank}(\mathcal{O}) \leq n_x$. By the Cayley-Hamilton Theorem [3], each term in $\mathcal{O}'_{21}$ can be written as a linear combination of terms in $\mathcal{O}'_{11}$, and as a consequence,

$$
\text{rank}\left(\begin{bmatrix}
\mathcal{O}'_{11} \\
\mathcal{O}'_{21}
\end{bmatrix}\right) = \text{rank}\left(\mathcal{O}'_{11}\right) = \text{rank}(\mathcal{O}) \leq n_x.
$$

On the other hand,

$$
\text{rank}\left(\begin{bmatrix}
\mathcal{O}'_{12} \\
\mathcal{O}'_{22}
\end{bmatrix}\right) \leq n_xd
$$

due to the size of the submatrix and the fundamental properties of the rank. Thus, if $\mathcal{O}'$ is to have (column) $\text{rank}(\mathcal{O}') = n_x + n_xd$, it is necessary to have $\text{rank}(\mathcal{O}) = n_x$. This occurs if and only if $(A, C)$ is observable.

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