Advanced Control Design for Wind Turbines

Yuan Yuan

PhD candidate
University of Connecticut

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Corning Incorporated
Corning, NY, USA

Outline

- PhD work
- background & Control Method
  - Disturbance Observed Based control
  - Robust control
  - Model predictive control
  - Adaptive control
- Work in Corning
  - Model predictive control in laminated glass
- Concluding Remarks

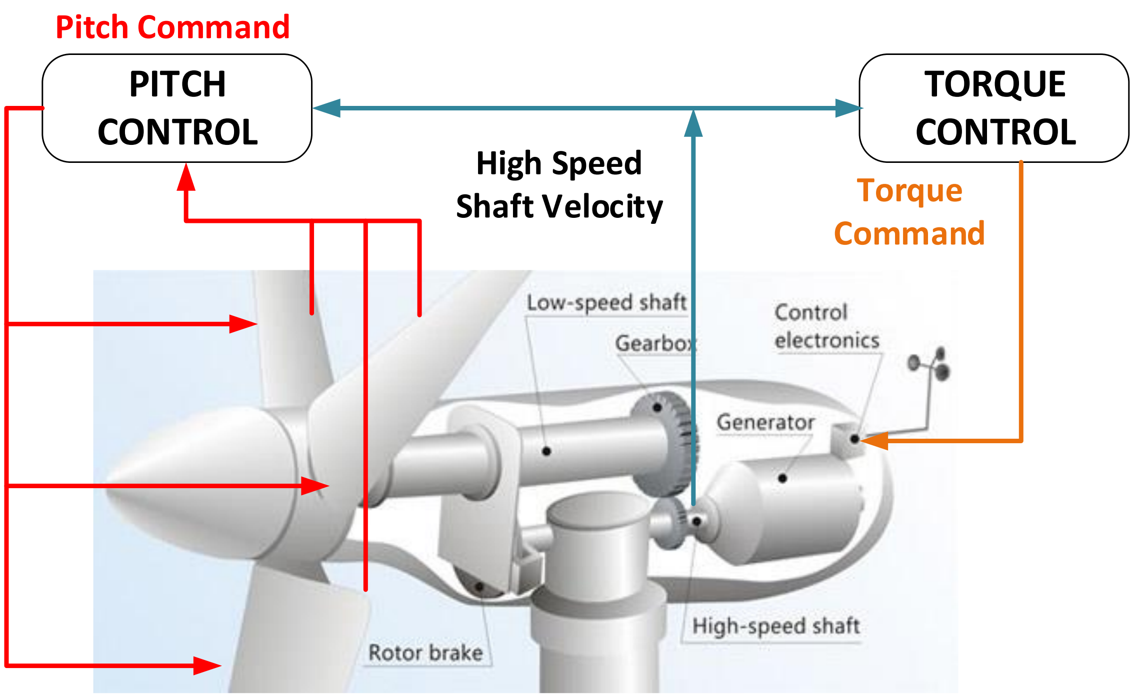
Me

- Current: Control scientist intern， Sullivan Park

- PhD candaite:
- Mechanical Engineering, University of Conneticut, Aug, 2013- December, 2018(expected)
- Master degree: Eletrical Engineering (control theory and control engineering)
- Northerwestern Polytechnical Unversity, China
- Bachlor degree: Electrical Engineering (automation),
- Northerwestern Polytechnical Unversity, China
- Hobbies: Boating, and badminton.

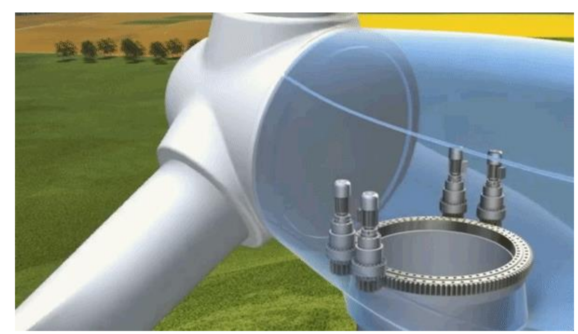
Background: Wind Turbine and Control

- Wind Energy
  - Fastest growing renewable energy source in the wind capacity reached over 400,000 MW by the
  - Low cost & environmentally friendly



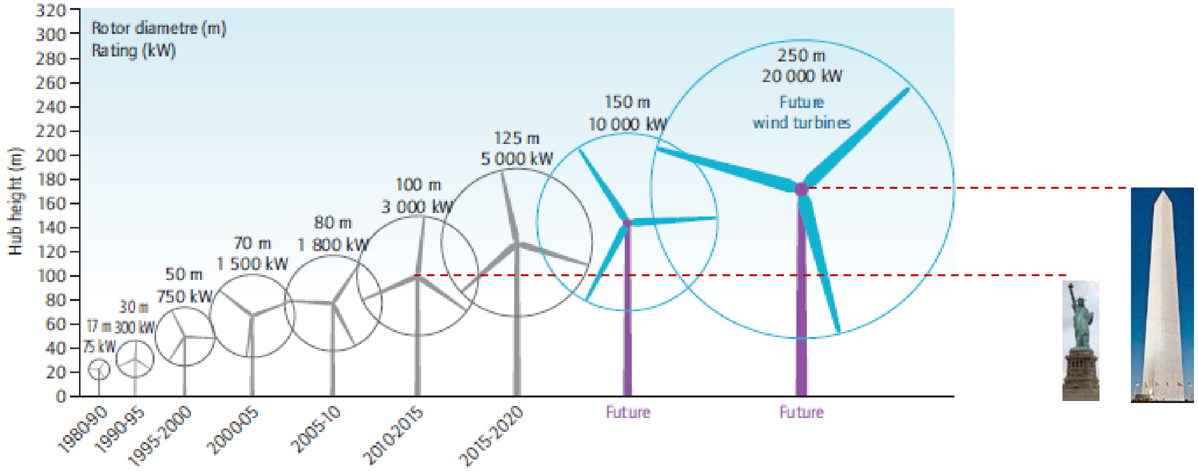
Pitch control animation

- Wind turbine control loops
  - Generator torque control
  - Blade pitch control
  - Nacelle yaw control



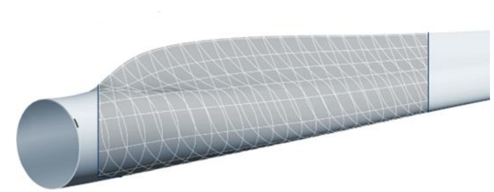
Yaw control animation

Challenges of Wind Turbines



Source: DOE

- Goal: to reduce the cost of wind energy
- Complex dynamics
  - Increased turbine size
  - Complex structures: airfoil-shaped blades



- Uncertain environments
  - Time-varying wind speeds
  - Weather changes, icing, and assemblage error of turbine
- Advanced controllers can help reduce maintenance cost and increase power capture

Research Objective

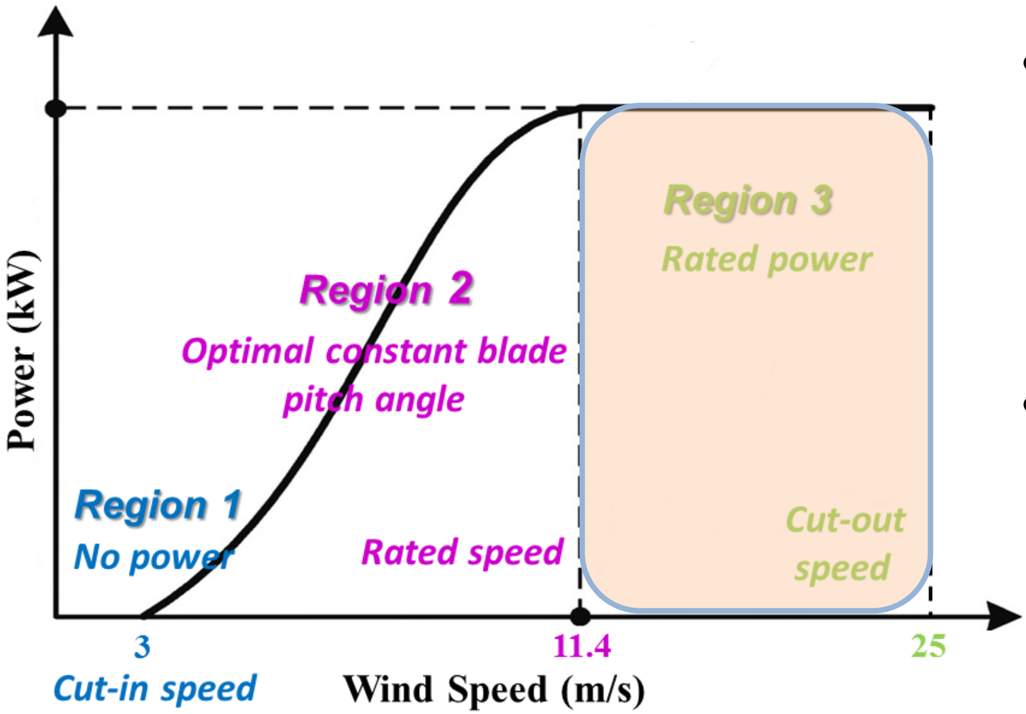
- Different control goals
  - Speed control
  - Power control
  - Load reduction on components
  - Prolonged actuator life

- Complex dynamics & uncertain environments
  - Conflicting objectives

→ Explore different control approach

Operating Regions

- Optimal balance between energy production performance and reliability of components



- Region 3: pitch control
  - Maintain the rated generator speed
  - Mitigate structural loads
- Control laws
  - Disturbance observer based control
  - Robust control
  - Model predictive control
  - Adaptive control
- Region 2: torque control[1]
  - Maximum power

[1] Jonkman et al., *National Renewable Energy Laboratory Technical Report*, 2009.

Dynamic modeling

- AeroDyn
  - An aero-elastic simulation code (by NREL) to predict the aerodynamics
  - Input: steady or turbulent wind file
  - Output: force and moment on the turbine components

- Nonlinear aero-elastic equations of motion of wind turbine system

$$M\left(\underline{q},\underline{u},t\right)\underline{\ddot{q}}+\underline{f}\left(\underline{q},\underline{\dot{q}},\underline{u},\underline{u}_d,t\right)=0$$

  - M: mass matrix
  - $\underline{f}$: force
  - $\underline{u}$: control input
  - $\underline{u}_d$: wind input
  - $\underline{q}$: DOF displacements
  - $\underline{\dot{q}}$: DOF velocities
  - $\underline{\ddot{q}}$: DOF accelerations
  - t: time

Model Linearization

- FAST (Fatigue, Aerodynamics, Structures, Turbulence)
  - FAST code (by NREL) used for simulating the coupled dynamic responses of wind turbines
- State space representation
  - Numerically linearize the equation by perturbing (Δ) each variable about their respective operating points (*op*):

linearization

$$M\Delta\ddot{\underline{q}} + C\Delta\dot{\underline{q}} + K\Delta\underline{q} = F\Delta\underline{u} + F_d\Delta\underline{u}_d$$

$$M = M\,\Big|_{op} \qquad C = \frac{\partial \underline{f}}{\partial \dot{\underline{q}}}\Big|_{op}$$

$$K = \left[\frac{\partial M}{\partial \underline{q}}\ddot{q} + \frac{\partial \underline{f}}{\partial \underline{q}}\right]\Big|_{op} \quad F = -\left[\frac{\partial M}{\partial \underline{u}}\ddot{q} + \frac{\partial \underline{f}}{\partial \underline{u}}\right]\Big|_{op} \quad F_d = -\frac{\partial \underline{f}}{\partial \underline{u}_d}\Big|_{op}$$

$$\underline{q} = \underline{q}_{op} + \Delta\underline{q}, \dot{\underline{q}} = \dot{\underline{q}}_{op} + \Delta\dot{\underline{q}}, \ddot{\underline{q}} = \ddot{\underline{q}}_{op} + \Delta\ddot{\underline{q}},$$
$$\underline{u} = \underline{u}_{op} + \Delta\underline{u}, \underline{u}_d = \underline{u}_{dop} + \Delta\underline{u}_d$$

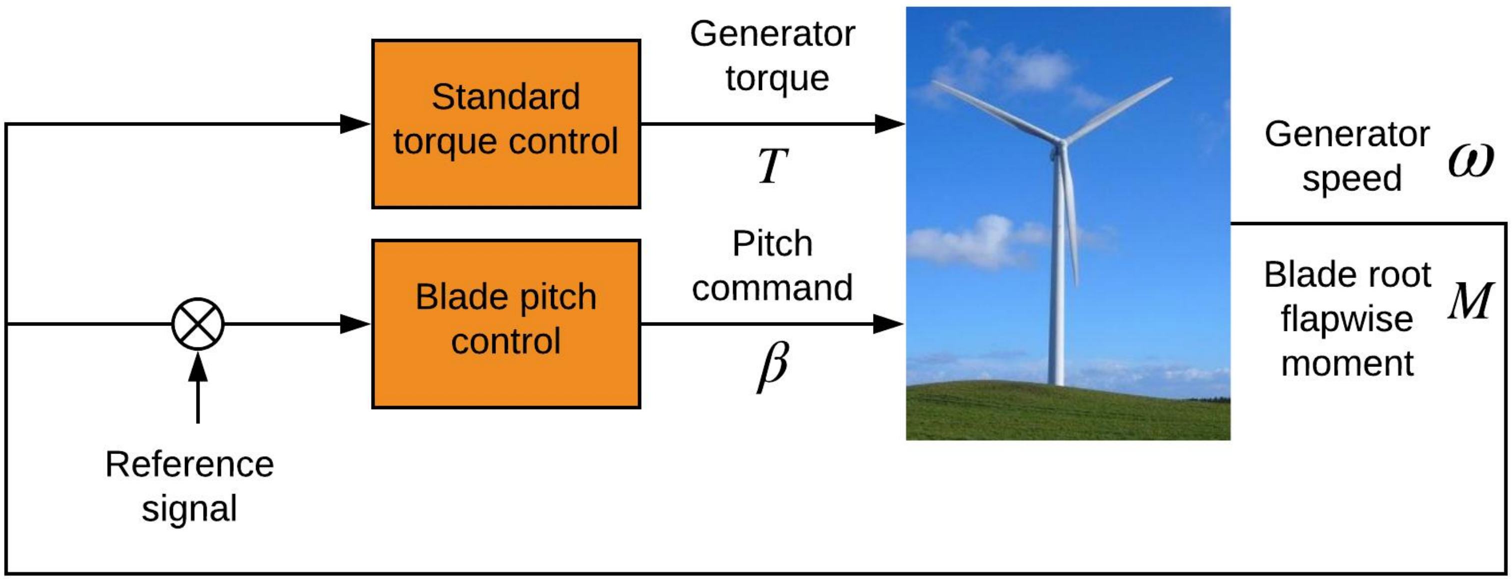
$$\Downarrow$$

$$M\left(\underline{q},\underline{u},t\right)\ddot{\underline{q}} + \underline{f}\left(\underline{q},\dot{\underline{q}},\underline{u},\underline{u}_d,t\right) = 0$$

$$\Delta\dot{\underline{x}} = A\Delta\underline{x} + B\Delta\underline{u} + B_d\Delta\underline{u}_d$$
$$\Delta\underline{y} = C\Delta\underline{x} + D\Delta\underline{u} + D_d\Delta\underline{u}_d$$

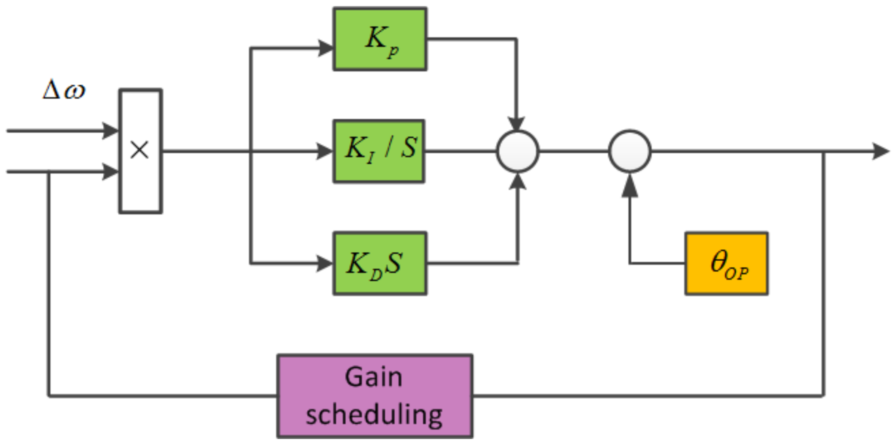
$$A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}, B = \begin{bmatrix} 0 \\ M^{-1}F \end{bmatrix}$$
$$B_d = \begin{bmatrix} 0 \\ M^{-1}F \end{bmatrix}, C = \begin{bmatrix} DspC & VelC \end{bmatrix}$$

Control Architecture



- Torque control: Standard torque control
- Pitch control: Model predictive control
- Yaw control: Not involved

Baseline Pitch Control



$$\Delta\theta = GK(\theta)\left\{K_p\Delta\omega + K_I\int_0^t \Delta\omega + K_D\Delta\dot{\omega}\right\}$$

- Baseline Gain Scheduling Proportional Integral Derivative pitch controller [1]
  - $\Delta\theta$: small perturbation of blade pitch angle about the operating point
  - $\Delta\omega$: error between measured generator speed and rated set point value

- Gain scheduling factor to accommodate time-varying operating wind condition

$$GK(\theta) = \frac{1}{1+\theta/\theta_k}$$

  - θ_k: blade pitch angle at which the pitch sensitivity is doubled from its value at the rated operating point.
  - Gain scheduling: K_p , K_I, K_D are changed

[1] Jonkman et al., *National Renewable Energy Laboratory Technical Report*, 2009.

