

Design and Evaluation of a Wind Speed Estimator for Hub Height and Shear Components

North American Wind Energy Academy
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Outline

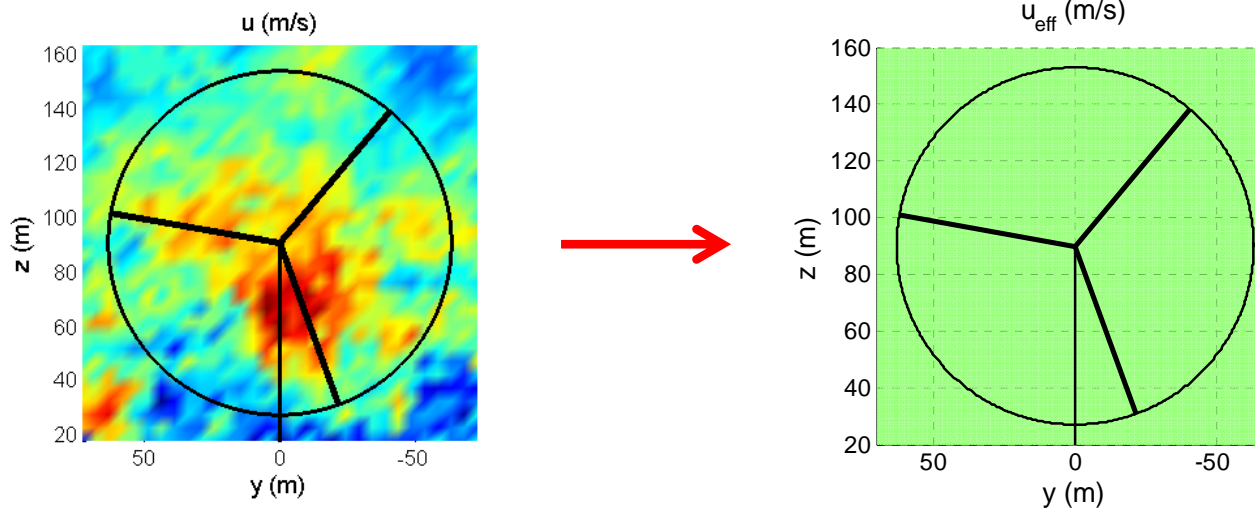
- Introduction to wind speed estimation
 - Why estimate wind speed?
 - Traditional estimation techniques
- Hub height and shear component wind field model
- Kalman filter wind speed estimator design
- Wind speed estimator performance
 - With and without measurement noise

Effective Wind Speed

Rotor Effective Wind Speed

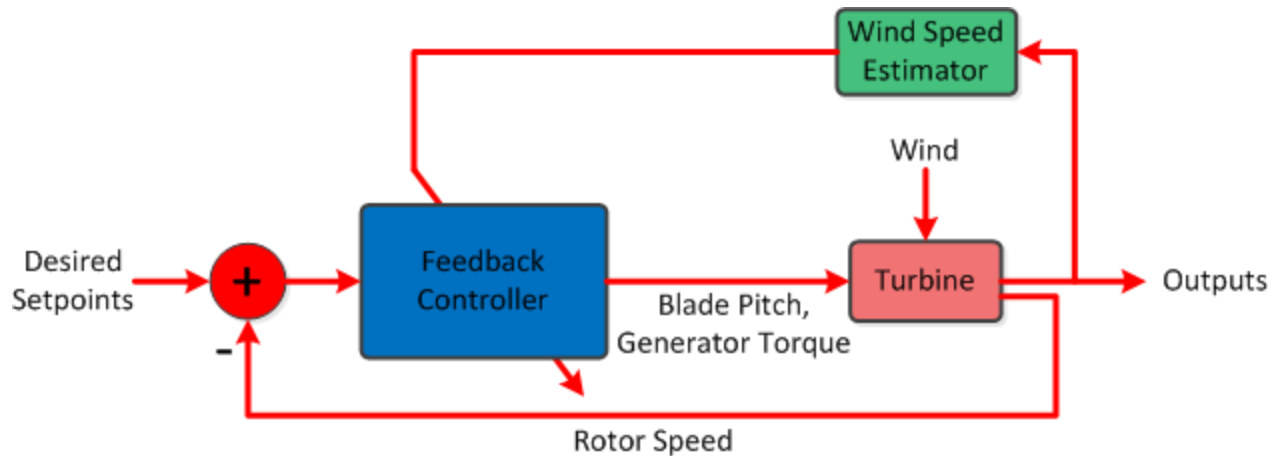
- The equivalent uniform wind speed that would produce the same turbine response as the actual spatial distribution of wind speeds

$$P = \frac{1}{2} \rho \pi R^2 C_P (\lambda, \beta) u_{eff}^3$$



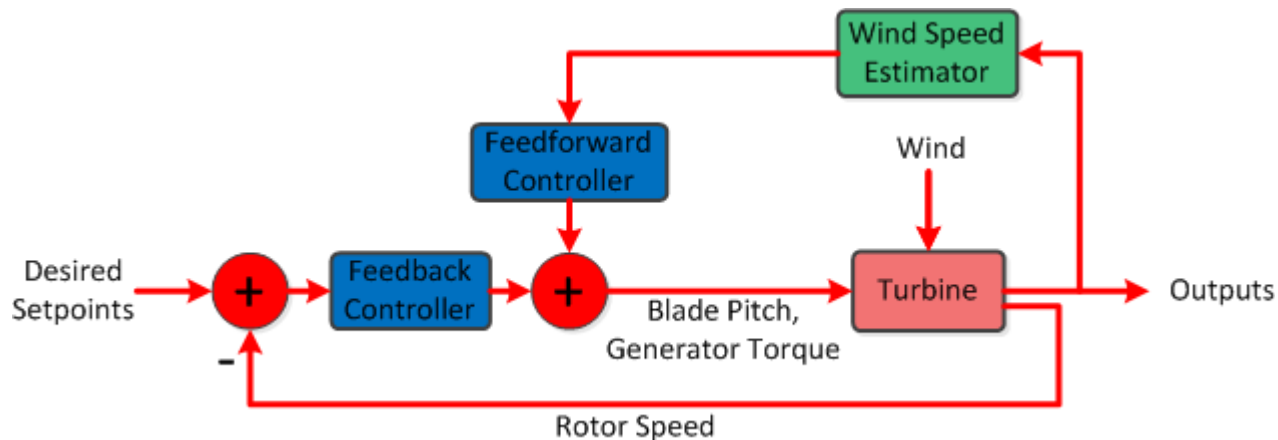
Why Estimate Effective Wind Speed?

