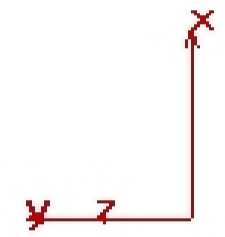
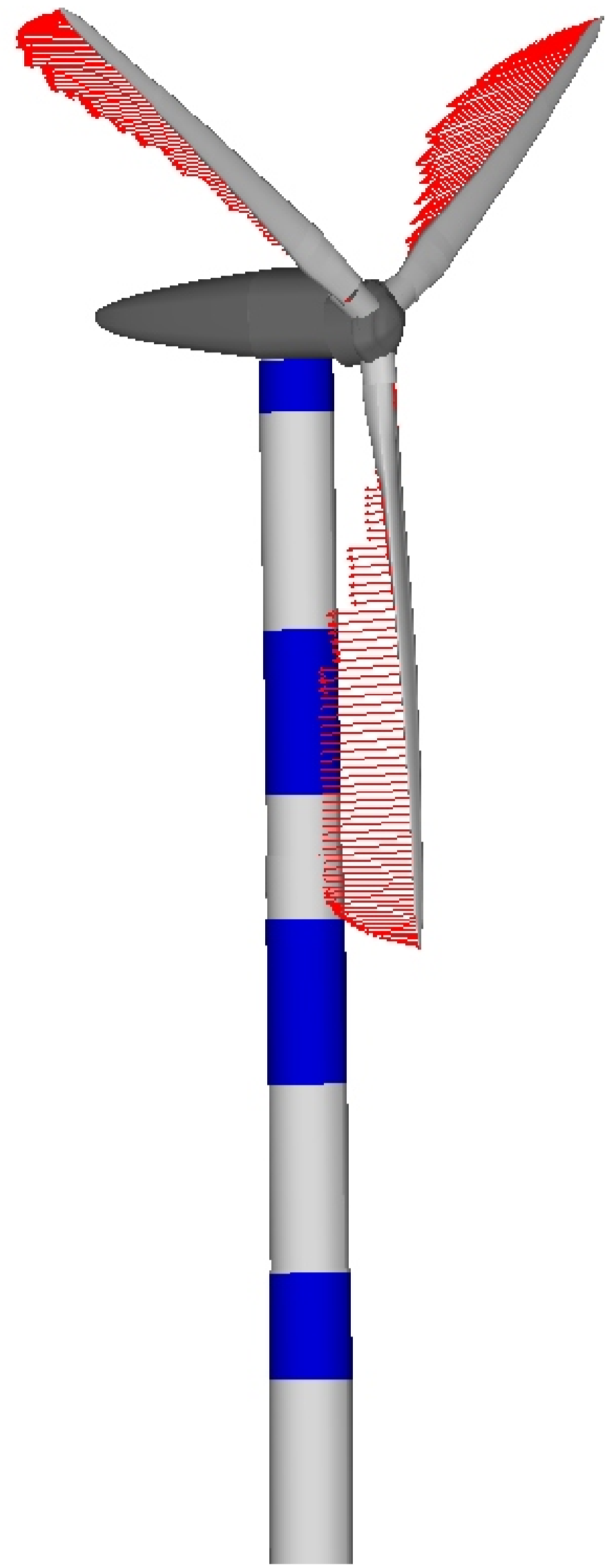




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# PERFORMANCE COMPARISON OF CONTROL SCHEMES FOR VARIABLE-SPEED PITCH-REGULATED WIND TURBINES

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## GOAL

Compare performance of different control laws:

- Optimized wind-scheduled PID
- Wind-scheduled LQR based on linearization of reference model
- Non-linear model adaptive controller based on Direct Transcription (DT)
- Reference Augmented Predictive Control (RAPC)