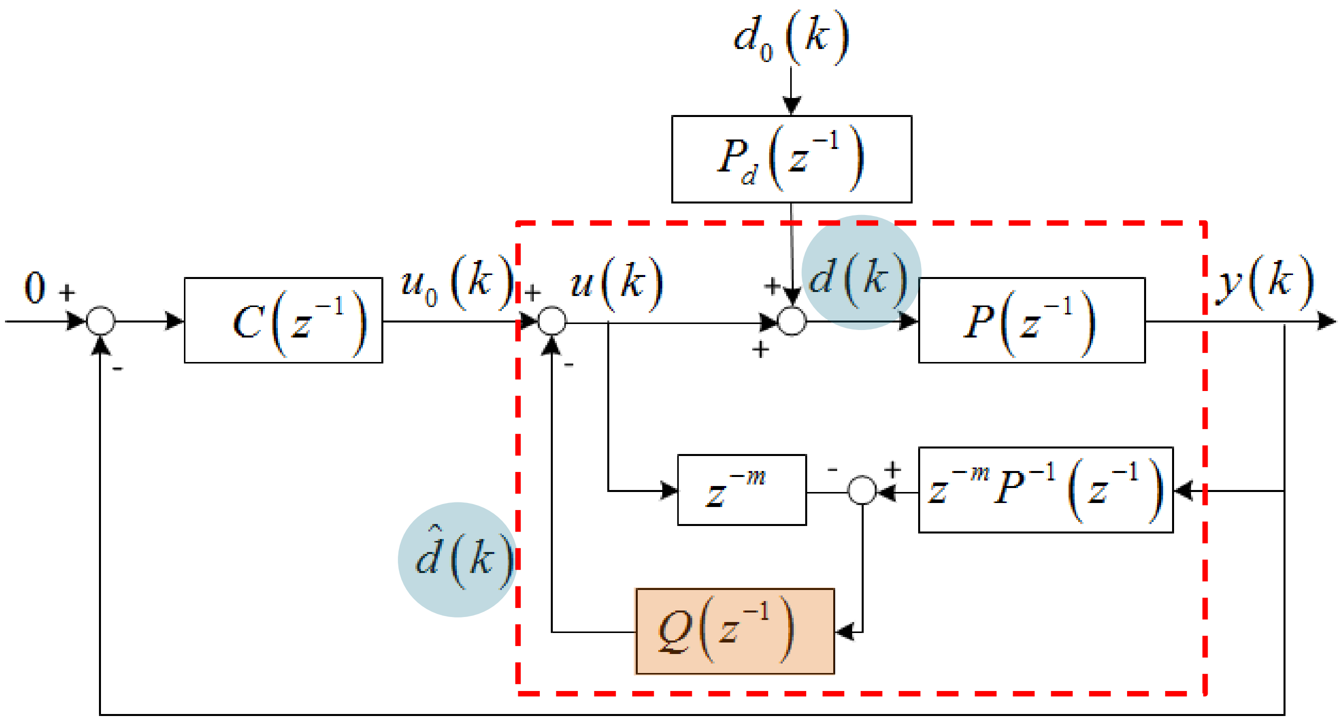
Outline

- Background
- Research Objective
- Disturbance observer based control
- Concluding Remarks
- Future Tasks

Disturbance Observer Based Control

- Disturbance observer based control
  - High precision motion control
  - Micronano manufacturing
  - Advantage: great disturbance rejection performance
  - Promising to make improvements in wind turbine control area
- Objective: speed and power control, load mitigation at some components
- How is this control strategy tailored for complex wind turbine dynamics

Disturbance Observer Based Controller



$d_0(k)$:
wind disturbance
$P_d(z^{-1})$:
disturbance model
$P(z^{-1})$:
plant model
$P^{-1}(z^{-1})$:
model inversion
$Q(z^{-1})$:
filter
$C(z^{-1})$:
PID controller

$$d(k)-\hat{d}(k)=d(k)-Q(z^{-1})\left[z^{-m}P^{-1}(z^{-1})\right]P(z^{-1})\left(d(k)+u(k)\right)+Q(z^{-1})z^{-m}u(k)$$

$$\approx\left[1-z^{-m}Q(z^{-1})\right]d(k)$$

$\hat{d}(k)$ directly cancels out $d(k)$

$$\left[1-z^{-m}\bullet B_Q(z^{-1})/A_Q(z^{-1})\right]=A_d(z^{-1})$$

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$$A_d(z^{-1})d(k)=B_d(z^{-1})\delta(k)\rightarrow 0$$

filter Q

- Why this controller?
  - Gain-scheduling PID: perfect gain correction is not strictly guaranteed
  - Augmented controller: inner-loop can further reject low frequency disturbance based on the disturbance suppression of the outer-loop.

Disturbance Observer based controller

Persistent wind disturbance input:

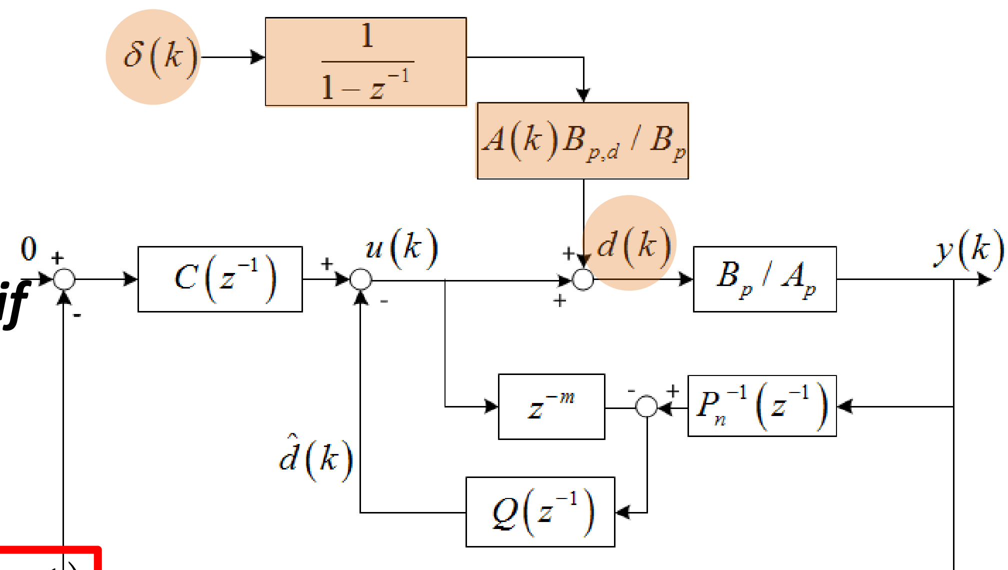
$$\dot{\mathbf{z}}_d = \mathbf{F}\mathbf{z}_d$$

$$\mathbf{u}_d = \boldsymbol{\Theta}\mathbf{z}_d$$

unknown amplitude, known waveform

step disturbance $\mathbf{F} \equiv 0$ $\quad \boldsymbol{\Theta} \equiv 1$

Wind disturbance: Variance between nominal wind speed and the operating wind speed



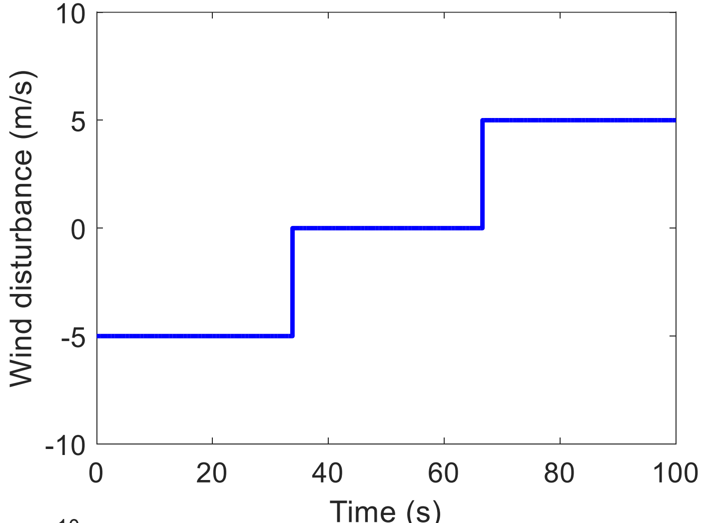
$$Z\{d_0(k)\} = A(k)\cdot\frac{1}{1-z^{-1}}$$

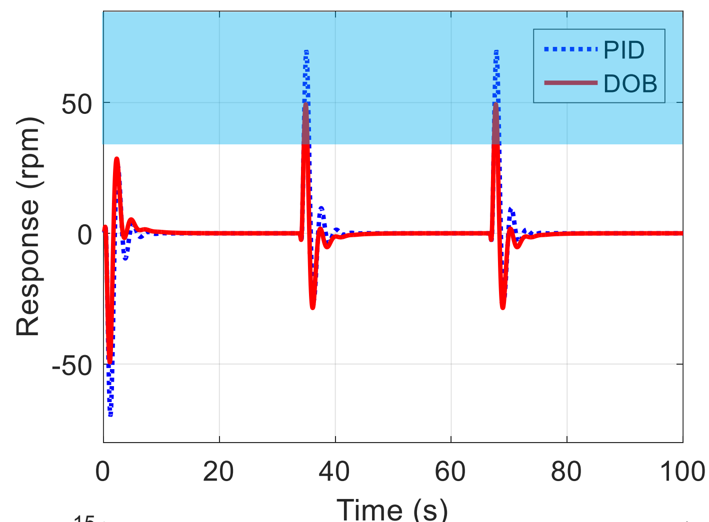
Disturbance rejection is achieved if

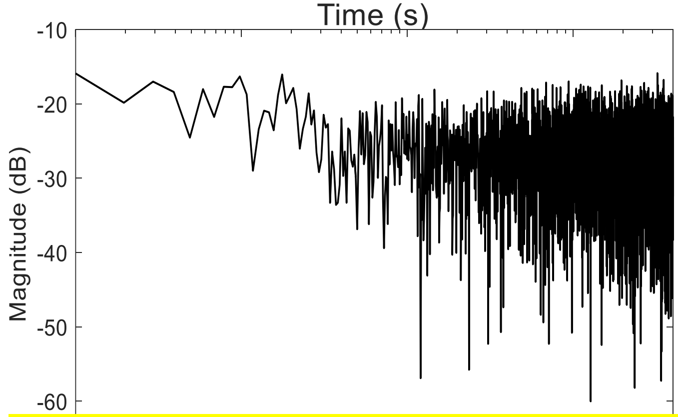
$$\boxed{1 - z^{-m}Q(z^{-1}) = \frac{(1-z^{-1})B_p(z^{-1})}{(1-\beta z^{-1})B_p(\beta z^{-1})}\frac{K(z^{-1})}{A(k)}}$$

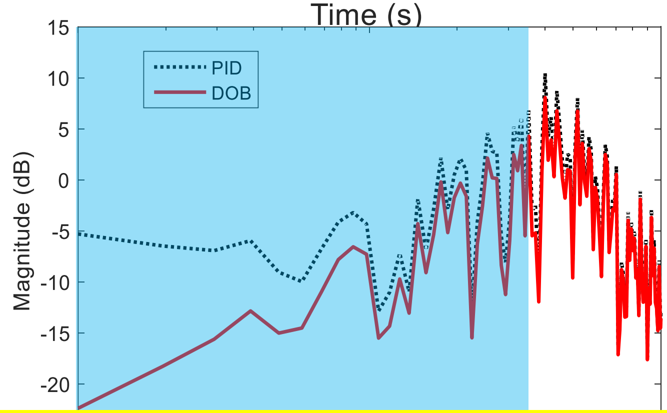
5-DOF Linearized Model (Preliminary Result)

5 DOF: Generator DOF, drivetrain torsional flexiblity DOF, and first flapwise blade mode DOF (three blades)







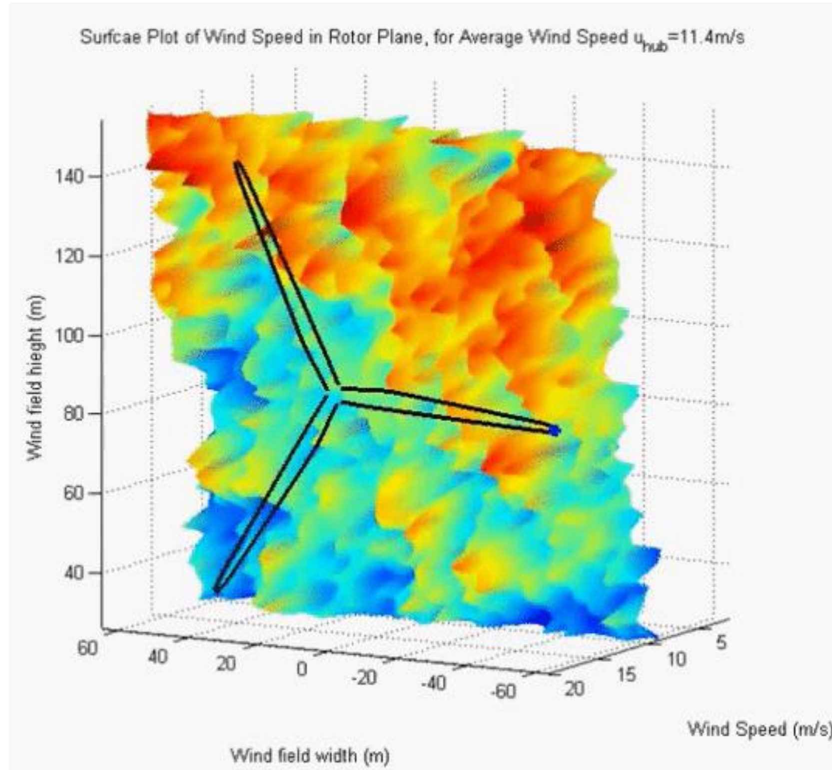


Further analysis is needed to deal with the nonlinearities

Case Study: Nonlinear plant

Case study:

- Test wind turbine
  - ✓ NREL offshore 5-MW baseline wind turbine
- Degree of freedom (DOF)
  - ✓ 16 DOFs*
- Turbulent wind field
- Simulation time
  - ✓ Run time: 0 to 600 s
  - ✓ Integration step size: 0.0125 s