- Gain scheduling for control (Østergaard, 2007)
- Active power control for grid ancillary services (Aho, Buckspan, 2013)



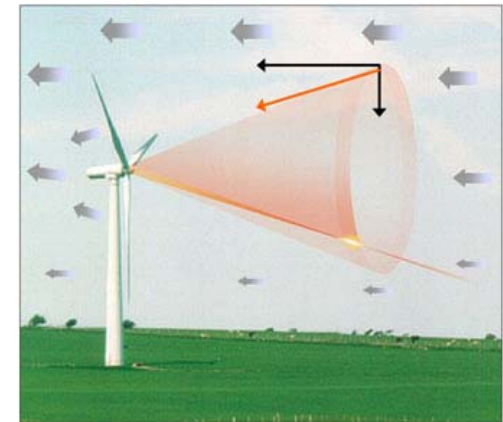
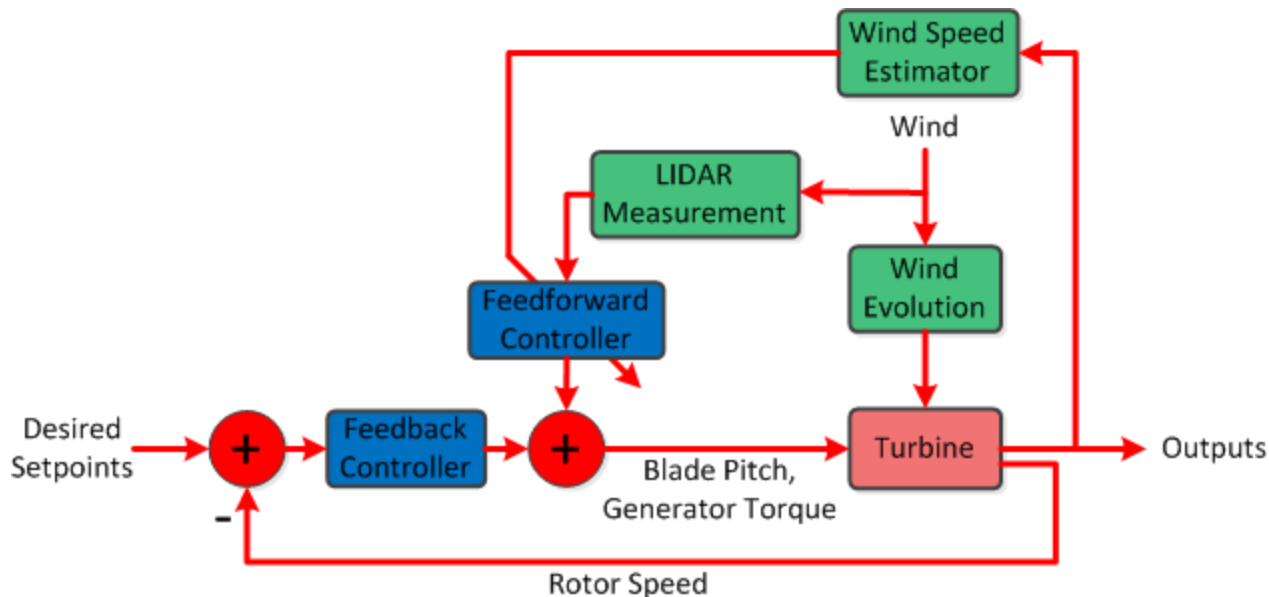
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Why Estimate Effective Wind Speed?

- Gain scheduling for control (Østergaard, 2007)
- Active power control for grid ancillary services (Aho, Buckspan, 2013)
- Control using estimated wind speed as a feedforward input (van der Hooft, 2004)
- Optimal filtering of lidar measurements for feedforward control with preview (Schlipf, 2012; Simley, 2013)



From Mikkelsen, *et al.*,
Wind Energy, 2013.

Methods for Estimating Effective Wind Speed

Nacelle anemometer provides poor estimate of rotor effective wind speed

- Point measurement
- Flow affected by rotor

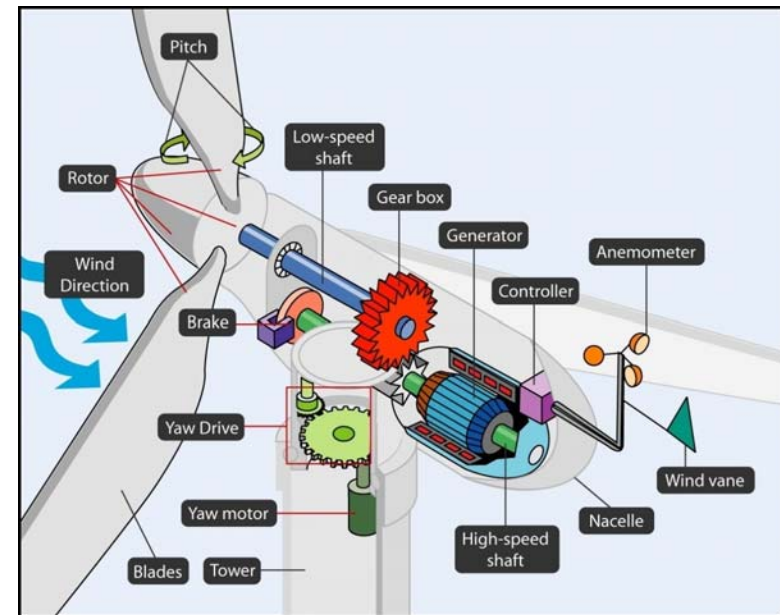


Image courtesy of U.S. Dept. of Energy

Methods for Estimating Effective Wind Speed

- Power balance method:

$$\tau_g \omega_g = \frac{1}{2} \rho \pi R^2 C_P (\lambda, \beta) u_{eff}^3$$

- Torque balance method:

$$J \dot{\omega}_g = \frac{\tau_r}{N_g} - \tau_g$$

$$\tau_r = \frac{\rho \pi R^2 C_P (\lambda, \beta) u_{eff}^3}{2 \omega_r}$$

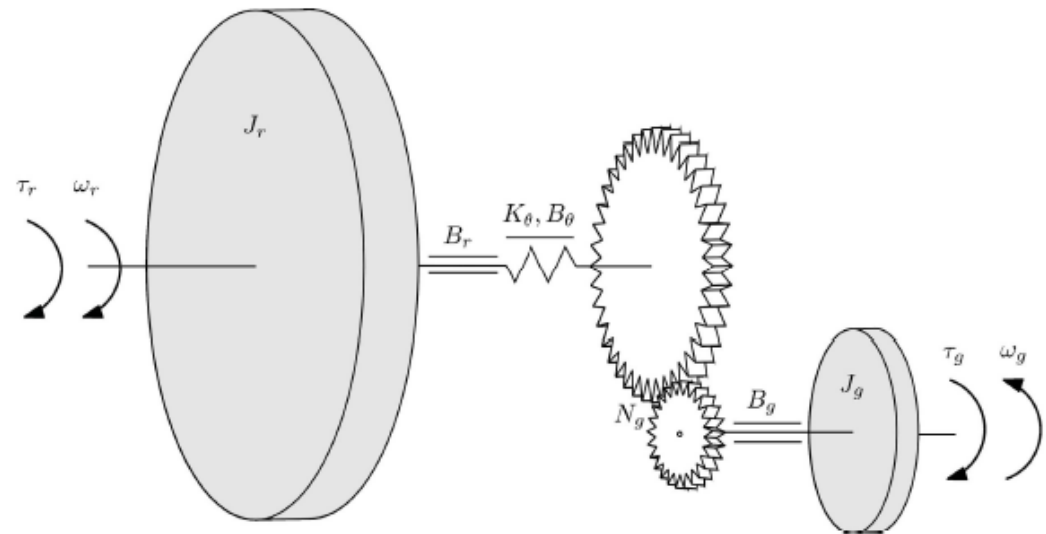


Fig. 1. Mechanical scheme of the wind turbine transmission system.

Figure from Soltani, *et al.*, "Estimation of Rotor Effective Wind Speed: A Comparison," *IEEE TCST*, 2013.

- Kalman filtering (Ma, 1995; Bottasso 2010; Knudsen, 2011)
 - Includes linearized turbine dynamics
 - Accounts for measurement noise
 - Uses wind speed statistics to improve performance

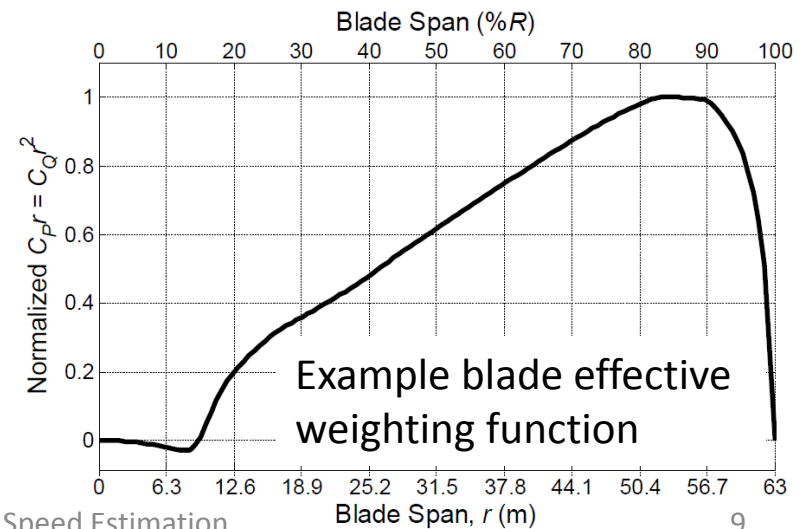
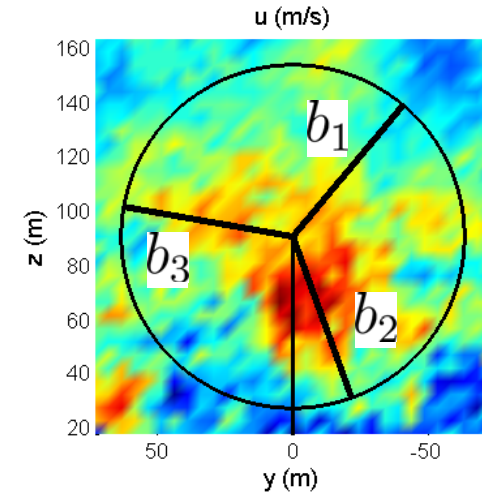
Wind Field Disturbance Model

The instantaneous wind field can be described as a combination of:

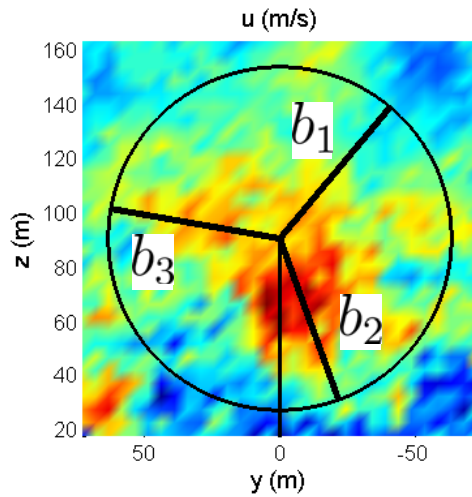
- Horizontal hub height wind speed (u_{hh})
- Horizontal wind direction (δ)
- Vertical wind speed (w)
- Linear horizontal wind shear (Δ_h)
- Power law vertical wind shear (α)
- Linear vertical wind shear (Δ_v)

Three linear “blade effective wind speeds” can be equivalently described as hub height and shear terms

$$u_i = f(u_{hh}, \Delta_h, \Delta_v, \psi_i)$$

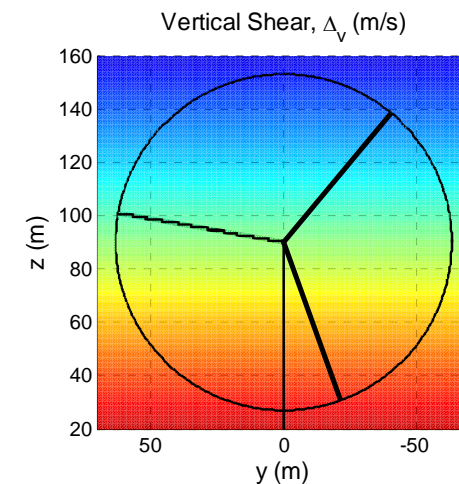
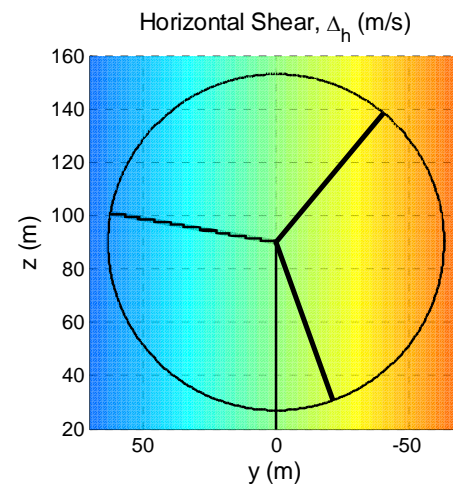
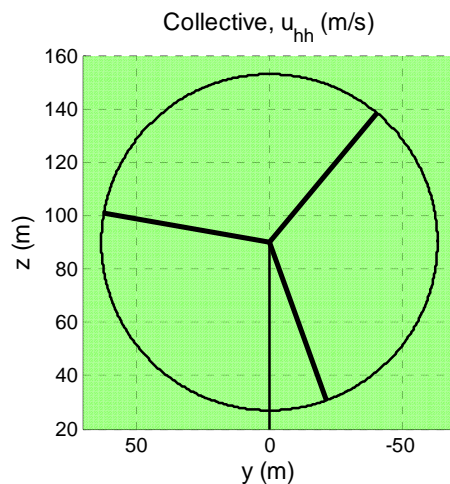