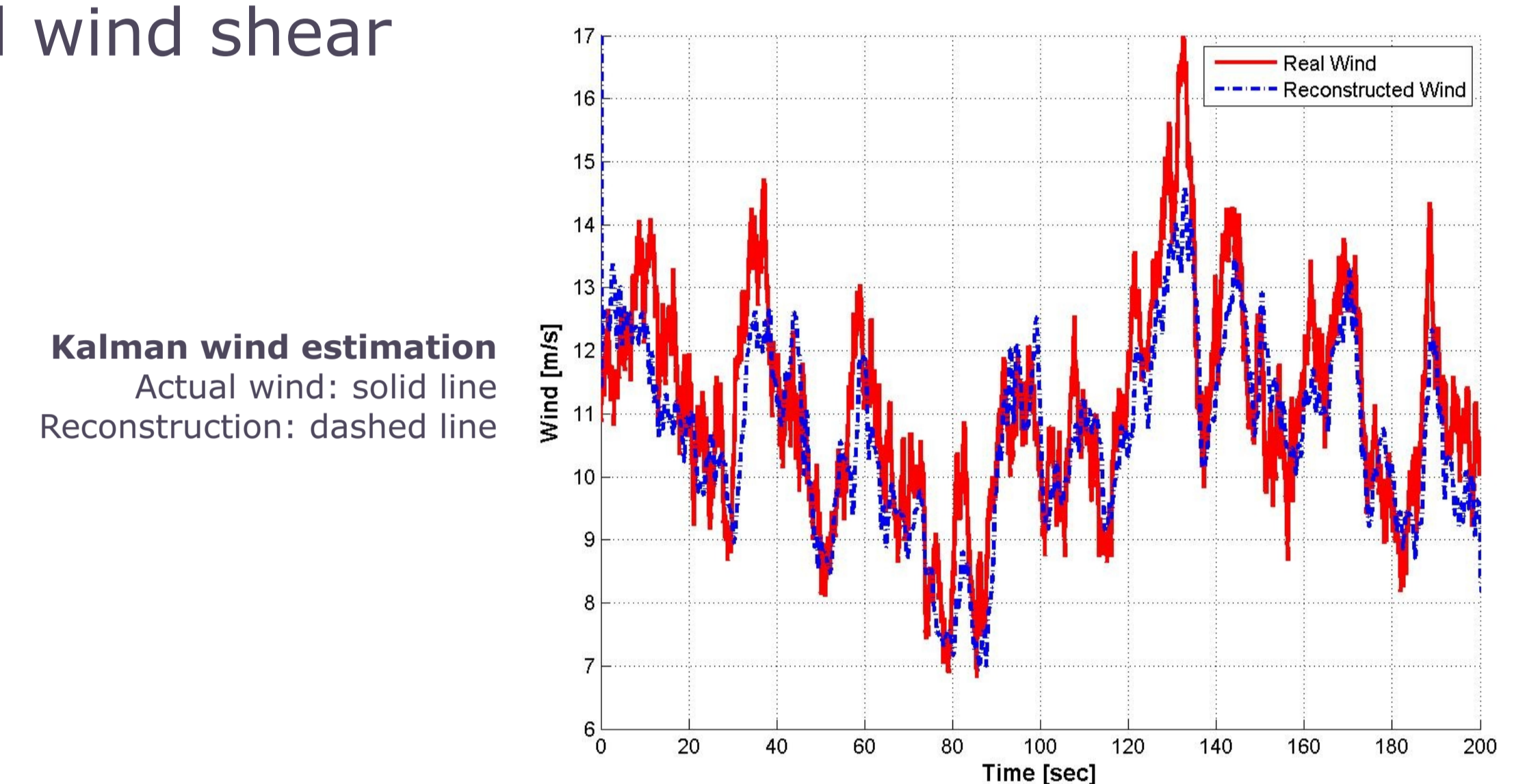
## WIND TURBINE MODEL

- Detailed multibody finite element model with axial-bending-shear-torsion deformable geometrically exact non-linear beam elements for blades and tower, actuator and sensor models, generator model, mechanical losses
- Aerodynamics: lifting lines with Pitts-Peters inflow model, IEC wind models, von Karman turbulence, tower shadow and wind shear

## WIND OBSERVER

Need wind estimate for wind-scheduled PID and model based controllers:

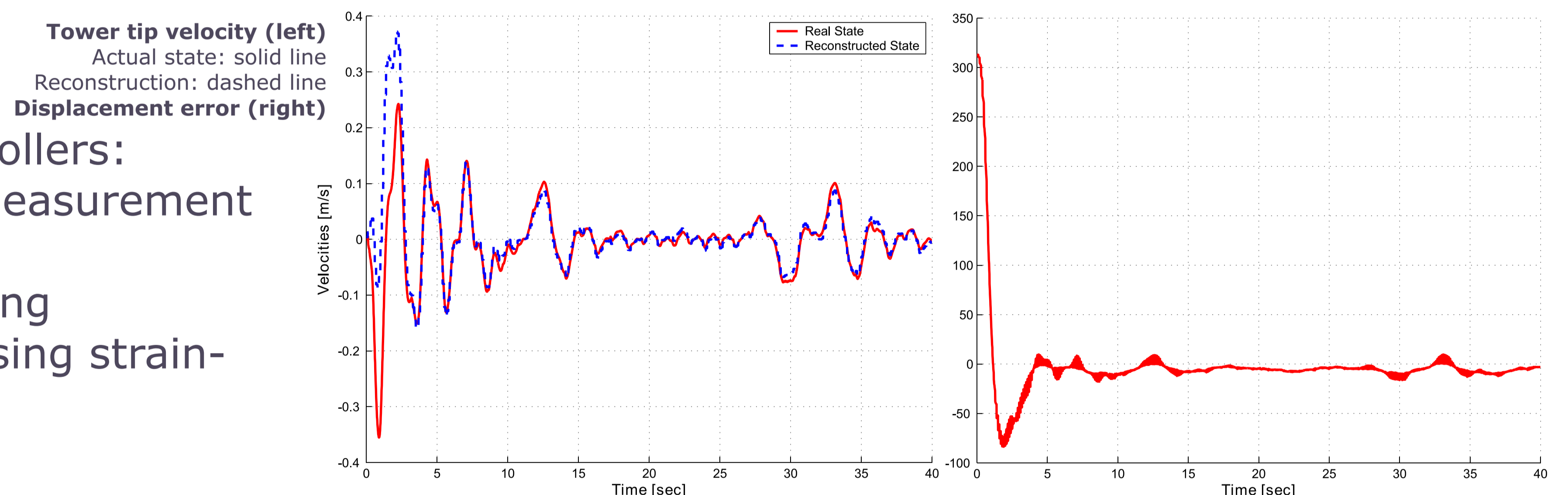
- Avoid use of anemometer: rotor wake disturbance, nacelle interference
- Reconstruct wind using rotor speed and blade pitch measurements
- Model based Kalman observer:
  - Predict wind based on spectral density model
  - Correct by enforcing satisfaction of rotor torque balance equation



## TURBINE STATE OBSERVER

Need estimate of tower tip velocity for model based controllers:

- Predict tower tip displacement/velocity by integrating measurement of nacelle accelerometer
- Compute tower modal amplitude from strain-gage reading
- Kalman filter: correct accelerometer-based prediction using strain-gage-based displacement measure



## MODEL BASED PREDICTIVE CONTROLLERS

**ALL:** reference wind turbine model for drive-train, tower fore-aft and pitch actuator dynamics

**LQR:** wind-scheduled output-feedback based on linearized reduced model

**DIRECT TRANSCRIPTION:** (Bottasso et al. 2006)

- Non-linear adaptive reduced model:
  - Augment reference model with unknown defect  $\mathbf{d}$ :  $\mathbf{f}_{\text{ref}}(\dot{\mathbf{x}}, \mathbf{x}, \mathbf{u}) = \mathbf{d}(\mathbf{x}, \mathbf{u})$ ,  $\mathbf{d}(\mathbf{y}, \mathbf{u}) = \mathbf{d}_p(\mathbf{x}, \mathbf{u}, \mathbf{p}_m) + \boldsymbol{\varepsilon}$
  - Approximate  $\mathbf{d}$  using single hidden layer neural network:  $\mathbf{d}_p(\mathbf{x}, \mathbf{u}, \mathbf{p}_m) = \mathbf{W}_m^T \boldsymbol{\sigma}(\mathbf{V}_m^T \mathbf{i} + \mathbf{a}_m) + \mathbf{b}_m$
- Turn optimal control pb. into parameter optimization pb. by time discretization
- Solve resulting non-linear programming pb. by sequential quadratic programming

**REFERENCE AUGMENTED PREDICTIVE CONTROL (RAPC):** (Bottasso et al. 2007)

- Adaptive control and adaptive model, no pre-training, fast adaption
- Adaptive control:
  - Reference control solution (LQR) augmented with neural element
  - Identify neural parameters to ensure that total control satisfies optimal control pb.