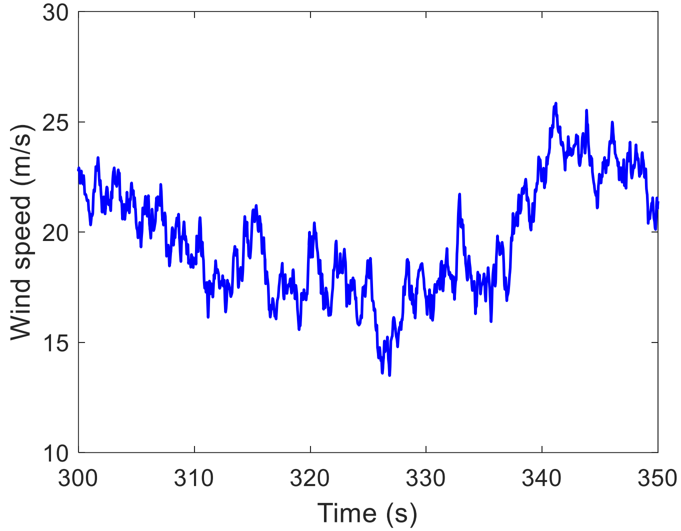


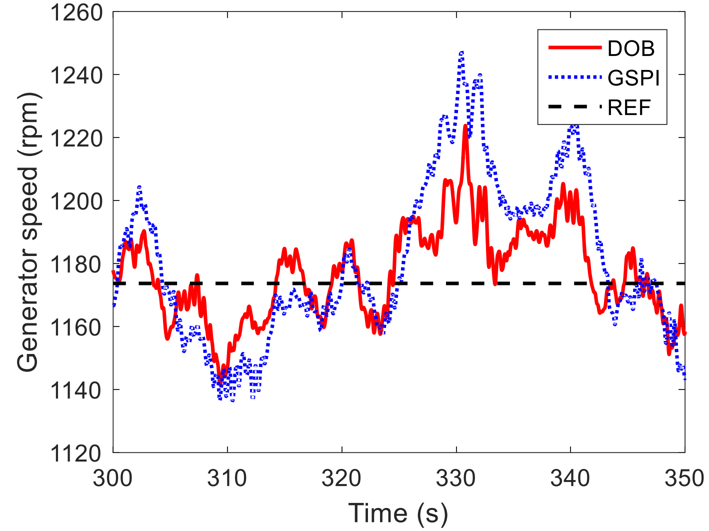
- Blade pitch limit and pitch rate limit [1]
  - ✓ Minimum/maximum blade pitch: 0 degree / 90 degree
  - ✓ Maximum absolute blade pitch rate: 8 degree/s

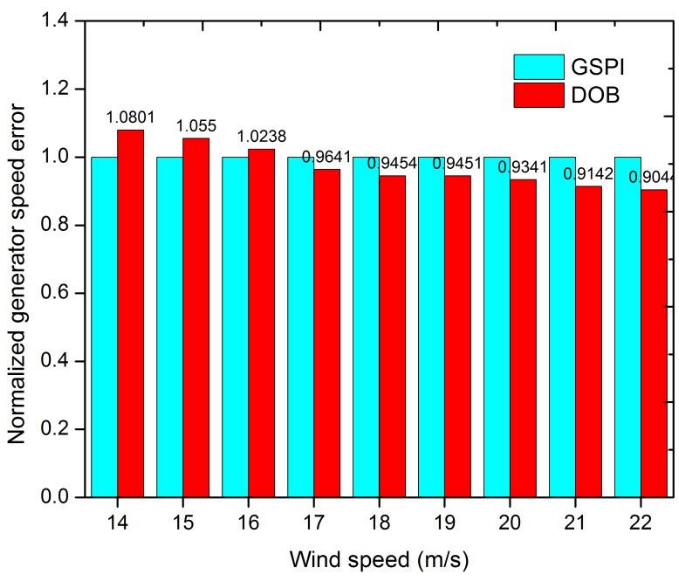
[1] Jonkman et al., **2009**, *National Renewable Energy Laboratory*, Golden, CO.

*First flapwise blade mode (3 blades), second flapwise blade mode (3 blades), first edgewise blade mode (3 blades), drivetrain rotational-flexibility, generator, yaw, first fore-aft tower bending-mode, second fore-aft tower bending-mode, first side-to-side tower bending-mode, second side-to-side tower bending-mode.

Performance comparison







Results:

- 3.59% - 9.56% decrease in 6 wind fields
- 2.38% - 8.01% increase in 3 wind fields
- Limited performance due to trade-off with respect to the stability issue

Trade-off in selection of Q filter

Trade-off between disturbance rejection region and disturbance amplification region:

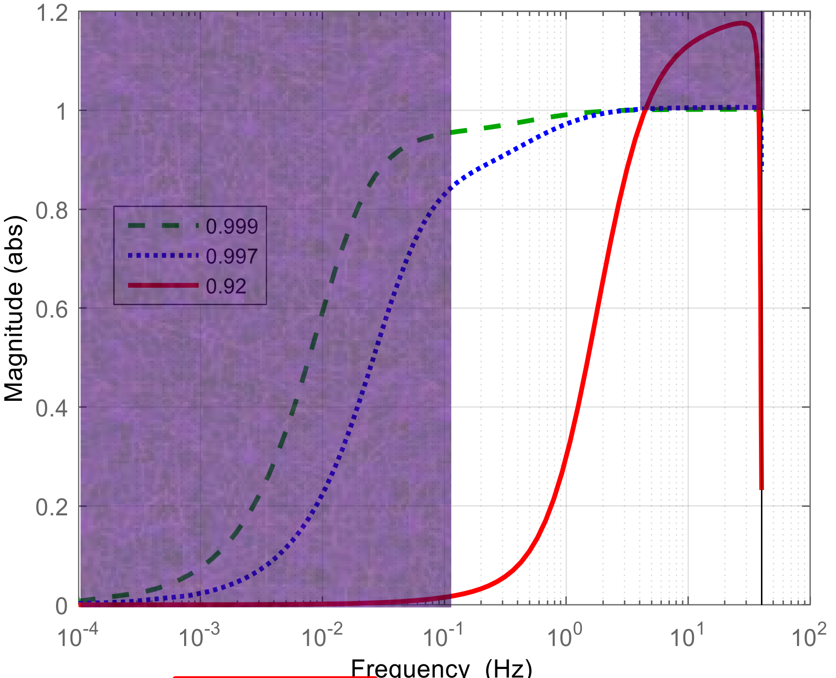
- Disturbance amplification:

  Instability of the nonlinear plant (model mismatch exists)[5]

$$\boxed{1-z^{-m}Q\left(z^{-1}\right)}=\frac{\kappa\left(z^{-1}\right)}{A(k)}\frac{\left(1-z^{-1}\right)B_p\left(z^{-1}\right)}{\left(1-\beta z^{-1}\right)B_p\left(\beta z^{-1}\right)}$$

Sensitivity function:

$$S\approx S_0\boxed{\left(1-z^{-m}Q\right)}$$

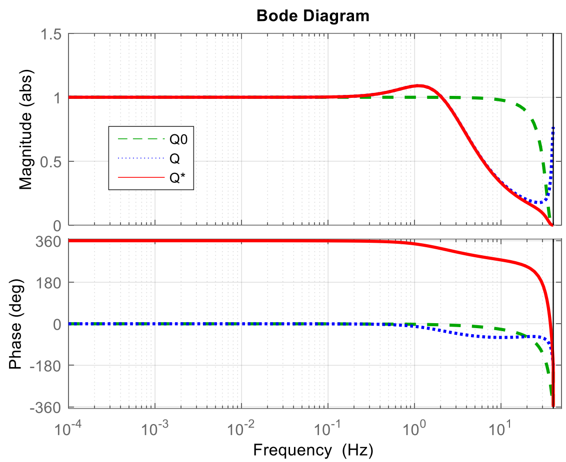


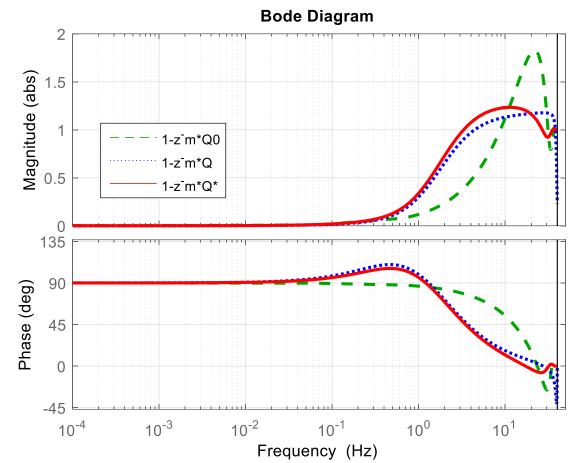
$\boxed{1-z^{-m}Q}$ under different β

[5] Doyle et al., *Feedback Control Theory*, 1990.

Add-on compensator

Faster roll-off at high frequencies

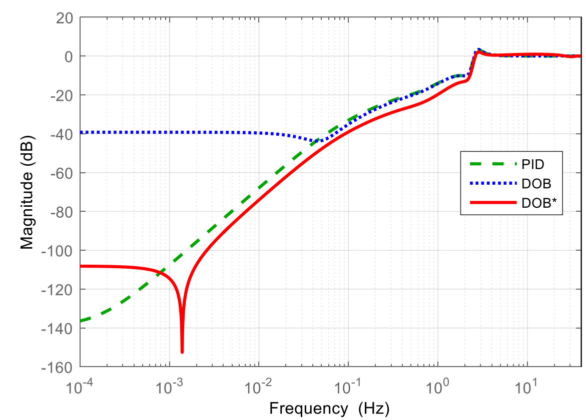




- Low pass filter $Q_0 = \dfrac{1}{(1+\tau s)^4}$ $\tau = 1/1256$
- *Q* filter (DOB)
- *Q** filter (DOB*) $Q^* = Q_0 \cdot Q$

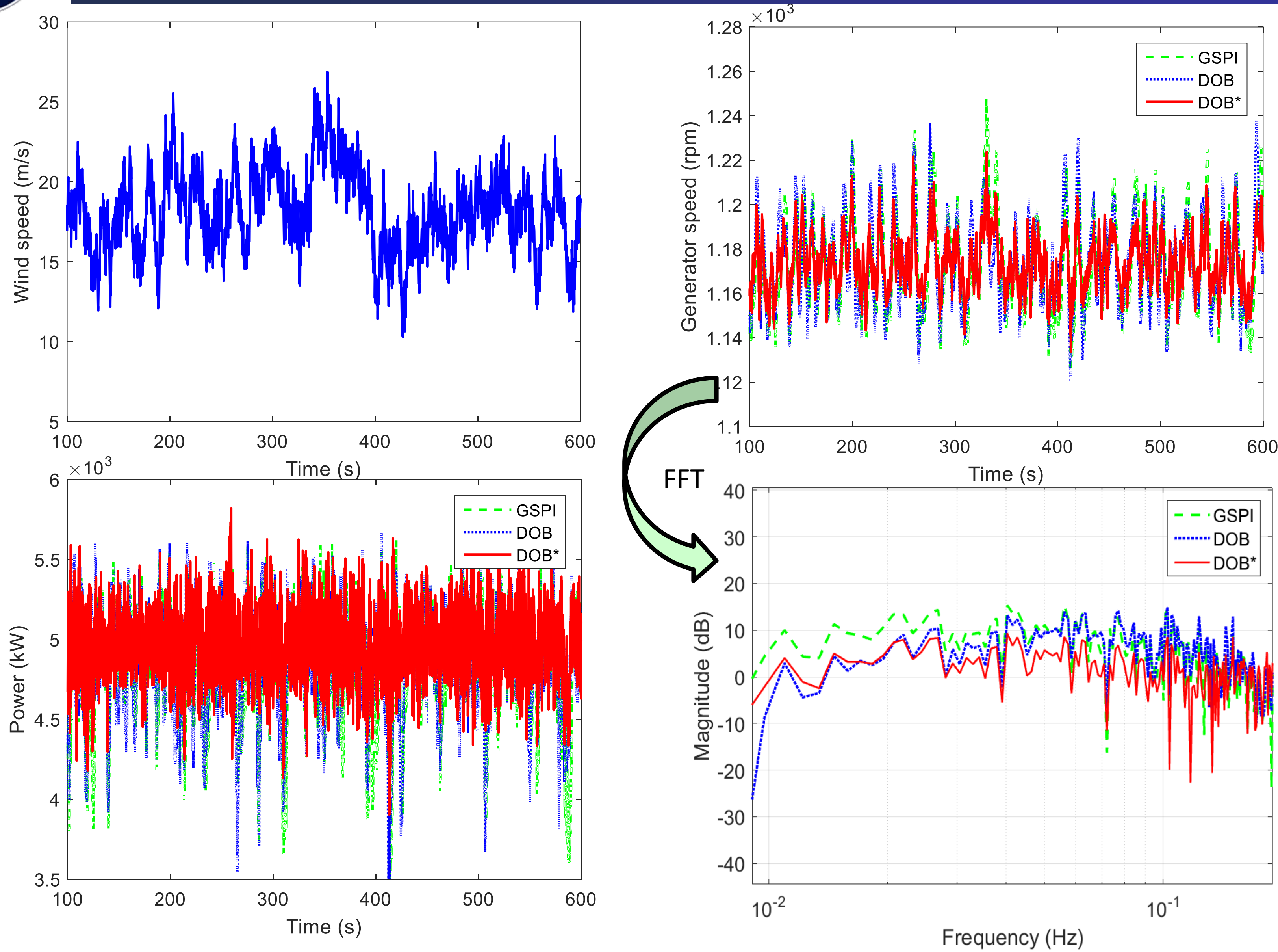
✓ Smaller disturbance amplification at certain high frequencies in Q*

✓ Better disturbance rejection in low freq.

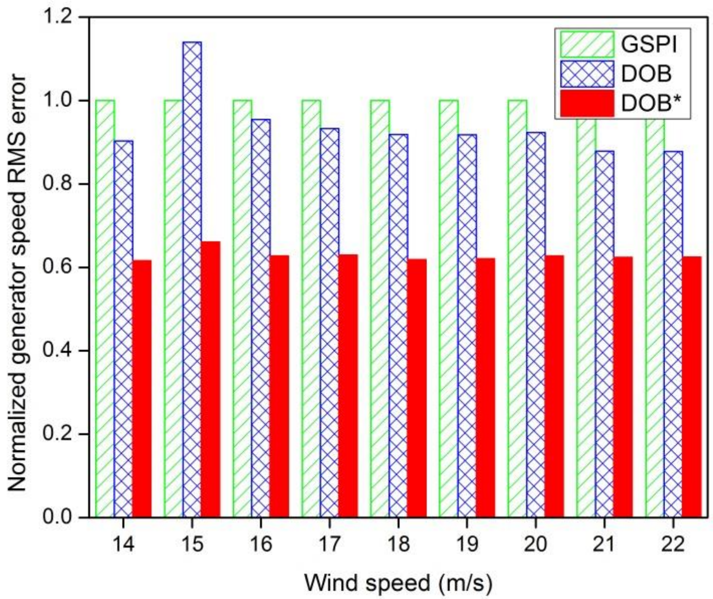


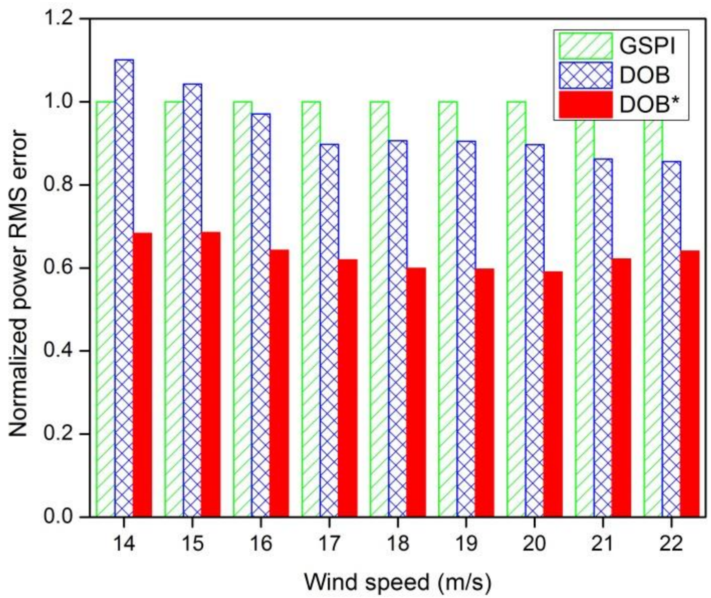
Sensitivity function

Performance comparison



Performance comparison





- Normalized generator speed RMS error: -28.13% to -39.14%
- Normalized power RMS error: -31.43% to -40.93%

Conclusion:

- Enhanced generator speed and power regulation with DOB* in Region 3

Concluding Remarks

- A general disturbance observer (DOB) based controller tailored for wind turbine is developed;
- The FIR filter $K(z^{-1})$ and a tuning factor β are introduced to facilitate better design of Q filter;
- Generator speed and power regulation performance is enhanced in DOB* controller for the actual nonlinear wind turbine under turbulent wind filed;
- DOB controller shows stability robustness under the entire Region 3.

