Making nonlinear state estimation techniques ready for use in industrial wind turbine control systems

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Session: Advanced control strategies for wind plants

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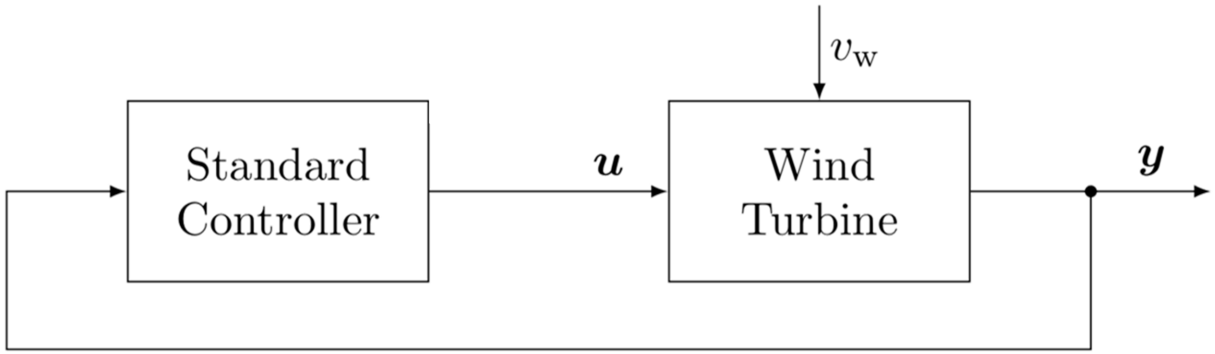
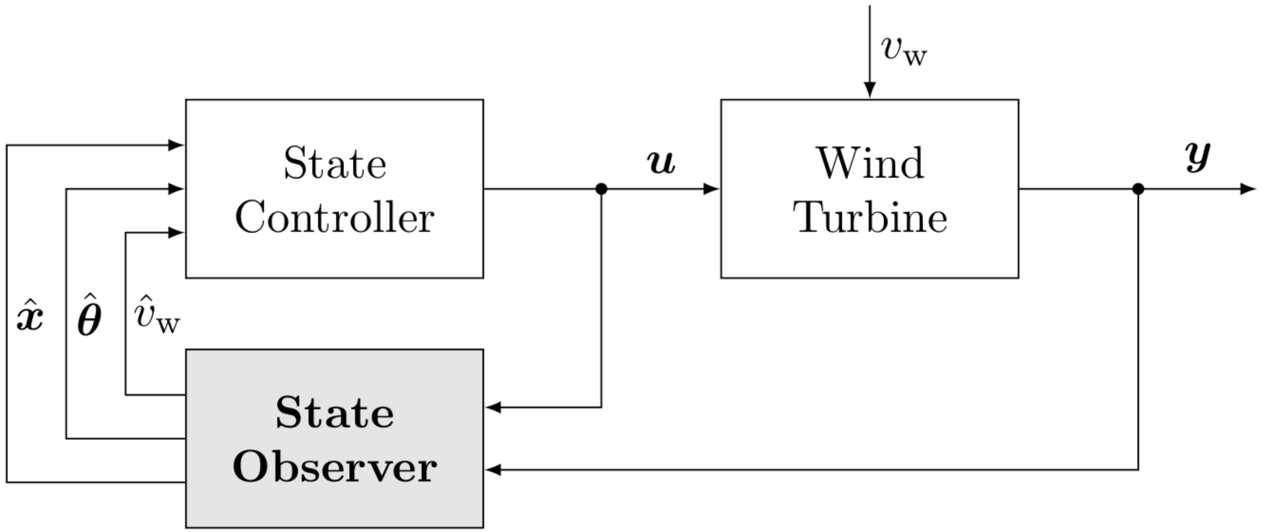
Motivation

output feedback controller



state feedback controller



Central contributions

1. Investigate **observability** and **identifiability** in detail
   (for a non-state of the art model)
2. Discuss **nonlinear filters and architecture** to address all relevant estimation sub-problems
3. Show that **state estimation is feasible**
   - with an advanced nonlinear model
   - with high estimation quality
   - in real-time.