Prediction optimal control problem:

$$\min_{\mathbf{u}, \mathbf{x}, \mathbf{y}} J = \int_{t_0}^{t_0+T_p} L(\mathbf{y}, \mathbf{u}) dt$$

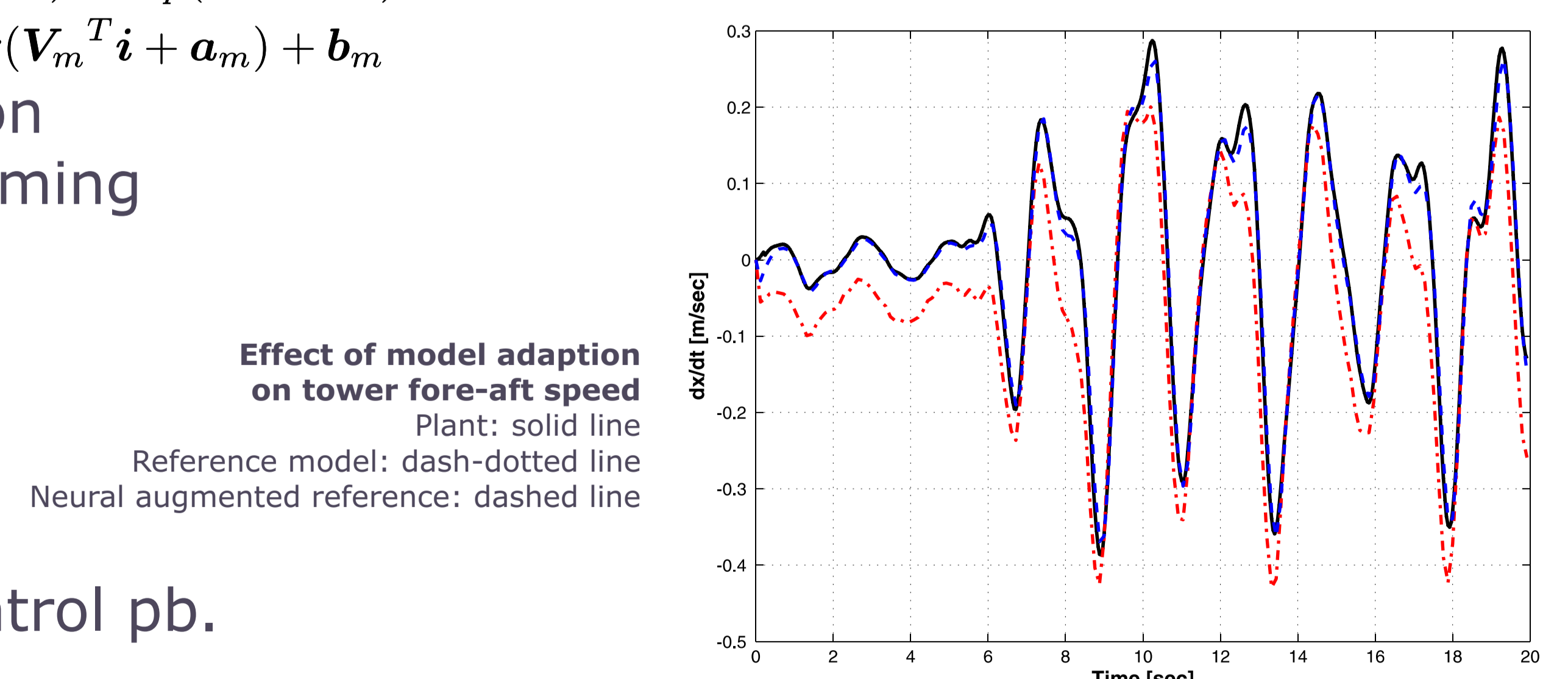