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Periodic Wind Disturbance Rejection using Robust Individual Control Strategy


Photo by NREL

Yuan Yuan, X. Chen, J. Tang

Mar 5, 2018

Department of Mechanical Engineering
University of Connecticut
Storrs, CT, USA

Motivation$_1$

- Individual pitch control to mitigate periodic loads

  → Enabled by recent hardware advancements

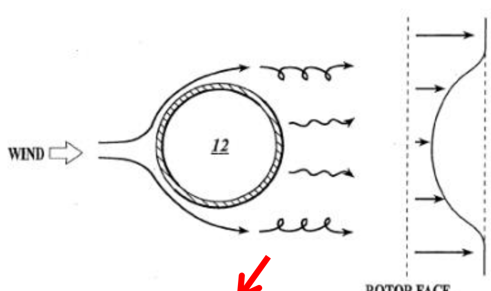
- Tower shadow and wind shear effects

Periodic loads

Tower shadow

upwind turbine

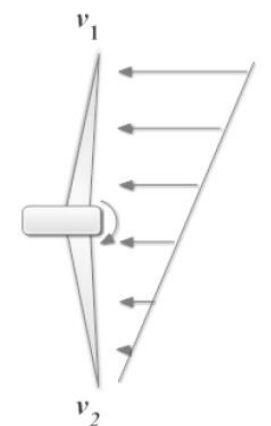
downwind turbine



Tower top

Wind shear

different wind speed at different height



v_1, v_2: prevailing wind speed at the tip of each blade

Motivation$_2$

- Challenges for wind turbine control:
  - Model uncertainties
  - Periodic loads on blades
  - Coupling dynamics of 3-bladed pitch system

Source: Liebherr

- Objective:
  - Speed and power regulation in high wind speeds
  - Mitigate periodic loads
  - Robust stability and robust performance

- Difficulties in designing controller:
  - Operating point varies constantly – actual dynamics is different from nominal model

→ Potential solution: Robust Controller (structured singular values (μ)-synthesis)

Dynamics and modeling

- Modeling including periodic dynamics

$$\mathbf{x}(k+1)=\mathbf{A}\mathbf{x}(k)+\mathbf{B}\mathbf{u}(k)+\mathbf{B}_d\mathbf{u}_d(k)$$
$$\mathbf{y}(k)=\mathbf{C}\mathbf{x}(k)+\mathbf{D}\mathbf{u}(k)+\mathbf{D}_d\mathbf{u}_d(k)$$

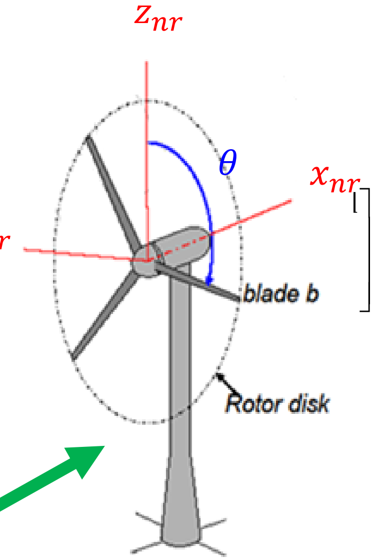
$$x=\begin{bmatrix}\text{blade 1 flap defelction}\\ \text{blade 2 flap defelction}\\ \text{blade 3 flap defelction}\\ \text{generator speed}\\ \text{blade 1 flap velocity}\\ \text{blade 2 flap velocity}\\ \text{blade 3 flap velocity}\end{bmatrix},\quad y=\begin{bmatrix}\text{generator speed}\\ \text{blade 1 flap bending moment}\\ \text{blade 2 flap bending moment}\\ \text{blade 3 flap bending moment}\end{bmatrix},\quad \mathbf{u}=\begin{bmatrix}\text{blade 1 pitch angle}\\ \text{blade 2 pitch angle}\\ \text{blade 3 pitch angle}\end{bmatrix},\quad \mathbf{u}_d=$$

Steady state: blade motion is a Fourier series equation

linearization → Periodic LTV state space model

A series of LTI state space model depends on azimuth θ

e.g. 36 models: θ = 0, 10, 20,...350 deg



- MBC transformation

transform from rotating coordinates to nonrotating coordinates

$$\begin{bmatrix}M_{avg}\\ M_{tilt}\\ M_{yaw}\end{bmatrix}=T_\theta\begin{bmatrix}M_1\\ M_2\\ M_3\end{bmatrix},\quad T_\theta=\frac{2}{3}\begin{bmatrix}1/2 & 1/2 & 1/2\\ \cos(\theta) & \cos\left(\theta+\frac{2}{3}\pi\right) & \cos\left(\theta+\frac{4}{3}\pi\right)\\ \sin(\theta) & \sin\left(\theta+\frac{2}{3}\pi\right) & \sin\left(\theta+\frac{4}{3}\pi\right)\end{bmatrix}$$

Bir, G.S., 2010. User's guide to MBC3: Multi-blade coordinate transformation code for 3-bladed wind turbine.

$$\mathbf{x}^{mbc}(k+1)=\mathbf{A}^{mbc}\mathbf{x}^{mbc}(k)+\mathbf{B}^{mbc}\mathbf{u}^{mbc}(k)+\mathbf{B}_d^{mbc}\mathbf{u}_d^{mbc}(k)$$
$$\mathbf{y}^{mbc}(k)=\mathbf{C}^{mbc}\mathbf{x}^{mbc}(k)+\mathbf{D}^{mbc}\mathbf{u}^{mbc}(k)+\mathbf{D}_d^{mbc}\mathbf{u}_d^{mbc}(k)$$

$$\mathbf{u}^{mbc}=\begin{bmatrix}\beta_{avg}\\ \beta_{tilt}\\ \beta_{yaw}\end{bmatrix}, y^{mbc}=\begin{bmatrix}y_{avg}\\ y_{tilt}\\ y_{yaw}\end{bmatrix}, \mathbf{u}_d^{mbc}=\begin{bmatrix}u_{d_{avg}}\\ u_{d_{tilt}}\\ u_{d_{yaw}}\end{bmatrix}$$

An average state-space system is obtained from the complete set of linearizations at N azimuth angles by computing

$$\mathbf{A}=\frac{1}{N}\sum_{i=0}^{N}\mathbf{A}^{mbc}(\theta_i)$$

Uncertain model structures

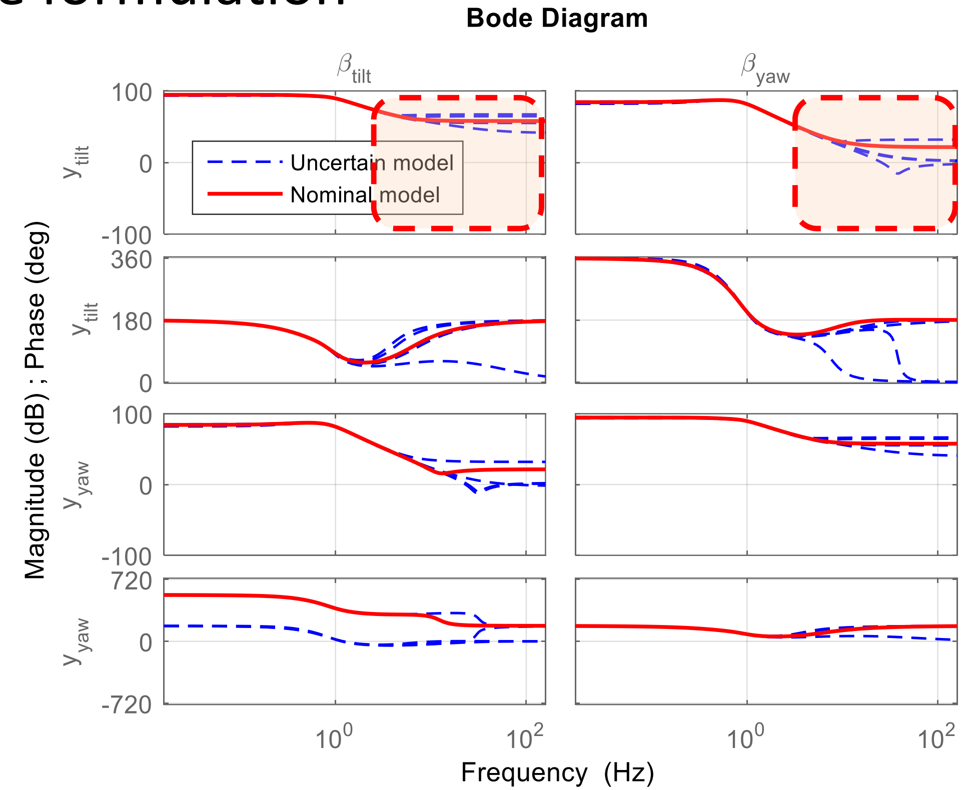
- Uncertain model structure formulation
  - LTI state space model
  - Pick nominal model: 18 m/s

    Challenge: wind speed changes so actual dynamics changes

  - Fit an uncertain model structure to an array of LTI responses :
  - 14 m/s, 16 m/s, 20 m/s, and 22 m/s

➢ Model mismatch in high frequency regions

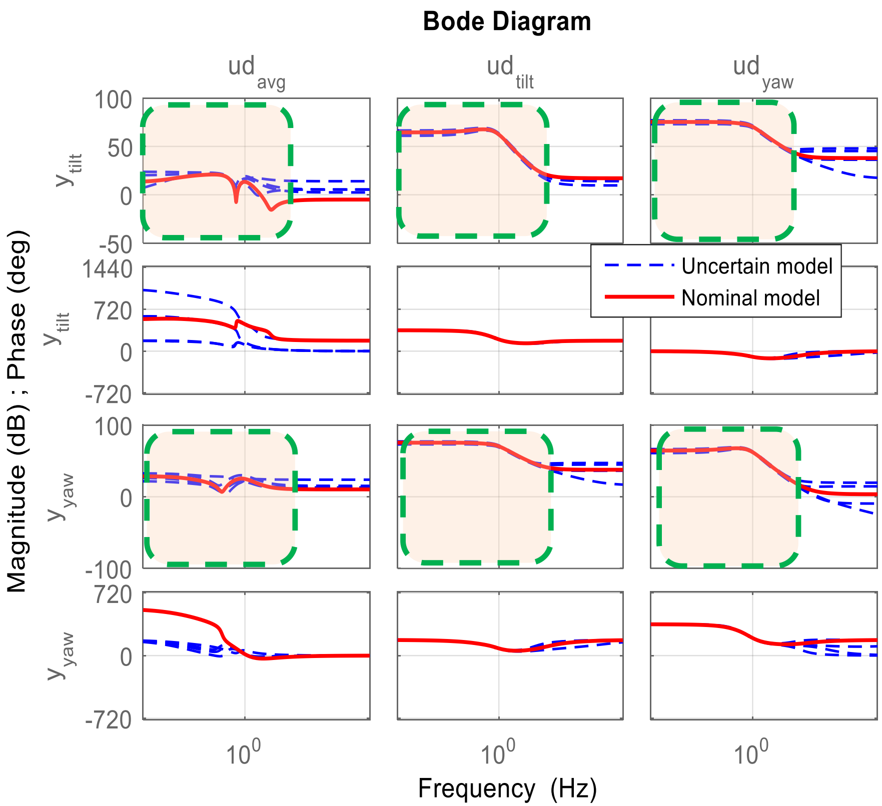
Uncertain model structures



Frequency responses comparison

Shear components

- Horizontal and vertical wind shear effects to dynamic modeling



– Magnitude of $u_{d_{tilt}}, u_{d_{yaw}}$ to moments y_{tilt}, y_{yaw} :
70 – 80 dB

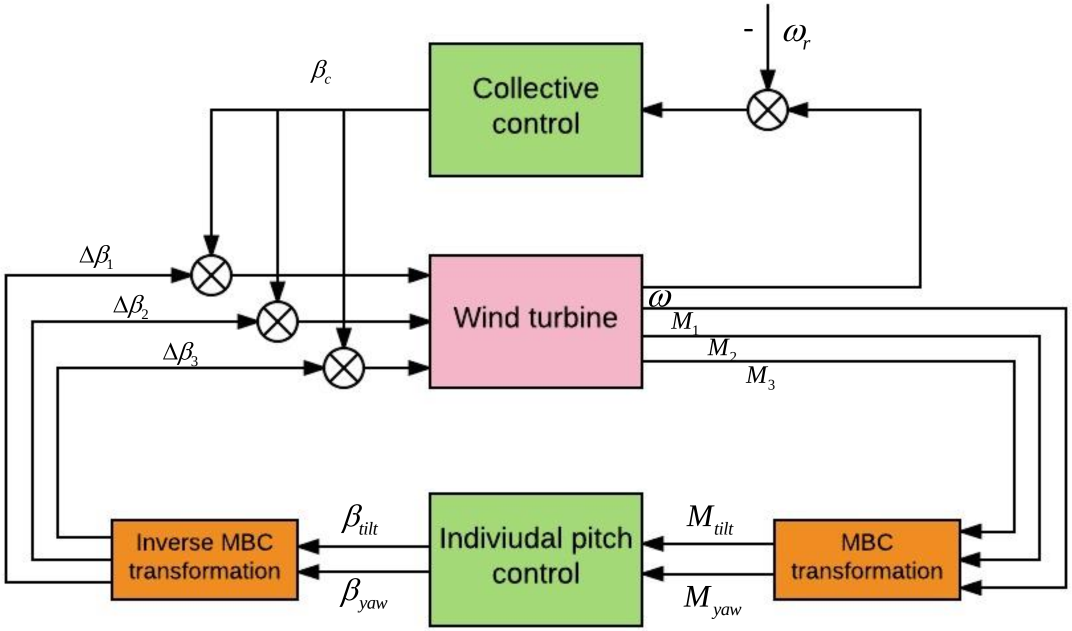
– Magnitude of horizontal wind $u_{d_{avg}}$ to moments y_{tilt}, y_{yaw} :
20 – 30 dB

– Bode Diagram has large magnitude

→ Include wind shear components in the model

Control architecture formulation

- Control architecture formulation



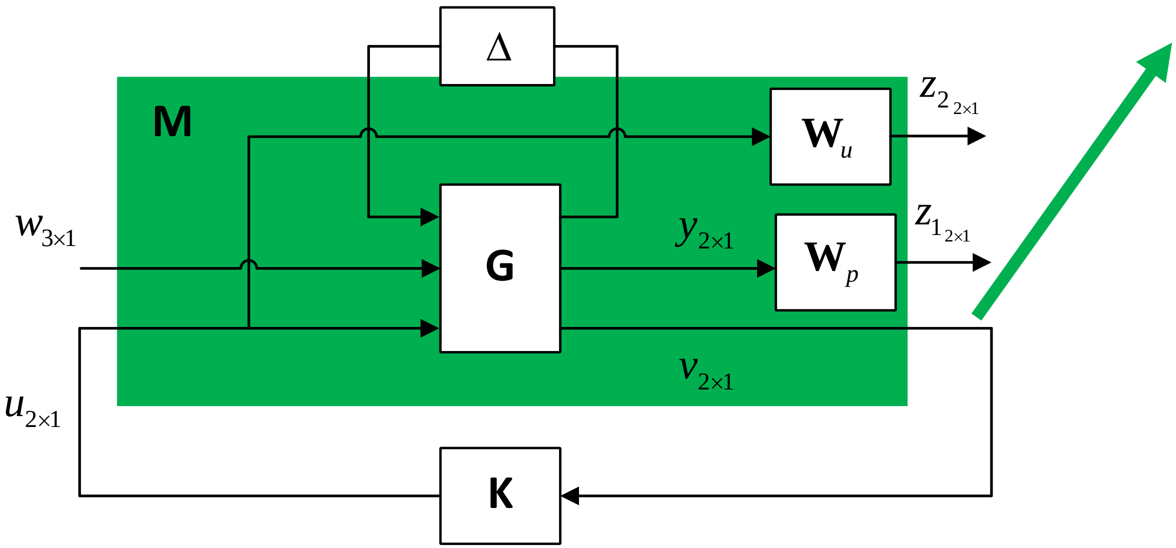
- Collective loop:
  - Speed and power regulation
  - GSPI/DOB [1]

[1] **Yuan, Y.**, Chen, X., and Tang, J., 2017, "Disturbance Observer-Based Pitch Control of Wind Turbines for Enhanced Speed Regulation," Journal of Dynamic Systems, Measurement, and Control, V139(7), pp. 071006.