Outline

1. Model analysis
2. State estimation
3. Simulation results
4. Conclusions

1. Model analysis

Prerequisites for wind turbine state estimation

industrial science powered by IAV

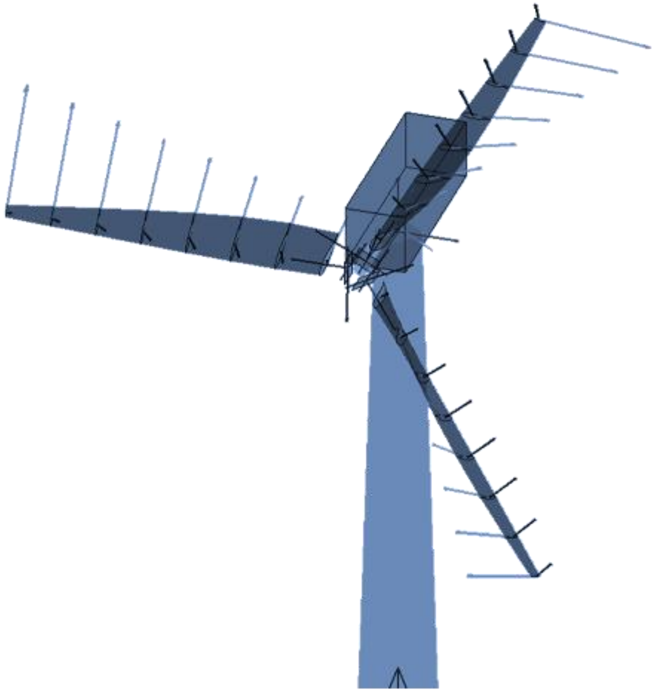
- Hi-fidelity nonlinear wind turbine model catching the relevant system dynamics with few physical parameters (< 20)

Nacelle dynamics
$$\begin{cases} \ddot{x}_{\mathrm{T}} = f_1(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \\ \ddot{y}_{\mathrm{T}} = f_2(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \end{cases}$$

Drive-train dynamics
$$\begin{cases} \ddot{\varphi}_{\mathrm{g}} = f_3(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \\ \Delta\ddot{\varphi} = f_4(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \end{cases}$$

Blade dynamics
$$\begin{cases} \ddot{x}_{\mathrm{B},1} = f_5(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \\ \ddot{x}_{\mathrm{B},2} = f_6(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \\ \ddot{x}_{\mathrm{B},3} = f_7(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d}) \end{cases}$$

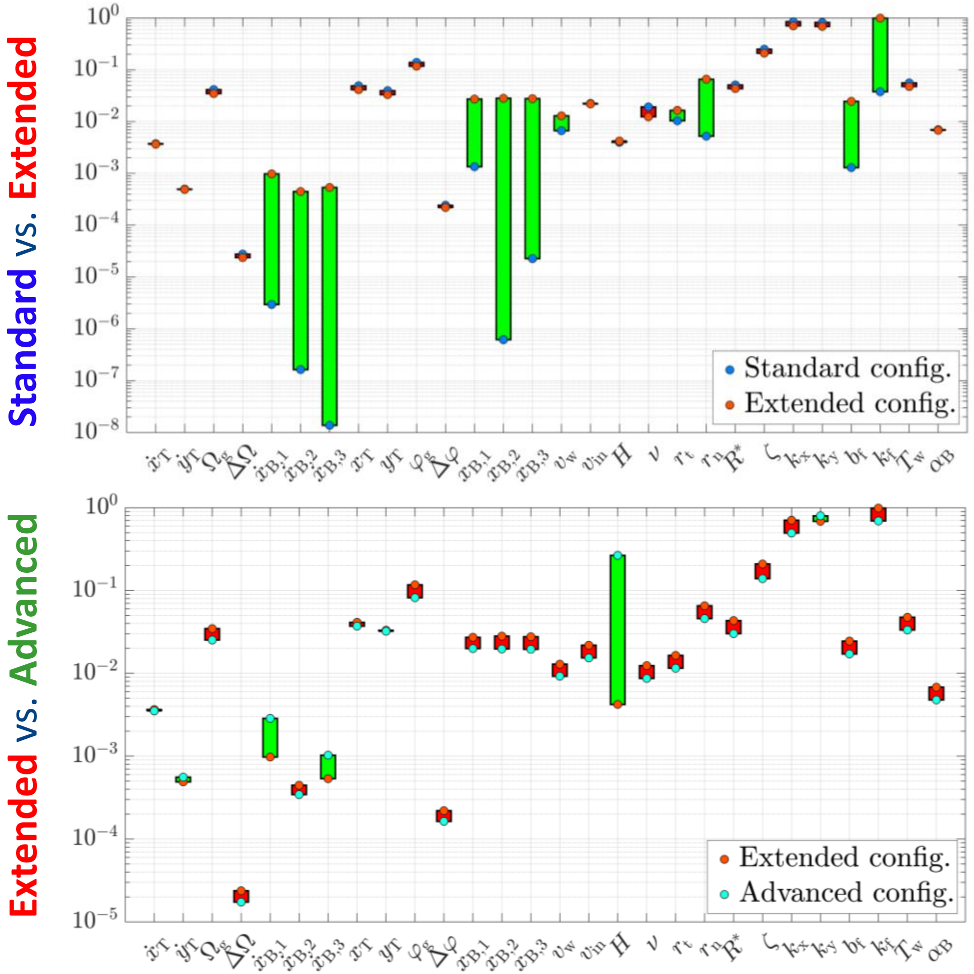
$\boldsymbol{x}$ **Dynamic states**
$\boldsymbol{u}$ **Control inputs**
$\boldsymbol{\theta}$ **Model parameters**
$\boldsymbol{d}$ **Disturbance inputs**