Wind Field Disturbance Model



From “blade effective wind speeds” to
hub height and linear shear components

$$\begin{bmatrix} u_{hh} \\ \Delta_h \\ \Delta_v \end{bmatrix} = T_{MBC}(\psi) \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$$





Kalman Filter Design

- Linear state-space turbine model:

- State update:
$$x(k+1) = Ax(k) + B \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix} + B_d \begin{bmatrix} u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix}$$

- Output:
$$y(k) = Cx(k) + D \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix} + D_d \begin{bmatrix} u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix}$$

Control input Wind disturbance

- Examples of states:
 - Generator speed
 - Tower deflection
 - Blade deflection

Kalman Filter Design


- Linear state-space turbine model:


- State update:

$$\begin{bmatrix} x(k+1) \\ u_{hh}(k+1) \\ \Delta_h(k+1) \\ \Delta_v(k+1) \end{bmatrix} = \begin{bmatrix} A & B_{d,u_{hh}} & B_{d,\Delta_h} & B_{d,\Delta_v} \\ \mathbf{0} & 1 & 0 & 0 \\ \mathbf{0} & 0 & 1 & 0 \\ \mathbf{0} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix} + \begin{bmatrix} B \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix}$$

- Output:

$$y(k) = \begin{bmatrix} C & D_{d,u_{hh}} & D_{d,\Delta_h} & D_{d,\Delta_v} \end{bmatrix} \begin{bmatrix} x(k) \\ u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix} + D \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix}$$


 Wind disturbance
states


 Control input

Kalman Filter Design

- Linear state-space turbine model:

- State update:

$$\begin{bmatrix} x(k+1) \\ u_{hh}(k+1) \\ \Delta_h(k+1) \\ \Delta_v(k+1) \end{bmatrix} = \begin{bmatrix} A & B_{d,u_{hh}} & B_{d,\Delta_h} & B_{d,\Delta_v} \\ \mathbf{0} & 1 & 0 & 0 \\ \mathbf{0} & 0 & 1 & 0 \\ \mathbf{0} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix} + \begin{bmatrix} B \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ n_1(k) \\ n_2(k) \\ n_3(k) \end{bmatrix}$$

State update noise



- Output:

$$y(k) = \begin{bmatrix} C & D_{d,u_{hh}} & D_{d,\Delta_h} & D_{d,\Delta_v} \end{bmatrix} \begin{bmatrix} x(k) \\ u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix} + D \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix} + \mathbf{v}(k)$$

Wind disturbance
states

Control input

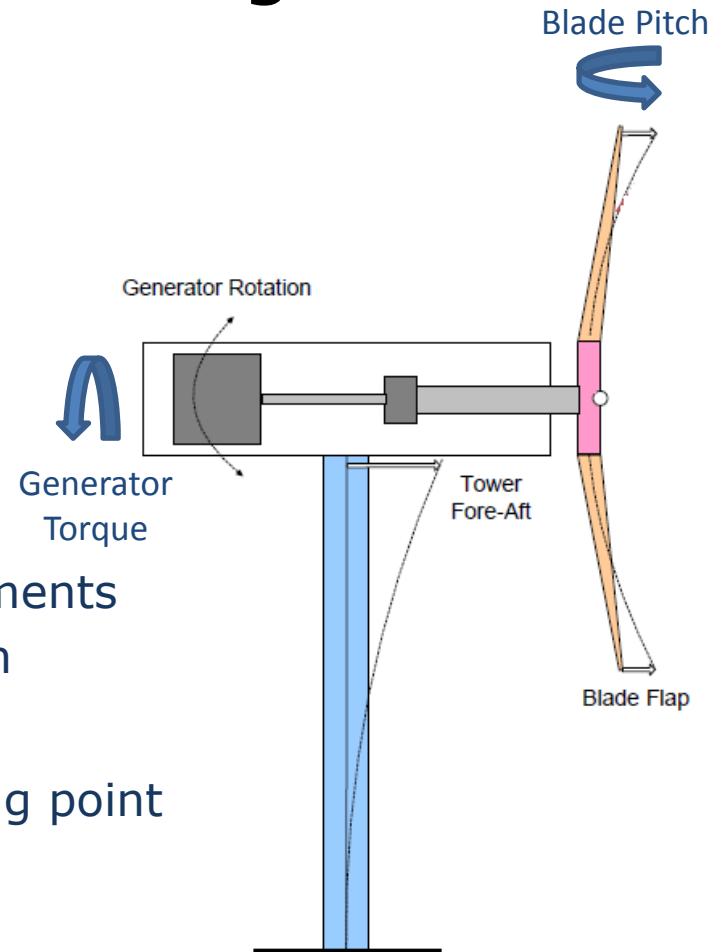
Sensor noise



Kalman Filter Design

- Linear state-space turbine model:
- Degrees of freedom
 - Generator
 - First flapwise blade bending mode
 - First tower fore-aft mode
- Sensors
 - Generator speed
 - Out-of-plane blade root bending moments
 - Nacelle IMU translational acceleration
- Sensor noise
 - Generator speed, $\sigma = 2\%$ of operating point
 - Strain gages, $\sigma = 2\%$ of RMS value
 - Accelerometer, $\sigma = 4\%$ of RMS value

Knudsen and Bak, "Simple Model for Describing and Estimating Wind Turbine Dynamic Inflow," ACC, 2013.