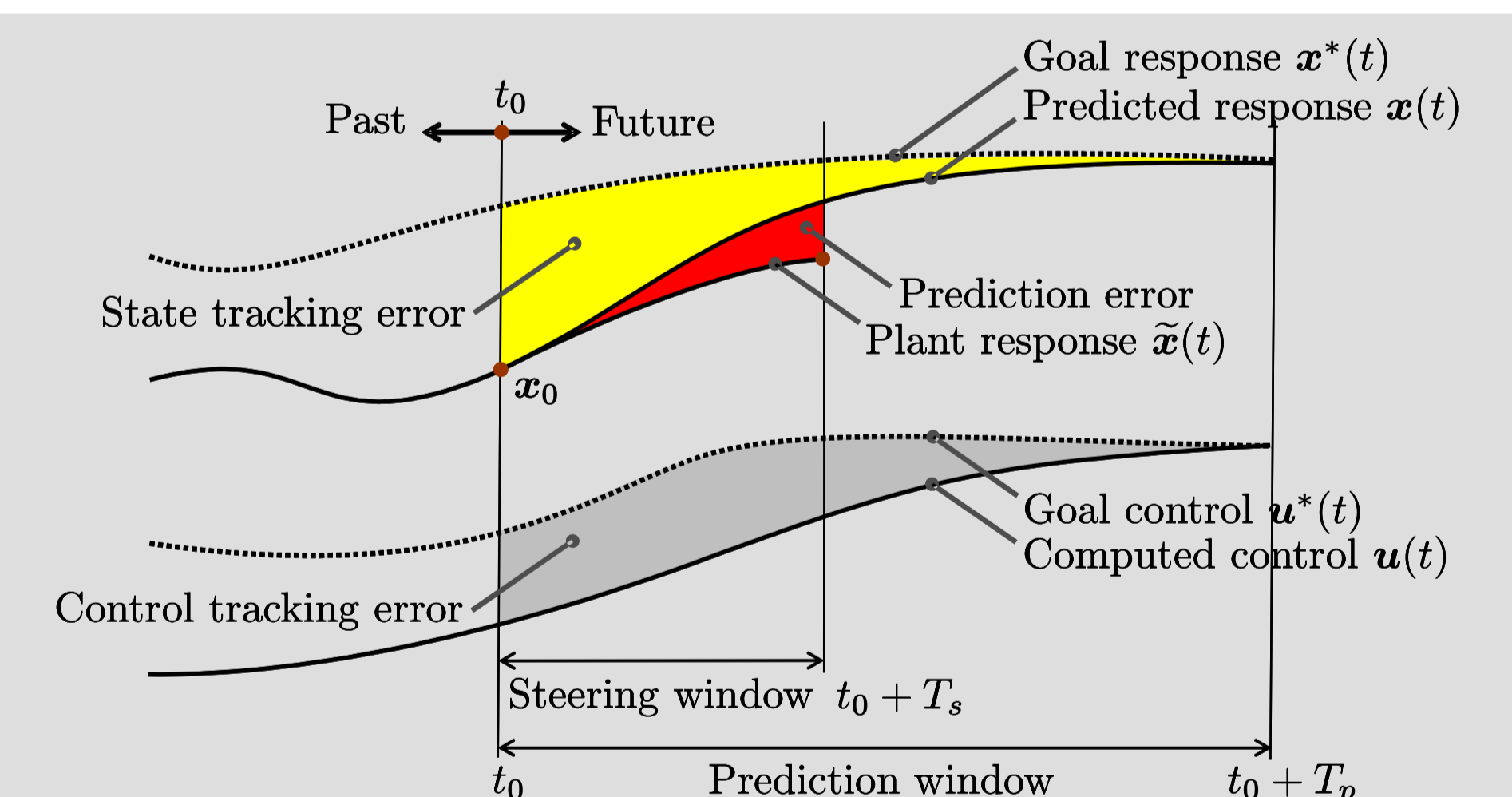
$$\text{s.t.: } \mathbf{f}(\dot{\mathbf{x}}, \mathbf{x}, \mathbf{u}) = 0 \quad t \in [t_0, t_0 + T_p]$$