- What are the benefits from additional load measurements?
- How good can the desired quantities be estimated?

1. Model analysis

Local observability analysis



- Observability depends on external excitation, number of measurements & **choice of sensors**
- **Gramian-based measure** [1] chosen among the various measures in literature [2]
- Investigated measurement configurations

  Standard: Nacelle acceleration + generator speed

  Extended: Standard + blade-root bending moments

  Advanced: Extended + tower-base bending moments

- Blade-root sensors show **significant improvement** of observability of certain states and parameters

References

[1] A. Krener et al.: “Measures of unobservability”, Proc. 48th IEEE Decision and Control Conference, Shanghai, 2009 S. 6401-6406.

[2] H. Miao et al.: ”On identifiability of nonlinear ODE models and applications in viral dynamics”, SIAM review, 2011, S. 3-39.

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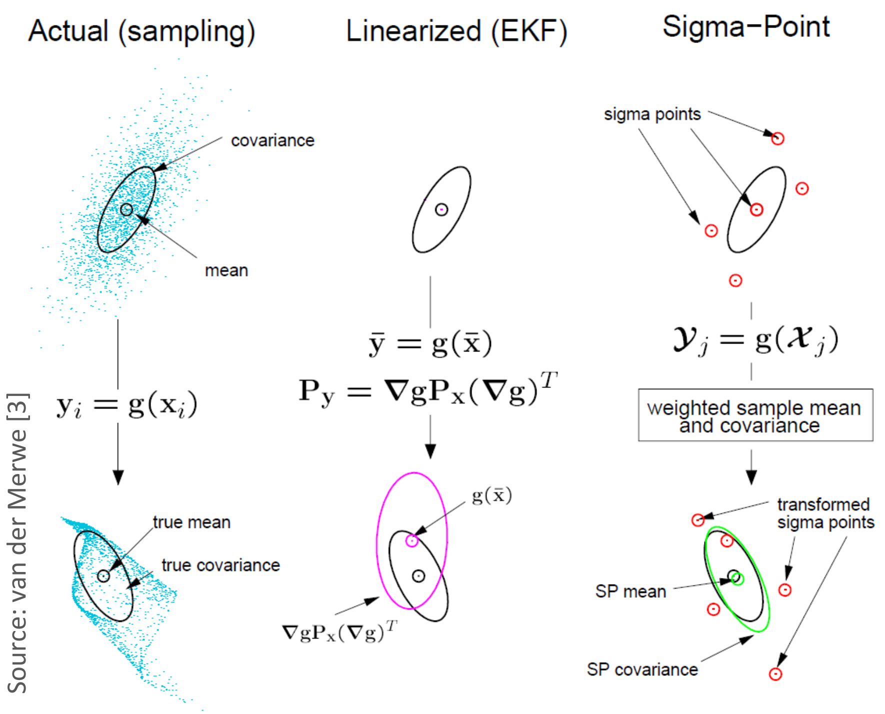
2. State estimation

Algorithms to solve the estimation problem



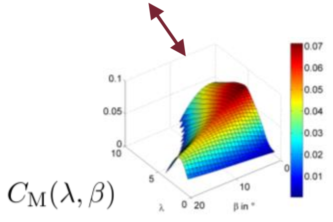
- **Sigma-point Kalman filters** [2,3] among others [1]