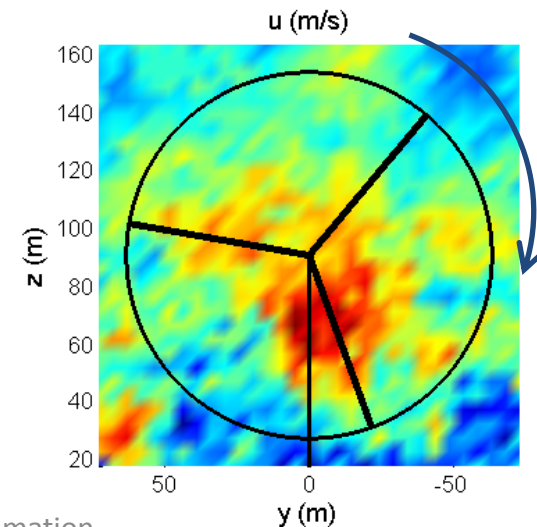
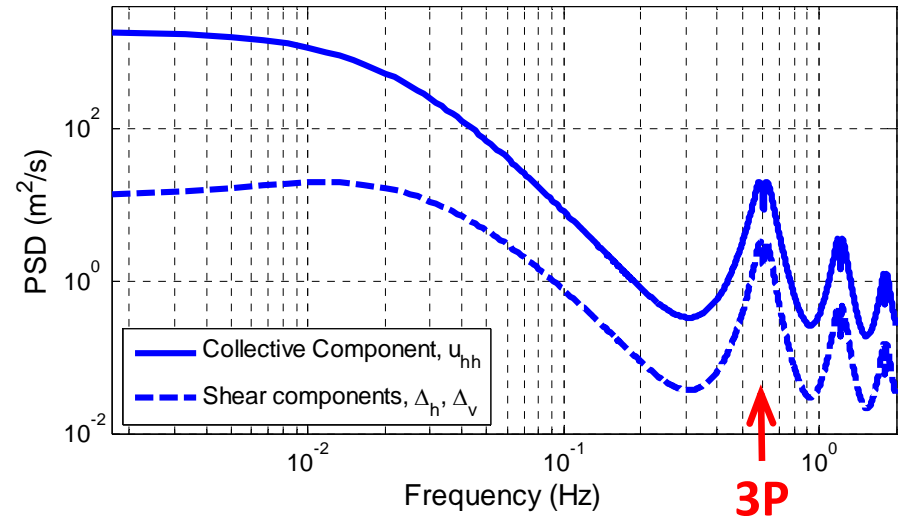
Simulation Environment

- NREL's FAST aeroelastic simulator
- NREL 5MW Reference Turbine
 - Baseline collective pitch controller
- Above rated wind speed 13 m/s
- No mean wind shear
- Hub height and shear components modeled using three rotating blade effective wind speeds
 - Von Karman turbulence spectrum
 - 7.7% turbulence intensity

Simley and Pao, "Correlation between Rotating LIDAR Measurements and Blade Effective Wind Speed," *AIAA ASM*, 2013.

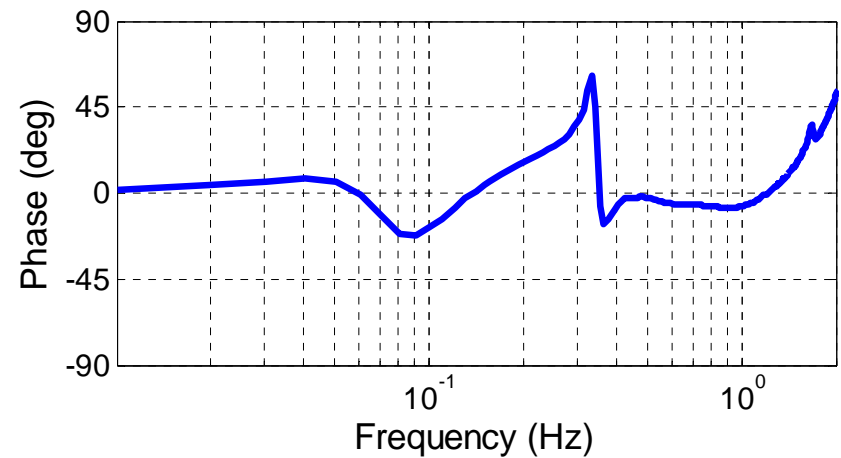
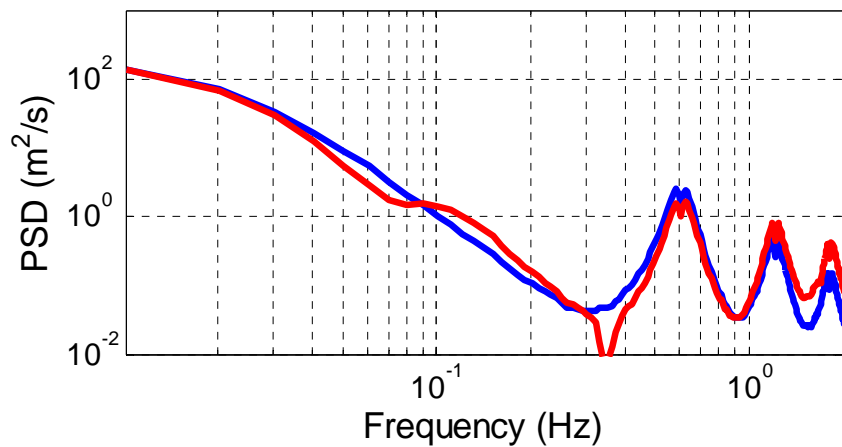
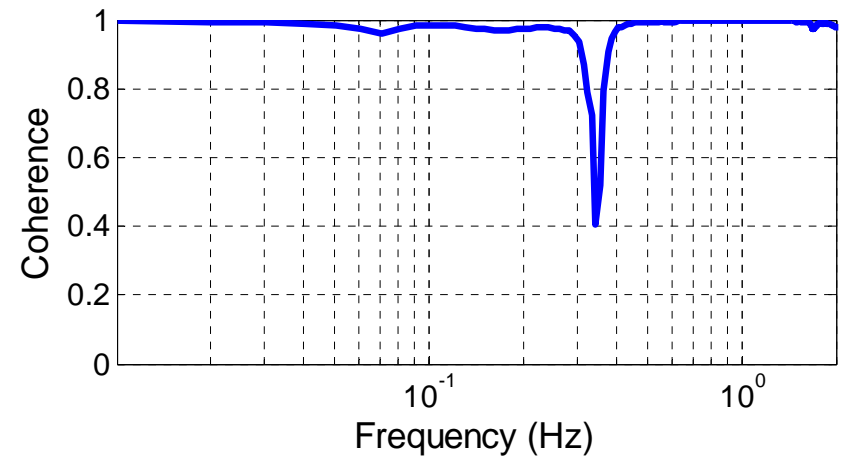
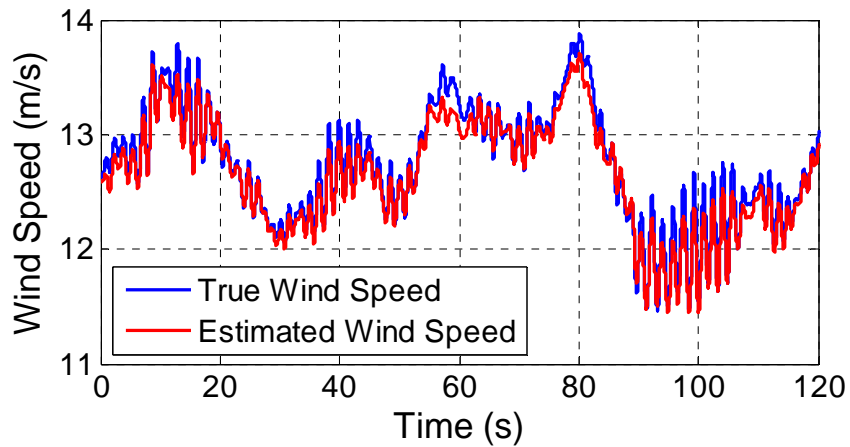
- **Want to estimate wind speeds accurately up to $\sim 1\text{Hz}$ (approximate bandwidth of pitch actuators)**