- Individual loop:
  - Periodic load mitigation and modeling uncertainties
  - Robust control with weighting function selection

Structural singular value (μ)-synthesis formulation

- Advantages using structural singular value-synthesis
  - RSRP (robust stability and robust performance) guarantee under model uncertainties due to operating point variation
  - Disturbance rejection via weighting function selection



M-Δ structure

w: disturbance
u: input
y :output
z : weighted output
G: generalized plant
K: robust controller
Δ: perturbation of **G**

- The performance of MIMO control systems are characterized using H_∞ norms

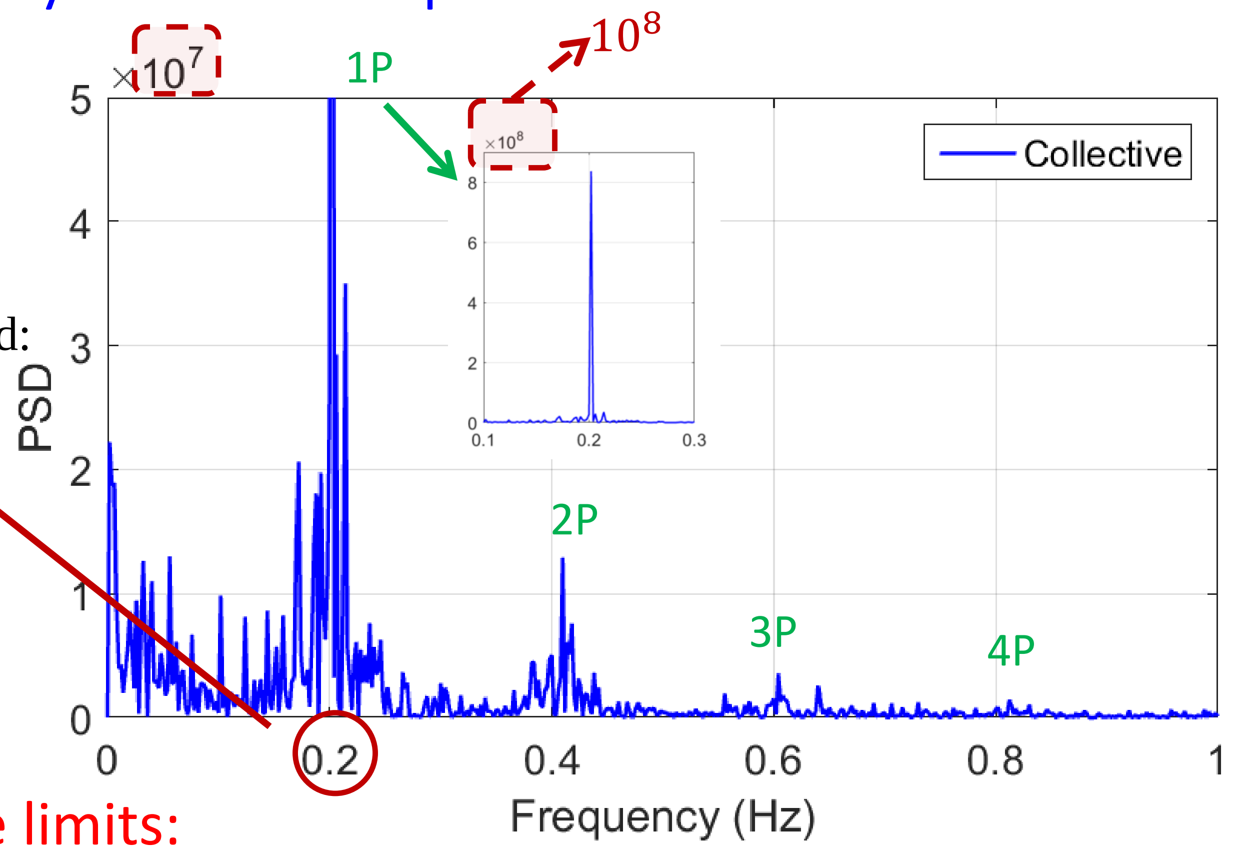
$$\|T\|_\infty := \max_{\omega \in \mathbf{R}} \bar{\sigma}\left(T\left(j\omega\right)\right) \le 1$$

$$\|T\|_\infty := \max_{\omega \in \mathbf{R}} \bar{\sigma}\left(T\left(j\omega\right)\right) \le 1$$

Power spectral density

- Power spectral density (PSD) of blade 1 root flapwise moment with only collective loop

Rated rotor speed: $12.1\ rpm \approx 0.2\ Hz$



- Severe limits:
  - Multiple peaks at 1P (*per revolution*), 2P, 3P, … frequencies due to periodic loads on → ***Component failure***

Weighting functions

- Frequency effects change due to coordinates change

Rotating coordinate	Non-rotating coordinate
1P	0P @ M_{tilt} and M_{yaw}
2P	3P@ M_{tilt} and M_{yaw}
3P	3P @ M_{avg}
4P	3P@ M_{tilt} and M_{yaw}
5P	6P@ M_{tilt} and M_{yaw}
6P	6P@ M_{avg}
7P	6P@ M_{tilt} and M_{yaw}

– Sensitivity function $\mathbf{S} = \left(\mathbf{I} + \mathbf{F}_u\left(\mathbf{M}, \mathbf{\Delta}\right)\mathbf{K}\right)^{-1}$

– Minimize the norm

$$\left\| \begin{bmatrix} \mathbf{W}_p\left(\mathbf{I} + \mathbf{F}_u\left(\mathbf{M}, \mathbf{\Delta}\right)\mathbf{K}\right)^{-1} \\ \mathbf{W}_u\mathbf{K}\left(\mathbf{I} + \mathbf{F}_u\left(\mathbf{M}, \mathbf{\Delta}\right)\mathbf{K}\right)^{-1} \end{bmatrix} \right\|_\infty \rightarrow$$

Further penalize the control input and output performance

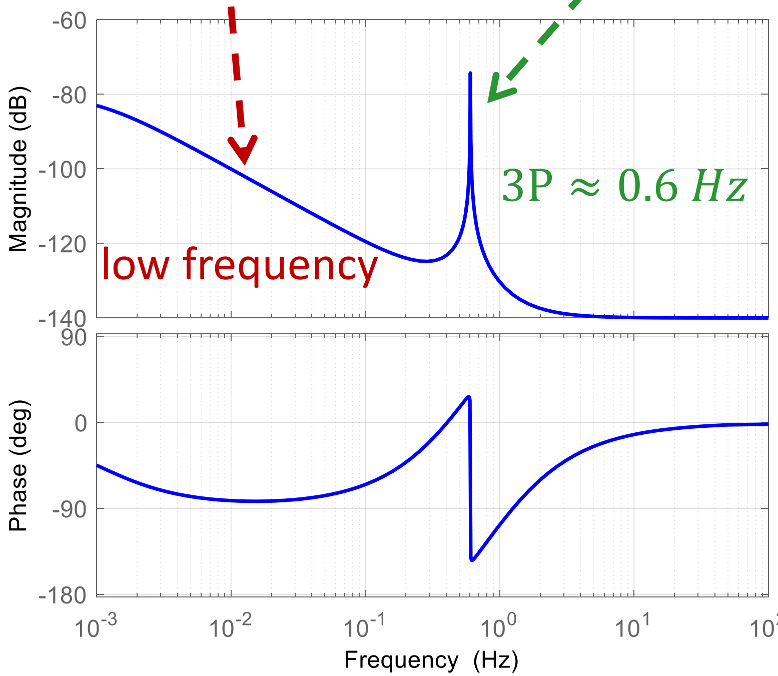
Weighting functions

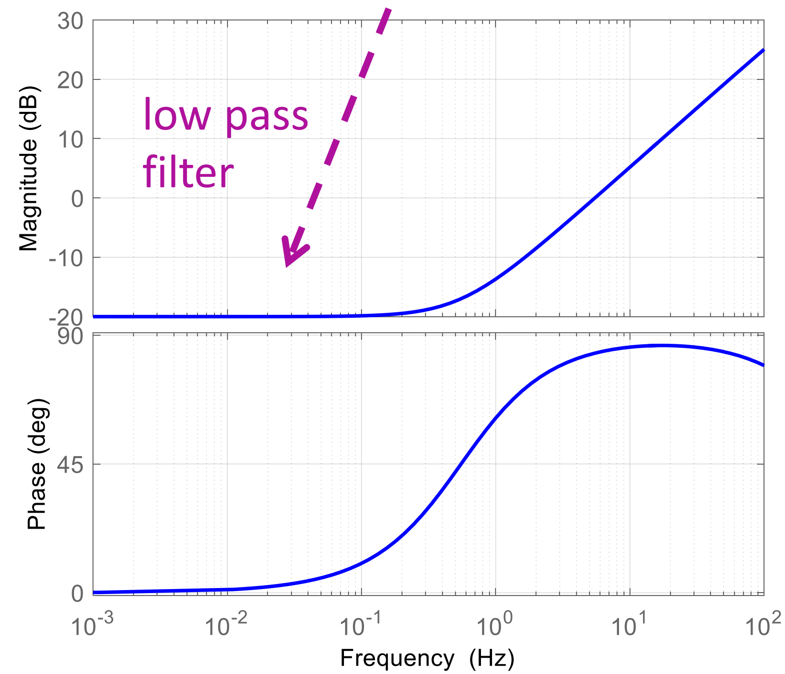
- Select weighting functions

$$\mathbf{W}_p = W_p I_{2\times2} \qquad W_p = W_l \bullet W_{3p} \qquad \mathbf{W}_u = W_u I_{2\times2}$$

$$W_l = K_1 \frac{s/M_p + \omega_p}{s + e_p\omega_p}, \quad W_{3p} = \frac{s^2 + 2\alpha\omega_{3p} + \omega_{3p}^2}{s^2 + 2\beta\omega_{3p} + \omega_{3p}^2}$$

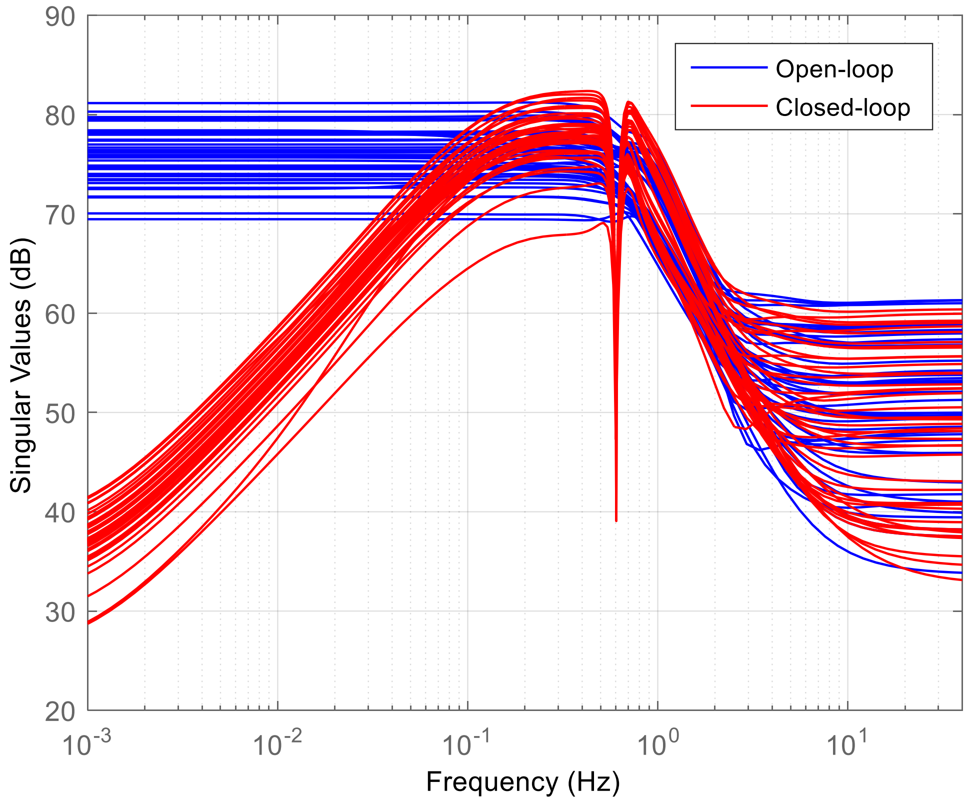
$$W_u = \frac{s + \omega_u / M_u}{e_u s + \omega_u}$$





Singular values

- Multivariate transfer functions: singular values of transfer function
  - Open-loop and closed-loop responses of the nonlinear wind turbine under turbulent wind excitations