$$\mathbf{x}(t_0) = \mathbf{x}_0$$

$$\mathbf{y} = \mathbf{g}(\mathbf{x}) \quad t \in [t_0, t_0 + T_p]$$

with cost:

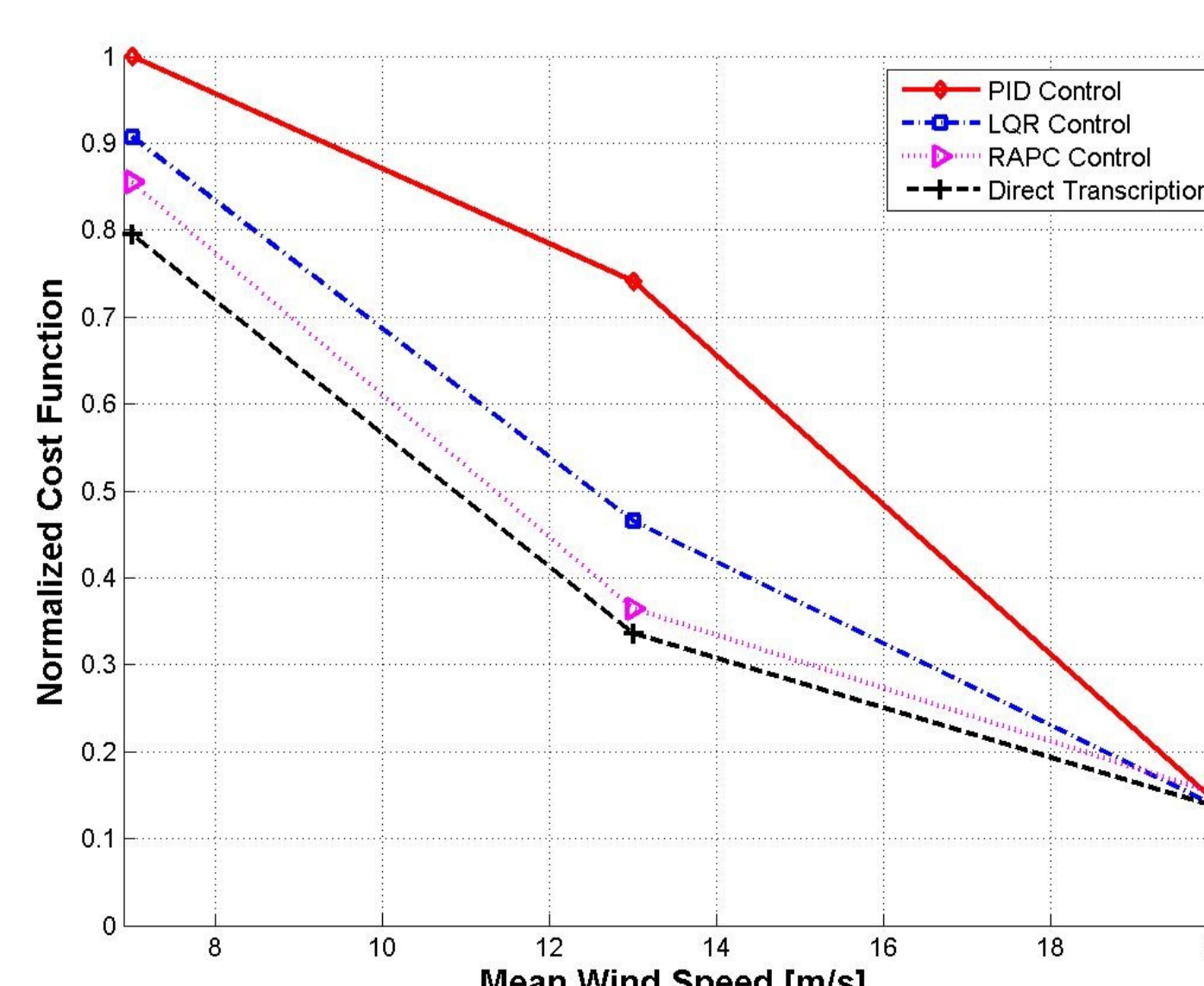
$$L(\mathbf{y}, \mathbf{u}) = (\mathbf{y} - \mathbf{y}^*)^T \mathbf{Q}(\mathbf{y} - \mathbf{y}^*) + (\mathbf{u} - \mathbf{u}^*)^T \mathbf{R}(\mathbf{u} - \mathbf{u}^*)$$



## RESULTS

Comparison of performance in turbulent wind with ice accretion on blades and cold air

- Direct transcription is best, but cannot guarantee hard real-time schedule
- RAPC has good performance and fixed operation count



## OUTLOOK

- Implementation and porting on PC-104 embedded hardware
- Test in the field on 1.5MW wind turbine