Rotating Spectra



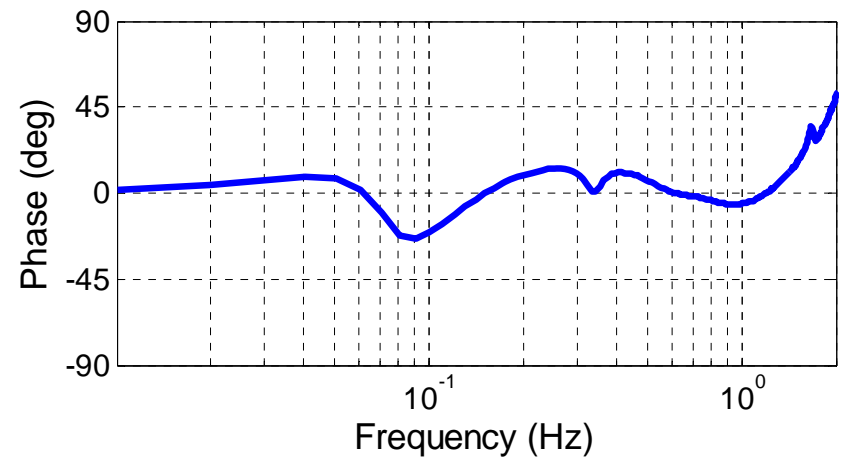
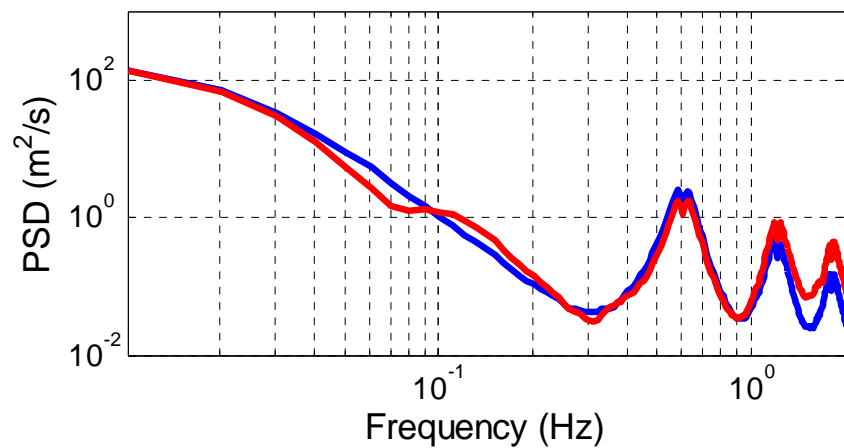
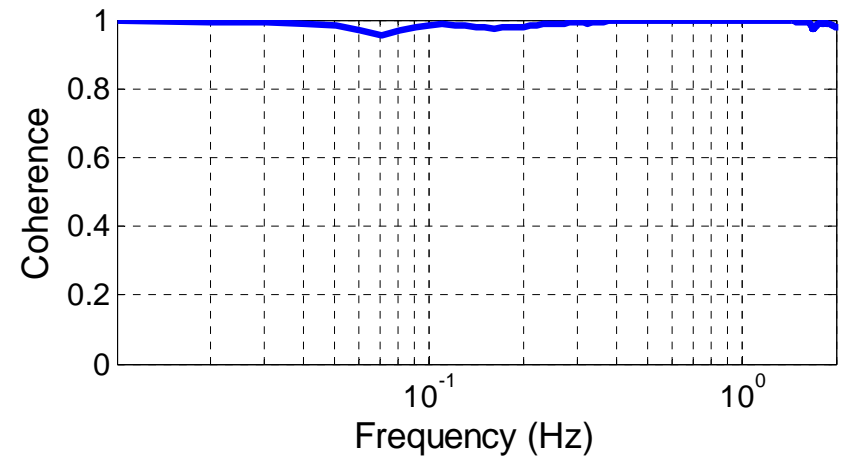
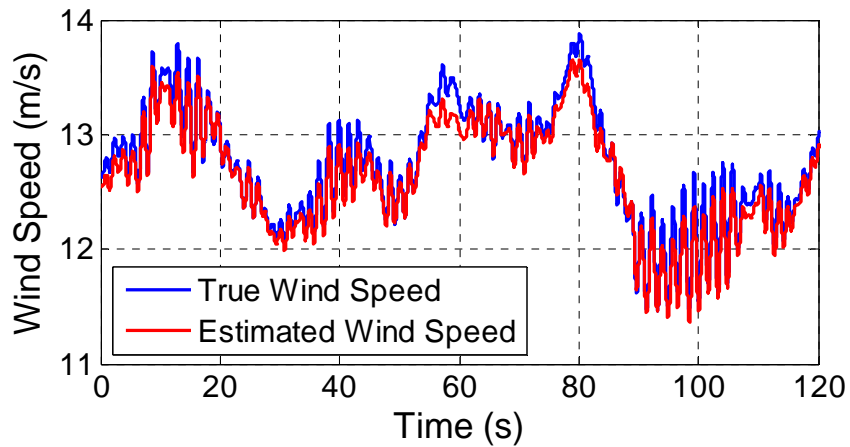
Wind Speed Estimator Performance