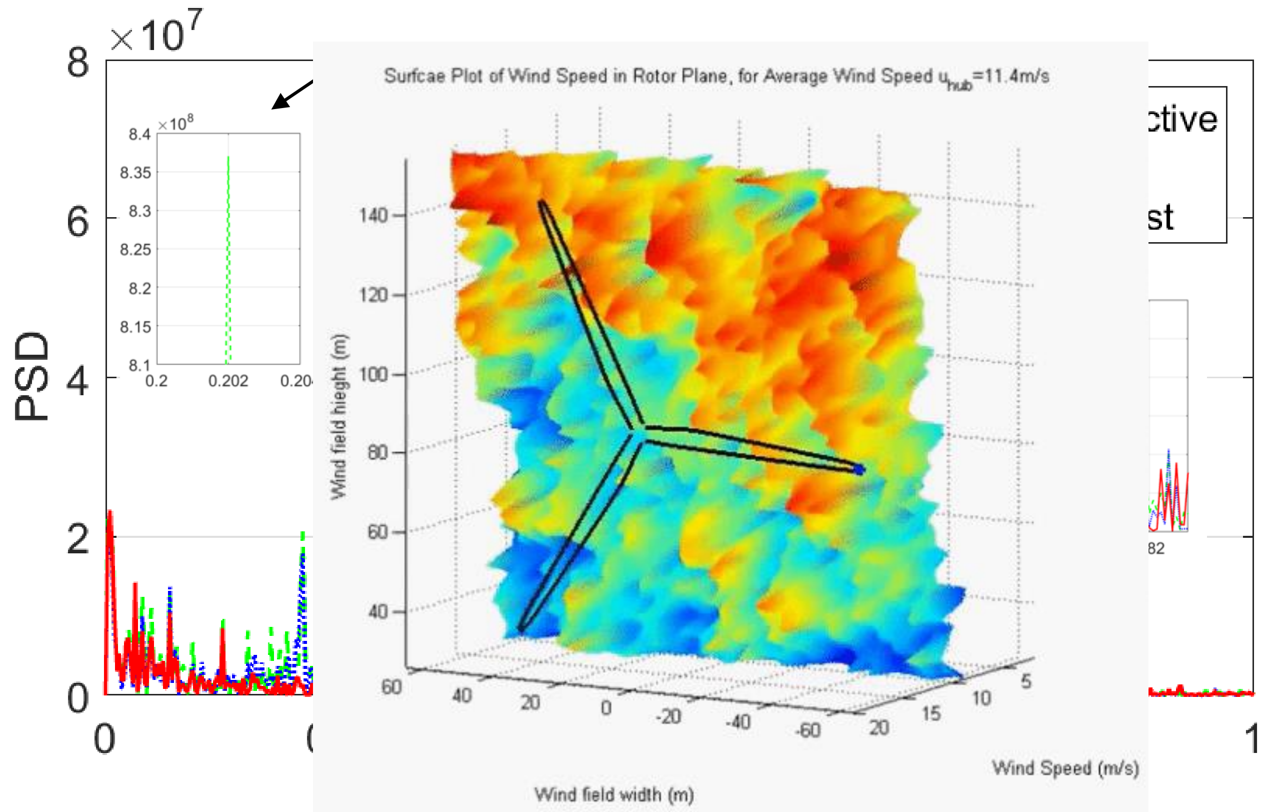


- ✓ Deal with uncertain model structure (a group of curves)
- ✓ 0P and 3P disturbance rejection
- ✓ $\mu = 0.1784 < 1 \rightarrow$ RSRP guaranteed

PSD results

- PSD result analysis at multiple frequencies

18 m/s turbulent wind field excitation

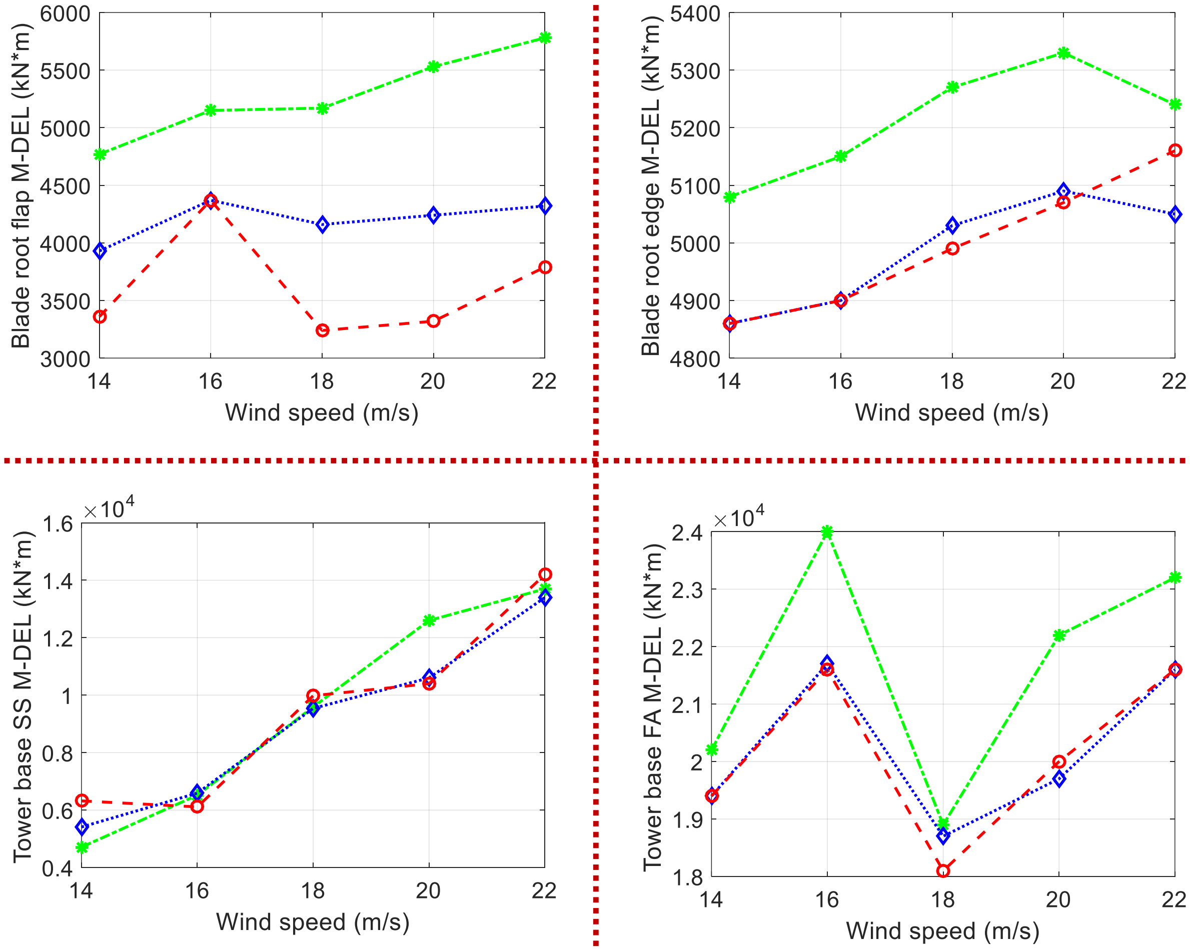


❖ Significant 1P, 2P, and 4P peak reduction

Load analysis

- Blade and tower fatigue damage equivalent load (DEL) comparison

(DEL: industrial standard)



Collective control

PID individual control

Robust individual control

- Blade flapwise: Robust: -20% of PID
- Blade edgewise: same level
- Tower base fore-aft: 3%-10% decrease
- Tower base side-side: same level

Concluding remarks

- A robust controller with mu synthesis for wind turbine is developed;
- Individual pitch control is utilized to reject periodic loads;
- Robust control strategy is formulated to tackle with modeling uncertainties;
- Periodic loads on blades are significantly reduced.

Multiple Objectives in Wind Turbines

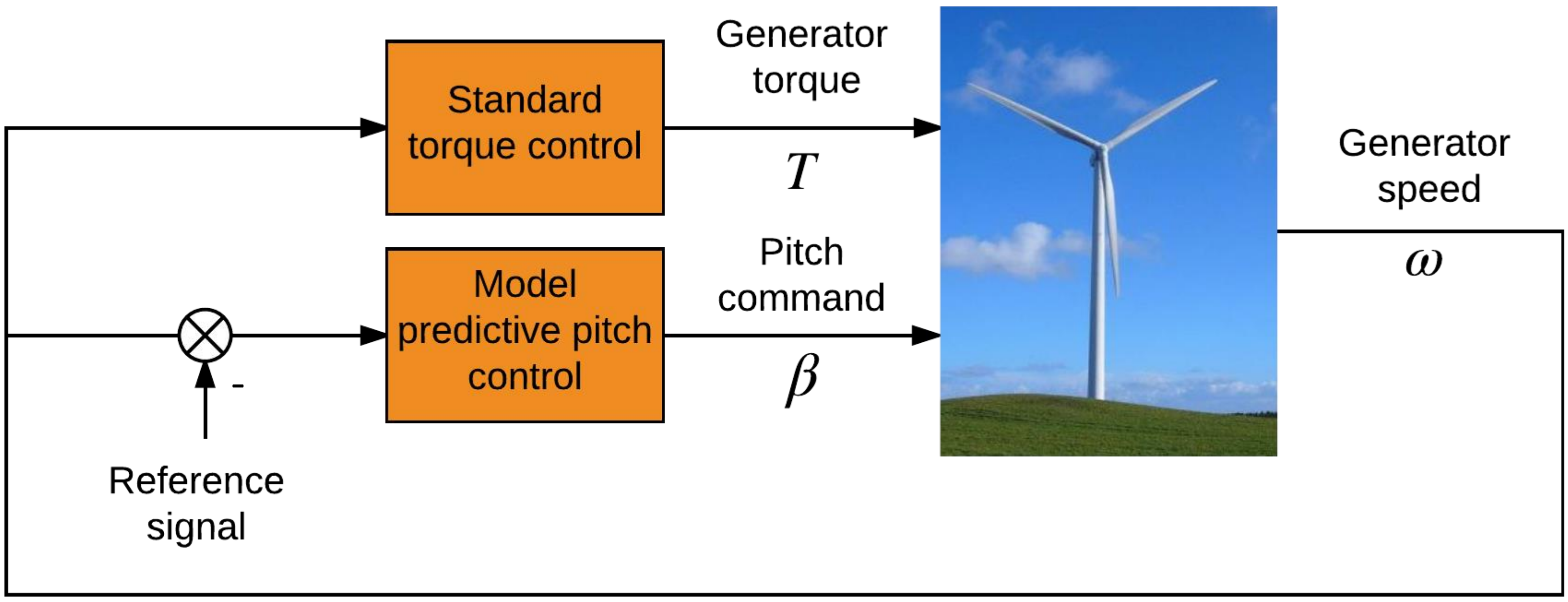
- Different control goals
  - Speed control
  - Power control
  - Load reduction on blades, tower and drive-train
  - Prolong actuator life

- Challenges of multiple objectives
  - Designing individual controllers for each objective is getting more and more complex
  - Conflicting with each other
  - We need **one controller** that can balance all the objectives together

Model predictive control:

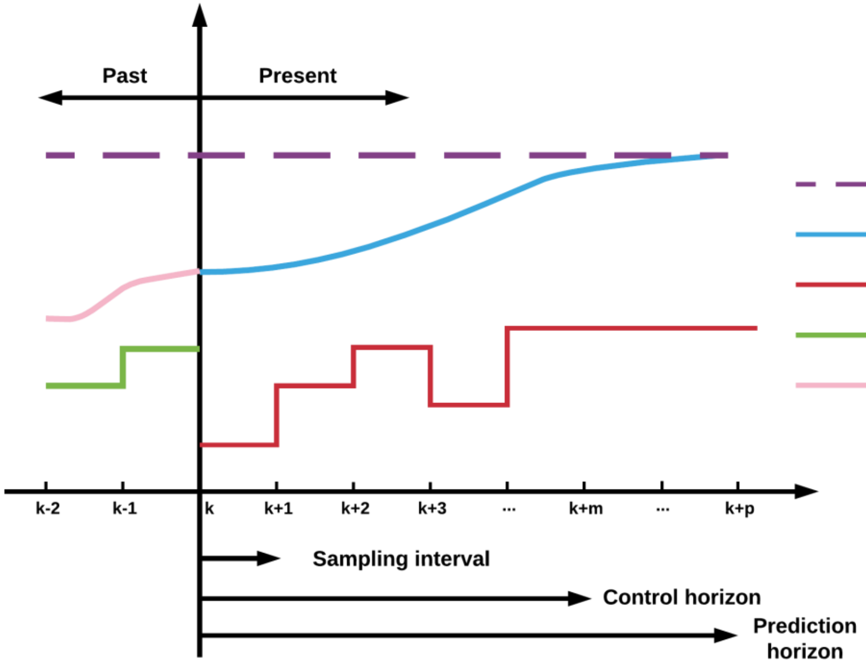
- Online optimization of multiple control objectives

Control Architecture

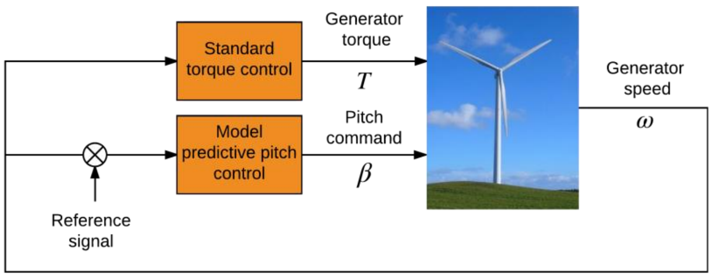


- ✓ Torque control: Standard torque control
- ✓ Pitch control: Model predictive control
- ✓ Yaw control: Not involved

Model Predictive Controller (MPC)



k: current time
p: prediction horizon
m: control horizon



- Model predictive control (MPC): regulatory controls that use an explicit dynamic model of the response of process variables to changes in manipulated variables to calculate control “moves”
- Control moves are intended to force the process variables to follow a pre-specified trajectory

Predicted outputs

$$
\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(p) \end{bmatrix} = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^p \end{bmatrix} x(0) + \begin{bmatrix} CB \\ CB+CAB \\ \vdots \\ \sum_{i=0}^{p-1} CA^p B \end{bmatrix} u(-1) + \begin{bmatrix} CB & 0 & \cdots & 0 \\ CB+CAB & CB & 0 & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \sum_{i=0}^{p-1} CA^i B & \sum_{i=0}^{p-2} CA^i B & \cdots & \sum_{i=0}^{p-m} CA^i B \end{bmatrix} \begin{bmatrix} \Delta u(0) \\ \Delta u(1) \\ \vdots \\ \Delta u(m) \end{bmatrix}
$$

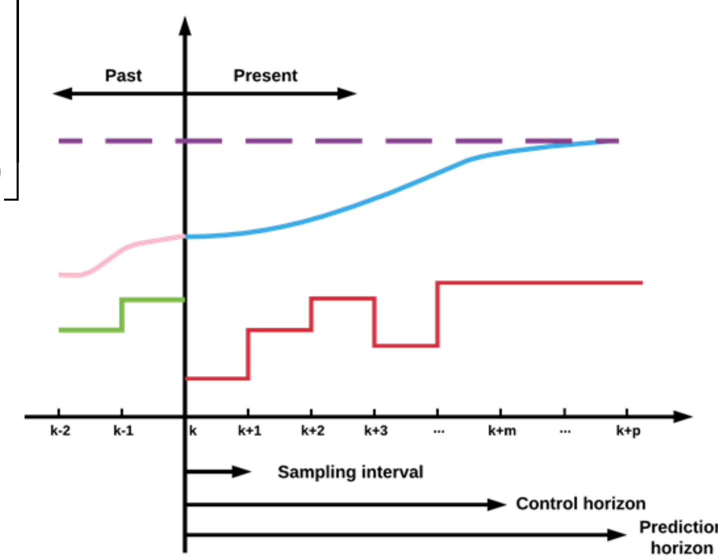
$$
+ \begin{bmatrix} CB_d & D_d & 0 & \cdots & 0 \\ CAB_d & CB & D_d & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{p-1}B & CA^{p-2}B & CA^{p-3}B & \cdots & D_d \end{bmatrix} \begin{bmatrix} u_d(0) \\ u_d(1) \\ \vdots \\ u_d(p) \end{bmatrix}
$$

Cost function

$$
J(z_k) = Q \sum_{i=0}^{p-1} \left(e(k+i) \right)^2 + R \sum_{i=0}^{m-1} \left(\Delta u(k+i) \right)^2
$$

$$
e(k+i) = y(k+i+1 \mid k) - r(k+i+1 \mid k)
$$

$$
\Delta u(k+i) = u(k+i \mid k) - u(k+i-1 \mid k)
$$



Model Predictive Controller (MPC)