Hub height component, above rated conditions, w/o tower mode



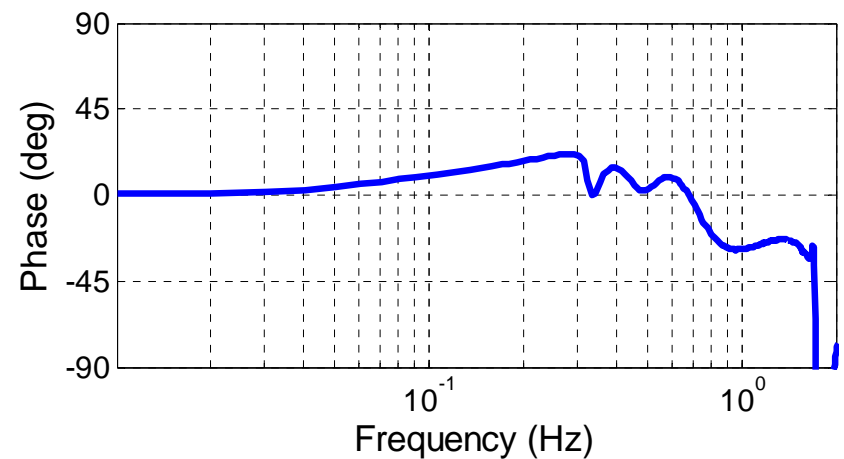
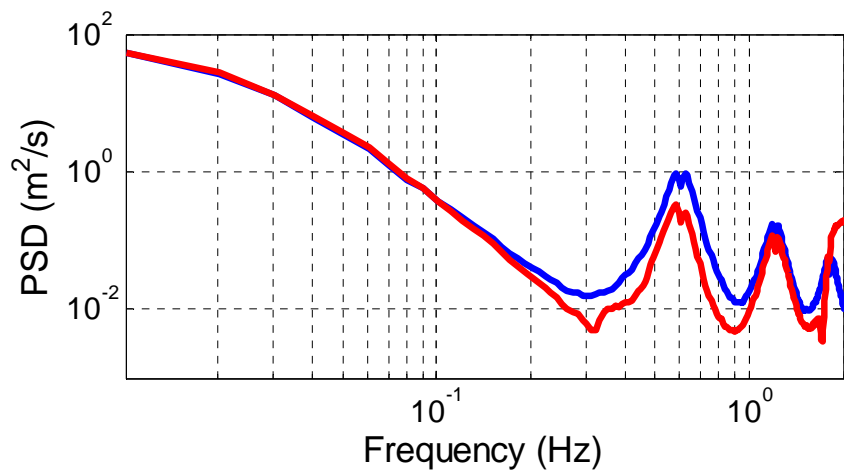
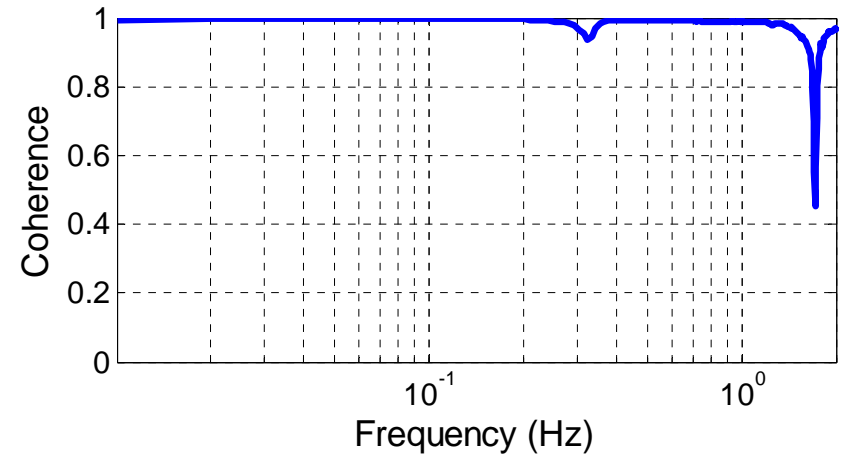
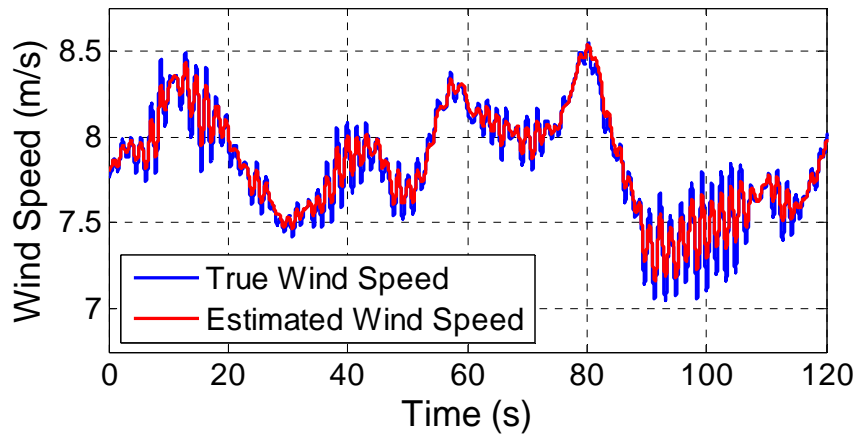
Wind Speed Estimator Performance

Hub height component, above rated conditions, w/ tower mode



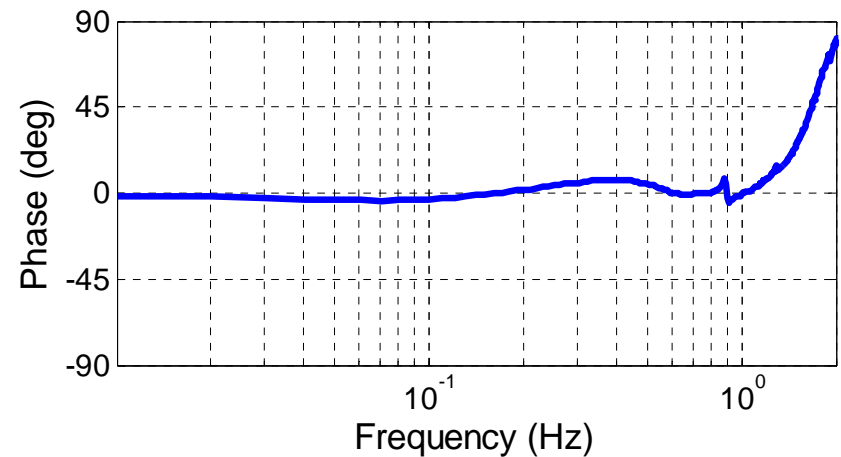
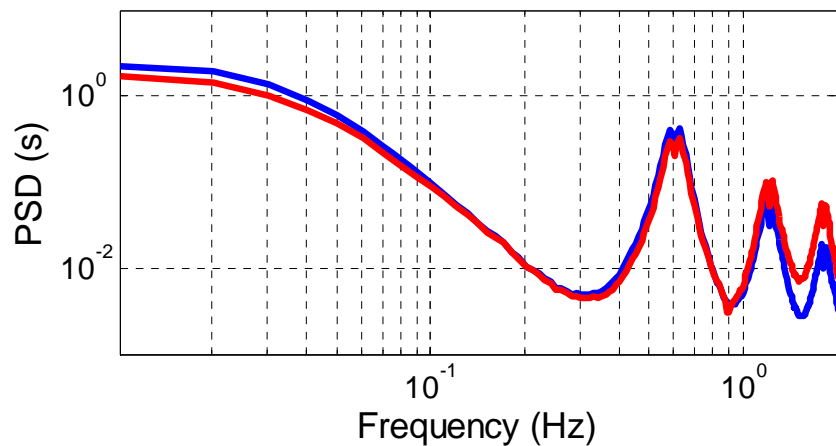
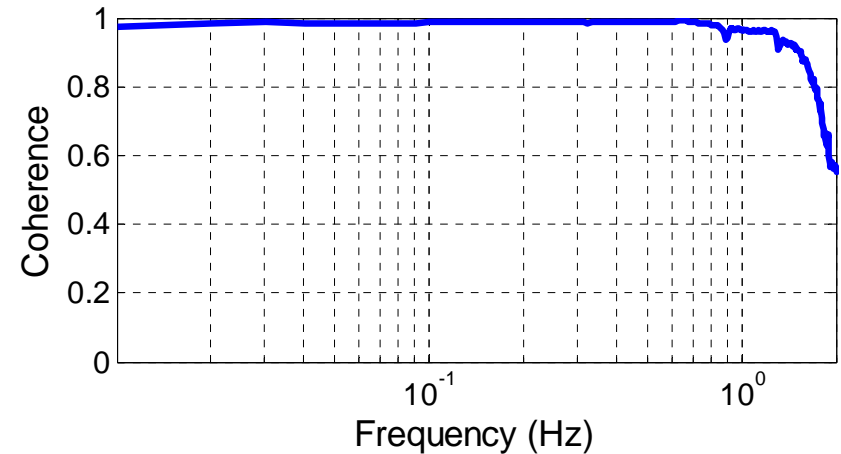
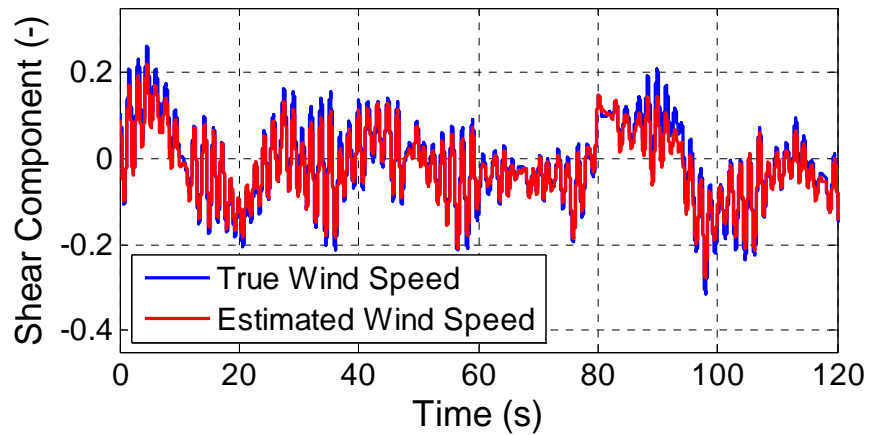
Wind Speed Estimator Performance

Hub height component, below rated conditions



Wind Speed Estimator Performance


Horizontal shear component, above rated conditions

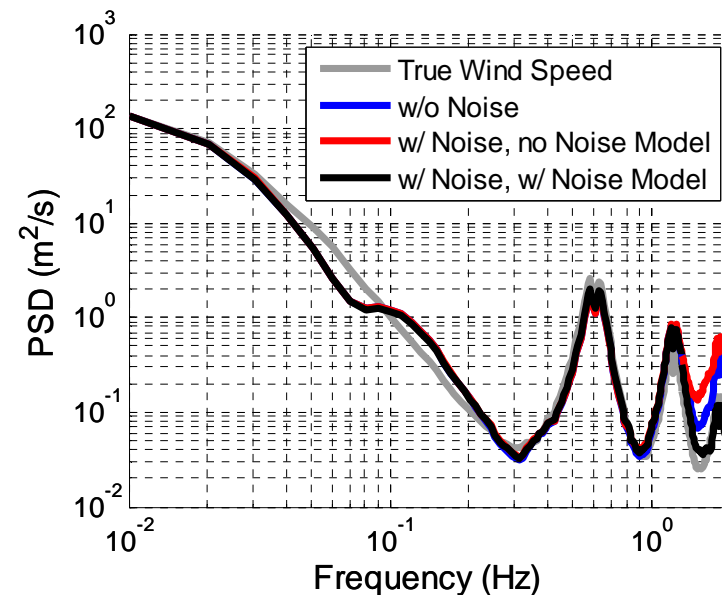
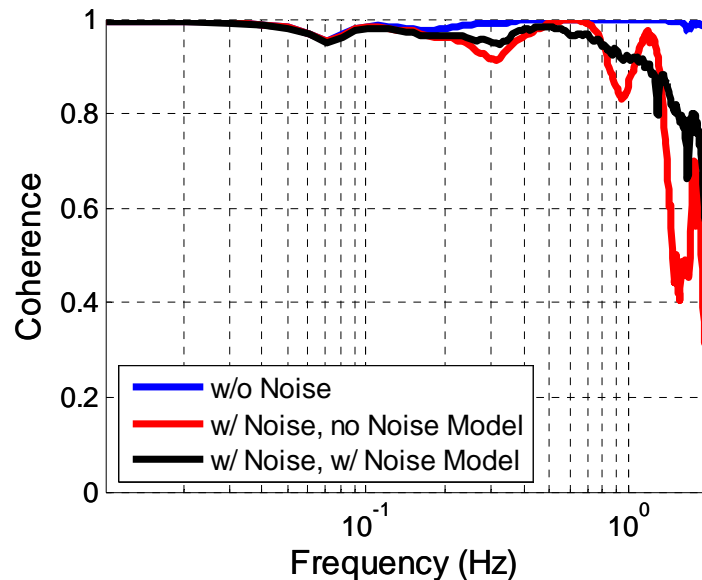


Wind Speed Estimator Performance

Hub height component, with measurement noise

$$y(k) = \begin{bmatrix} C & D_{d,u_{hh}} & D_{d,\Delta_h} & D_{d,\Delta_v} \end{bmatrix} \begin{bmatrix} x(k) \\ u_{hh}(k) \\ \Delta_h(k) \\ \Delta_v(k) \end{bmatrix} + D \begin{bmatrix} \tau_g(k) \\ \beta(k) \end{bmatrix} + v(k)$$


 Sensor noise variance
 must be estimated



Conclusions

- Wind speed estimation has many uses in wind turbine control
- A Kalman filter-based wind speed estimator can estimate hub height and shear components up to 1 Hz bandwidth
 - generator speed, blade root bending moment, and nacelle acceleration measurements
 - Difficult to model closed-loop modes
- Kalman filter accounts for measurement noise and state uncertainty
 - Requires knowledge of measurement noise and wind statistics
- Robust to measurement noise uncertainty up to 1 Hz bandwidth

Future Work

- Improve model of closed-loop system
- Implement a non-causal Kalman filter
 - Fixed estimation lag time
- Analyze performance during operating point transitions (time varying mean wind speed and mean shear)

Thank You

Questions?

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