Optimal solution

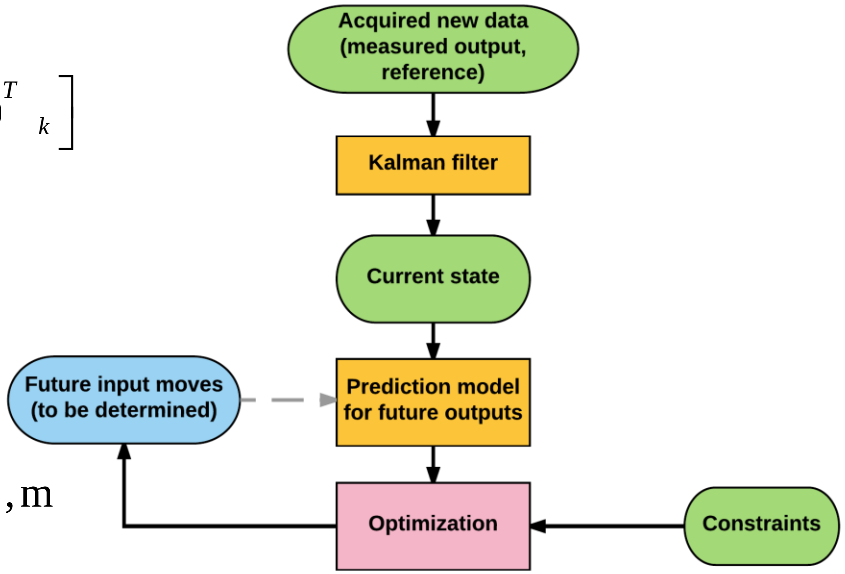
$$\mathbf{z}_k^T = \left[u(k\,|\,k)^T u(k+1\,|\,k)^T \cdots u(k+m-1\,|\,k)^T \quad_k \right]$$

Find $\mathbf{z}_k^T$

to minimize $J(\mathbf{z}_k)$

subject to

$$u_{\min} \le u(k+i) \le u_{\max}\,, \quad i = 1,2,\cdots,\mathrm{m}$$
$$\Delta u_{\min} \le \Delta u(k+i) \le \Delta u_{\max}, i = 1,2,\cdots,\mathrm{m}$$



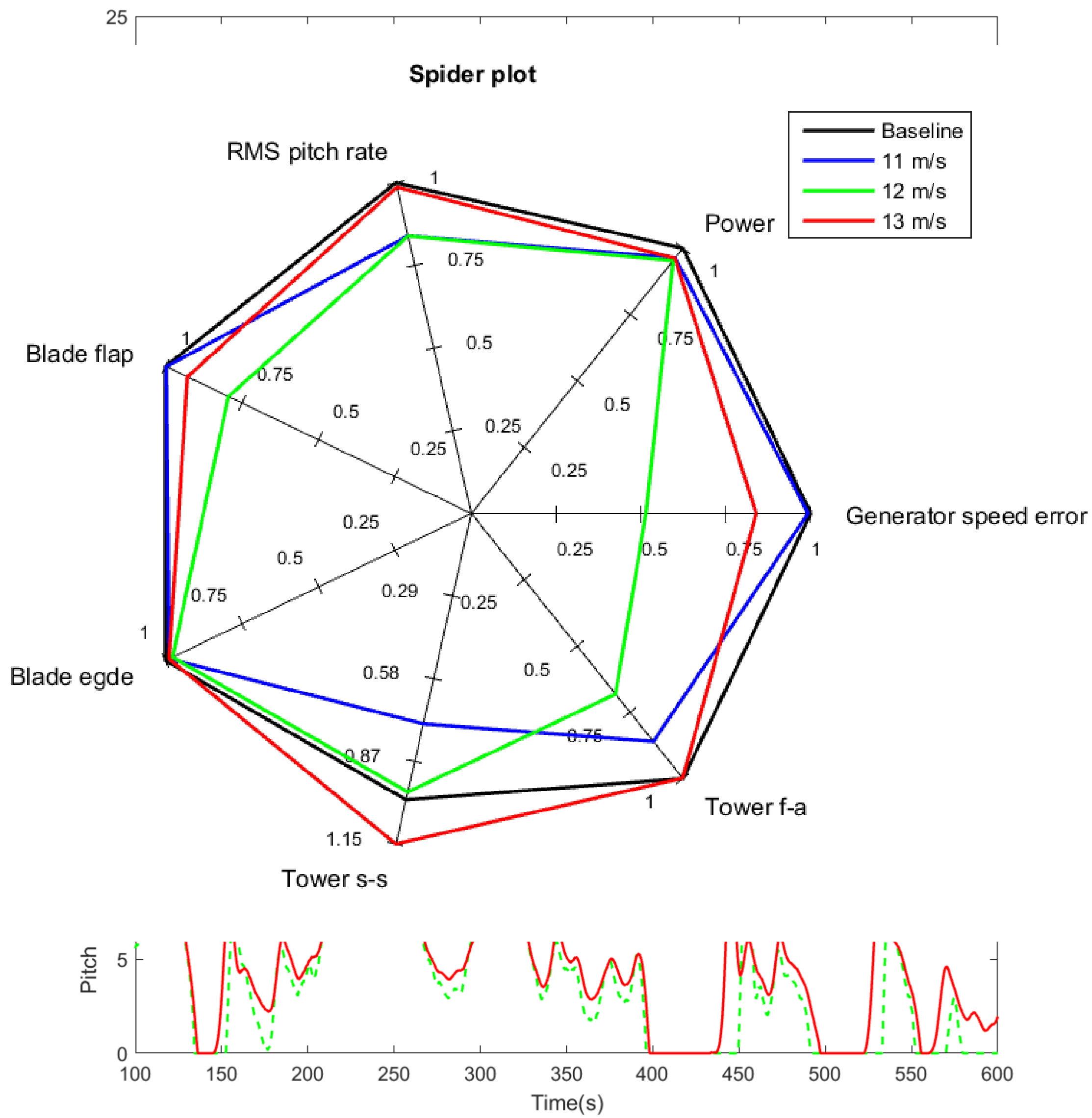
Optimization steps:

At time k:

- Acquire new data
- Estimate the current state $\mathrm{x}(k)$ though Kalman filter
- Solve the QP problem
  and let $z_k{}^T = [u(k|k)^T, u(k+1|k)^T \cdots u(k+m-1|k)^T]$ be the solution
- Apply only $\mathrm{u} = u(k|k)$ and discard the remaining inputs

Repeat optimization at time $k+1$, and so on…

Switching Region Performance



- Wind fields:
  - 11 m/s, 12 m/s, 13 m/s
- Results:
  - Power: Nearly same
  - Speed : better
  - Tower fore-aft loads: reduced
  - Tower side-side loads: mixed
  - Blade edgewise loads: nearly same
  - Blade flapwise loads: reduced
  - Pitch actuator: reduced

Adaptive Controller

- Challenges for wind turbine systems:
  - Complex dynamics
  - Uncertain environments
- Objective:
  - Generator speed at rated value and reduce oscillation
  - Mitigate loads
  - Near-term performance(constant speed)
  - Long-term reliability (less failure)
- Difficulties in designing controller:
  - System parameters not completely known

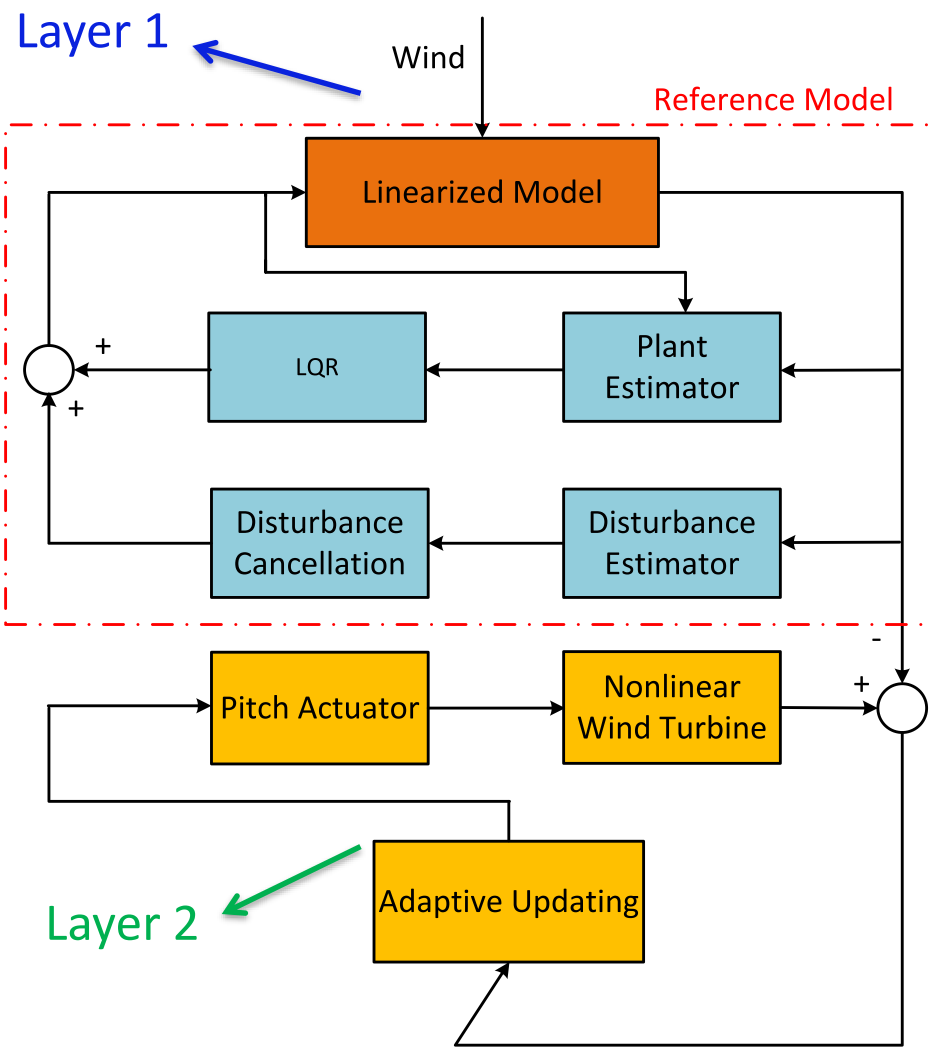
Source: Liebherr

❖ inherent model nonlinearities
❖ unmodeled modes
❖ manufacturing and assemblage tolerances
❖ external operating uncertainties

→ Adaptive Controller

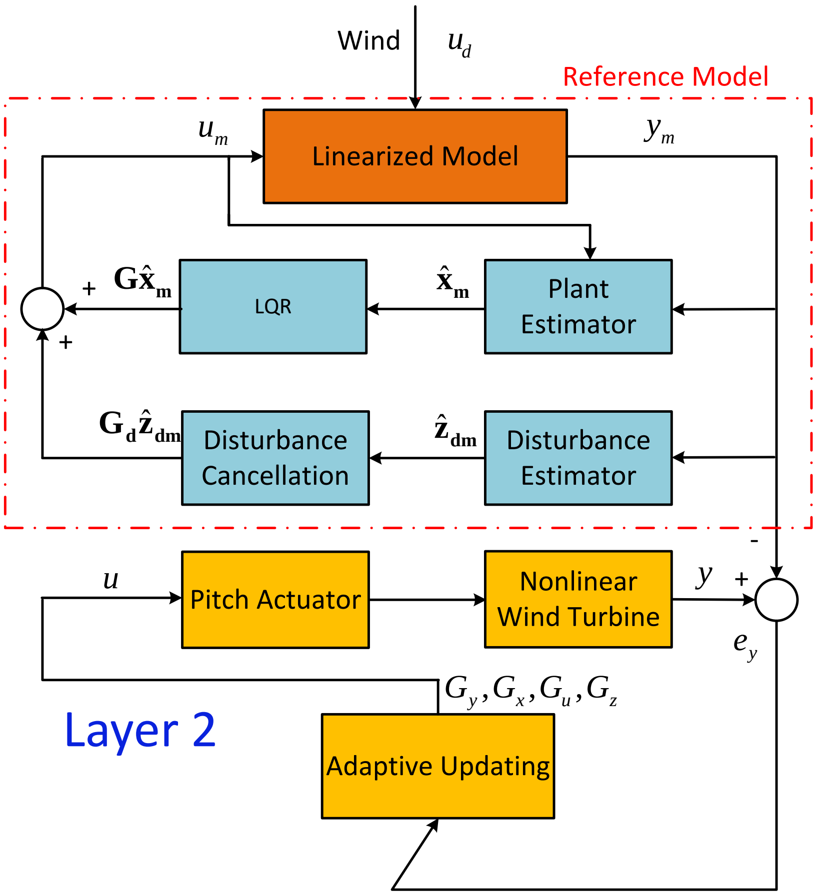
Adaptive Controller

- Method:
  - Model reference adaptive control (MRAC) with a disturbance accommodation controller (DAC): Two-layer structure
  - Control layer 1: DAC layer (closed-loop DAC: reference model)
    - disturbance accommodation
    - optimal trade-off between power capture and load mitigation
  - Control layer 2: Adaptive control layer
    - adapt to internal and external uncertainties



Control Layer 2: Adaptive Approach

- Limitations of DAC
  - Not designed to be robust
  - May sensitive to errors in the turbine model



- Adaptive control
  - Consider uncertainties: varying wind speed, unmodeled dynamics, and nonlinear aerodynamic loads

- Theoretical assumption:
  - Actual wind turbine: linear, time-invariant, finite dimensional plant

$$\dot{\mathbf{x}}_p = \mathbf{A}\mathbf{x}_p + \mathbf{B}\mathbf{u}_p + \mathbf{B}_d\mathbf{u}_d$$

$$\mathbf{y}_p = \mathbf{C}\mathbf{x}_p$$

- Adaptive control law

$$\mathbf{u} = \mathbf{G}_y\mathbf{e}_y + \mathbf{G}_x\hat{\mathbf{x}}_m + \mathbf{G}_u\mathbf{u}_m + \mathbf{G}_z\hat{\mathbf{z}}_d$$

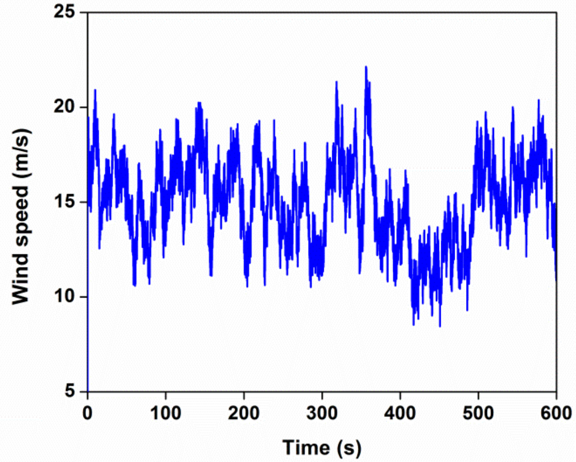
$$\dot{\mathbf{G}}_y = -\mathbf{K}_y\mathbf{e}_y\mathbf{e}_y^T \qquad \dot{\mathbf{G}}_x = -\mathbf{K}_x\mathbf{e}_y\hat{\mathbf{x}}_m^T$$

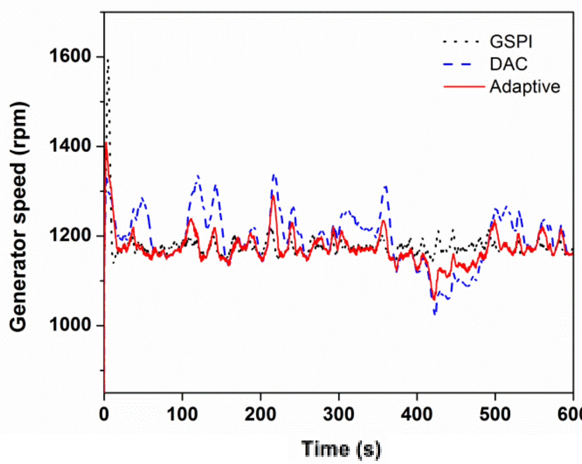
$$\dot{\mathbf{G}}_u = -\mathbf{K}_u\mathbf{e}_y\mathbf{u}_m^T \qquad \dot{\mathbf{G}}_z = -\mathbf{K}_z\mathbf{e}_y\hat{\mathbf{z}}_d^T$$

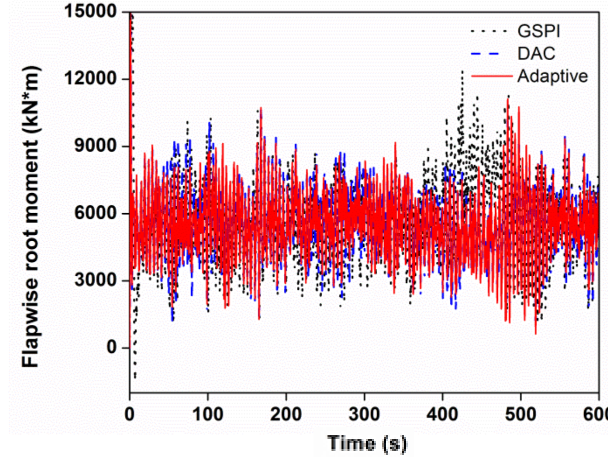
$$\mathbf{e}_y = \mathbf{y} - \mathbf{y}_m$$

Case Study: Results

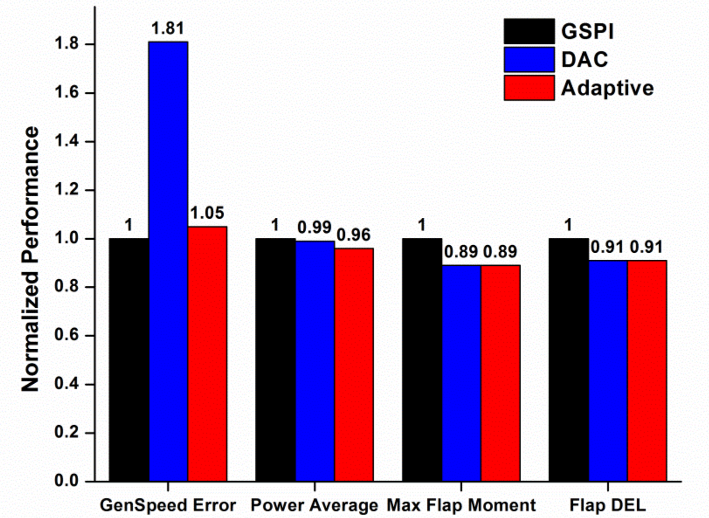
Case 1: Mean wind speed 15 m/s



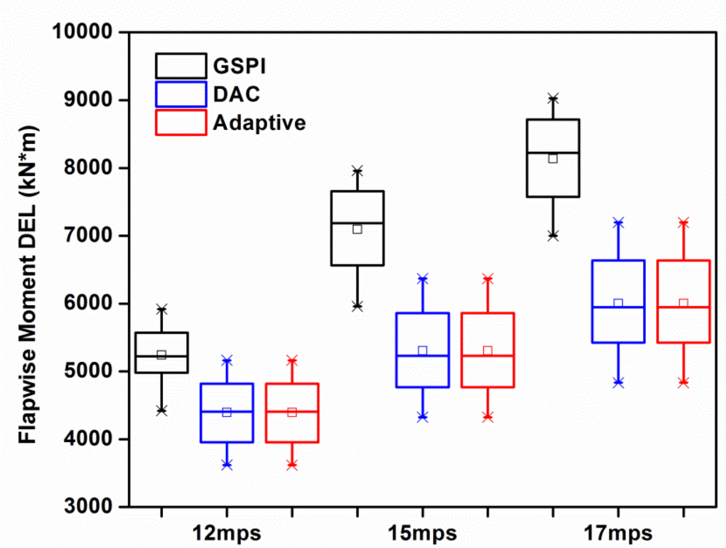


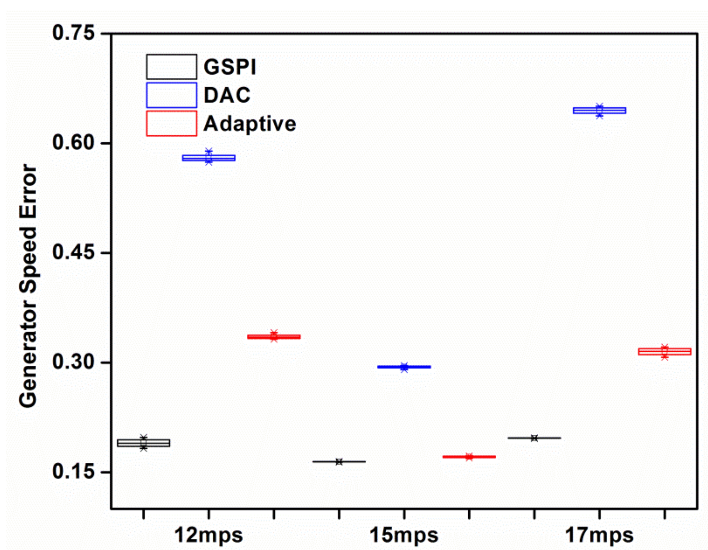


- The flapwise moment of GSPI from 360 s to 480 s is much higher compared to DAC and adaptive control
- Flapwise moment: 9% reduce
- Max flap moment: 11% reduce



Performance under Structural Uncertainties





- Results
  - Flap DEL (damage equivalent load) :
    - ✓ 12 m/s 21%-23% reduce
    - ✓ 15 m/s 20%-28% reduce
    - ✓ 17 m/s 21%-31% reduce
  - Generator speed RMS error:
    - ✓ Adaptive control is better than DAC, worse than GSPI

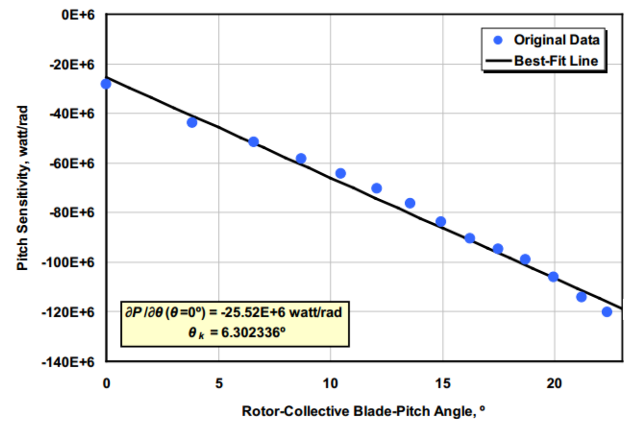
- Discussion:
  - Larger load reduction: GSPI, no consideration of model uncertainties
  - Speed regulation: GSPI only for speed regulation, no efforts on others
  - Adaptive: speed regulation & load mitigation

The End

Questions?

Gain Scheduling PID

$$T_{Aero} - N_{Gear} T_{Gen} = \left(I_{Rotor} + N_{Gear}^2 I_{Gen} \right) \frac{d}{dt} \left(\Omega_0 + \Delta\Omega \right) = I_{Drivetrain} \Delta\dot{\Omega}$$



$$T_{Gen}\left(N_{Gear} \Omega \right) = \frac{P_0}{N_{Gear} \Omega} \qquad T_{Gen} \approx \frac{P_0}{N_{Gear} \Omega_0} - \frac{P_0}{N_{Gear} \Omega_0^2} \Delta\Omega$$

$$T_{Aero}(\theta) = \frac{P(\theta, \Omega_0)}{\Omega_0} \qquad T_{Aero} \approx \frac{P_0}{\Omega_0} + \frac{1}{\Omega_0} \left(\frac{\partial P}{\partial \theta} \right) \Delta\theta$$

$$\Delta\theta = K_P N_{Gear} \Delta\Omega + K_I \int_0^t N_{Gear} \Delta\Omega dt + K_D N_{Gear} \Delta\dot{\Omega}$$

$$\underbrace{\left[I_{Drivetrain} + \frac{1}{\Omega_0} \left(-\frac{\partial P}{\partial \theta} \right) N_{Gear} K_D \right]}_{M_\varphi} \ddot{\varphi} + \underbrace{\left[\frac{1}{\Omega_0} \left(-\frac{\partial P}{\partial \theta} \right) N_{Gear} K_P - \frac{P_0}{\Omega_0^2} \right]}_{C_\varphi} \dot{\varphi} + \underbrace{\left[\frac{1}{\Omega_0} \left(-\frac{\partial P}{\partial \theta} \right) N_{Gear} K_I \right]}_{K_\varphi} \varphi = 0$$

P_0: rated power

P: power

$$K_P = \frac{2 I_{Drivetrain} \Omega_0 \zeta_\varphi \omega_{\varphi n}}{N_{Gear} \left(-\frac{\partial P}{\partial \theta} \right)} \qquad K_I = \frac{I_{Drivetrain} \Omega_0 \omega_{\varphi n}^2}{N_{Gear} \left(-\frac{\partial P}{\partial \theta} \right)}$$

$\omega_{\varphi n} = 0.6$ rad/s and $\zeta_\varphi = 0.6$ to 0.7

$$\frac{\partial P}{\partial \theta} = \left[\frac{\frac{\partial P}{\partial \theta}(\theta = 0)}{\theta_K} \right] \theta + \left[\frac{\partial P}{\partial \theta}(\theta = 0) \right] \qquad \frac{\partial P}{\partial \theta}(\theta = \theta_K) = 2 \frac{\partial P}{\partial \theta}(\theta = 0)$$

$$K_P(\theta) = \frac{2 I_{Drivetrain} \Omega_0 \zeta_\varphi \omega_{\varphi n}}{N_{Gear} \left[-\frac{\partial P}{\partial \theta}(\theta = 0) \right]} GK(\theta) \qquad K_I(\theta) = \frac{I_{Drivetrain} \Omega_0 \omega_{\varphi n}^2}{N_{Gear} \left[-\frac{\partial P}{\partial \theta}(\theta = 0) \right]} GK(\theta)$$

DOB backup1

Persistent wind disturbance input:

$$\dot{\mathbf{z}}_d = \mathbf{F}\mathbf{z}_d$$

$$\mathbf{u}_d = \mathbf{\Theta}\mathbf{z}_d$$

unknown amplitude, known waveform

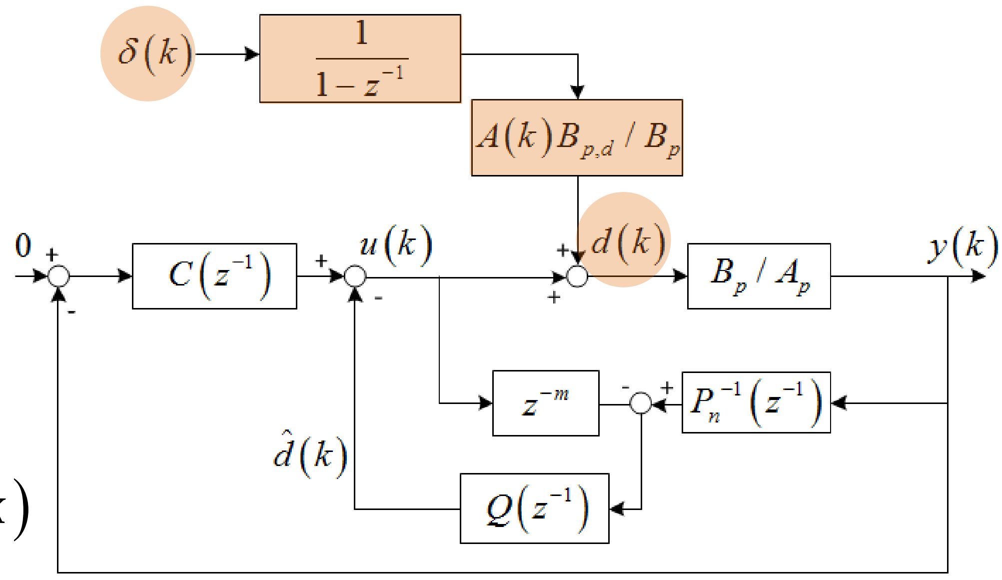
step disturbance $\mathbf{F} \equiv 0 \qquad \mathbf{\Theta} \equiv 1$

Wind disturbance: Variance between nominal wind speed and the operating wind speed

$$Z\{d_0(k)\} = A(k)\cdot\frac{1}{1-z^{-1}}$$

$$d(k) = \frac{B_{p,d}(z^{-1})}{B_p(z^{-1})}\frac{1}{1-z^{-1}}A(k)\delta(k)$$

$$\frac{(1-z^{-1})B_p(z^{-1})}{A(k)}d(k) = B_{p,d}(z^{-1})\delta(k)$$



$$P_n^{-1}(z^{-1}) = z^{-m}P^{-1}(z^{-1})$$

DOB backup2

Step disturbance goes through disturbance model

Disturbance rejection is achieved if

$$d(k) = \frac{A(k)}{1-z^{-1}} \frac{B_{p,d}(z^{-1})}{B_p(z^{-1})} \Rightarrow \frac{(1-z^{-1})B_p(z^{-1})}{A(k)} d(k) = B_{p,d}(z^{-1})\delta(k) \to 0$$

$$\boxed{1-z^{-m}Q(z^{-1}) = \frac{(1-z^{-1})B_p(z^{-1})}{(1-\beta z^{-1})B_p(\beta z^{-1})} \frac{K(z^{-1})}{A(k)}}$$

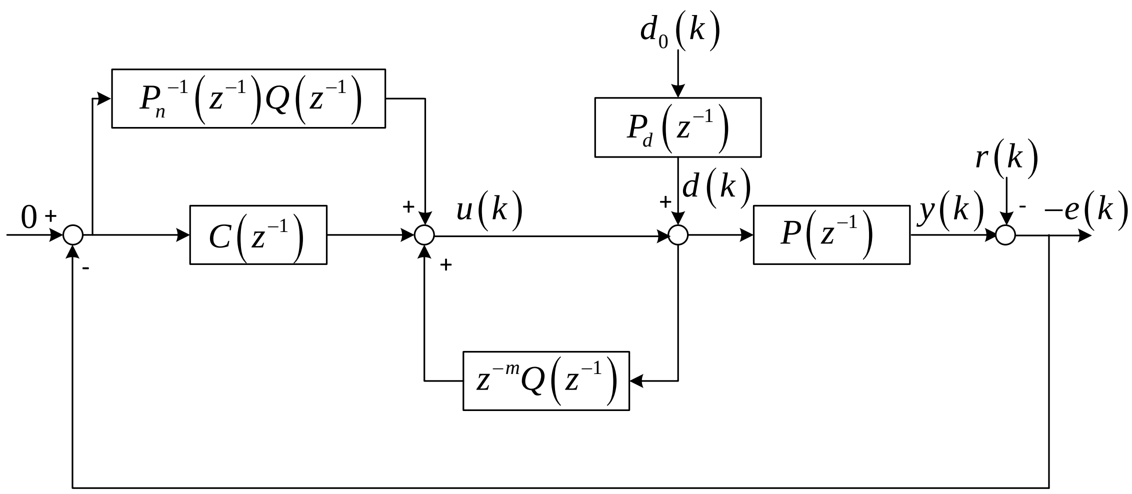
- $K(z^{-1})$: FIR filter, ensure causality of Q filter

$$K(z^{-1}) = k_0 + k_1 z^{-1} + \cdots + k_{n_k} z^{-n_k}$$

- β: tune the local loop shaping based on the damped pole – zero pair principle

$$0 < \beta \le 1$$

Stability and Robustness



$$P_n^{-1}(z^{-1}) = z^{-m}P^{-1}(z^{-1})$$

$$C_{aug}(z^{-1}) = \frac{C(z^{-1}) + P_n^{-1}(z^{-1})Q(z^{-1})}{1 - z^{-m}Q(z^{-1})}$$

$$T = G_{r\to y} = \frac{PC_{aug}}{1+PC_{aug}} = \frac{P(C + P_n^{-1}Q)}{1 - z^{-m}Q + PC + PP_n^{-1}Q}$$

No mismatch

between actual model and nominal model

$$G_{r\to y} = \frac{PC_{aug}}{1+PC_{aug}} \approx 1$$

Mismatch

bounded perturbed model uncertainty: $\Delta(z^{-1})$

$$P_r(z^{-1}) = P(z^{-1})(1 + \Delta(z^{-1}))$$

Stability Robustness [5]

$$\left\| T(e^{-j\omega})\Delta(e^{-j\omega}) \right\|_\infty < 1$$

[5] Doyle et al., *Feedback Control Theory*, 1990.

Nonlinear plant model