→ Preferable alternative to Extended Kalman Filter (EKF)

→ Suitable for nonlinear systems with **characteristic maps**

→ Free-of-charge tools available [4]

→ Mature and industry-tested techniques



- **Implementation in Matlab/Simulink**

→ Efficient code generation for UKF, CDKF & CKF and their square-root realizations

→ Computational time **$<$ 10ms** with 28th order nonlinear model on Beckhoff Industrial Controller (**monolithic filter**)

References

[1] B. Ritter et al.: “The design of nonlinear observers for wind turbine dynamic state and parameter estimation”, Torque Conf. (accepted), 2016

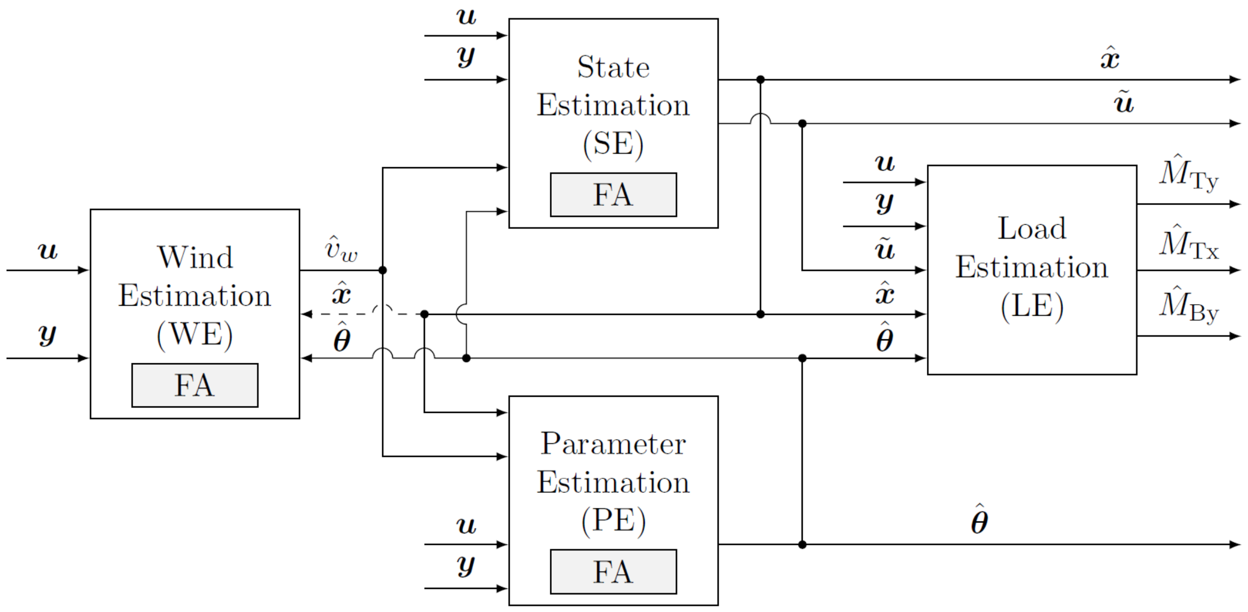
[2] S. J. Julier et al.: “A new extension of the Kalman filter to nonlinear systems“, 11th Intern. Symp. on Aerosp./Def. Sensing, Sim. & Control, 1997

[3] R. van der Merwe: “Sigma-Point Kalman Filters for Probabilistic Inference in Dynamic State-Space Models“, PhD-Thesis, 2004

[4] J. Hartikainen et al.: ”Optimal Filtering with Kalman Filters and Smoothers a Manual for the Matlab toolbox EKF/UKF”, Manual, 2011

2. State estimation

Composition of observer architecture for real-time application



Reference

[1] B. Ritter et al.: "The design of nonlinear observers for wind turbine dynamic state and parameter estimation", Conf. on The science of making torque from wind, 2016

- **Several subproblems** to manage (wind, state, parameter & load estimation)
- How to compose an observer with low computational cost and high accuracy?
- Distributed architecture allows for…

→ exploiting system properties explicitly to save computational time

→ employing different linear/nonlinear filter types, different sample times

→ selective filter adaptation & situational by-passing (triggered by observability measures)

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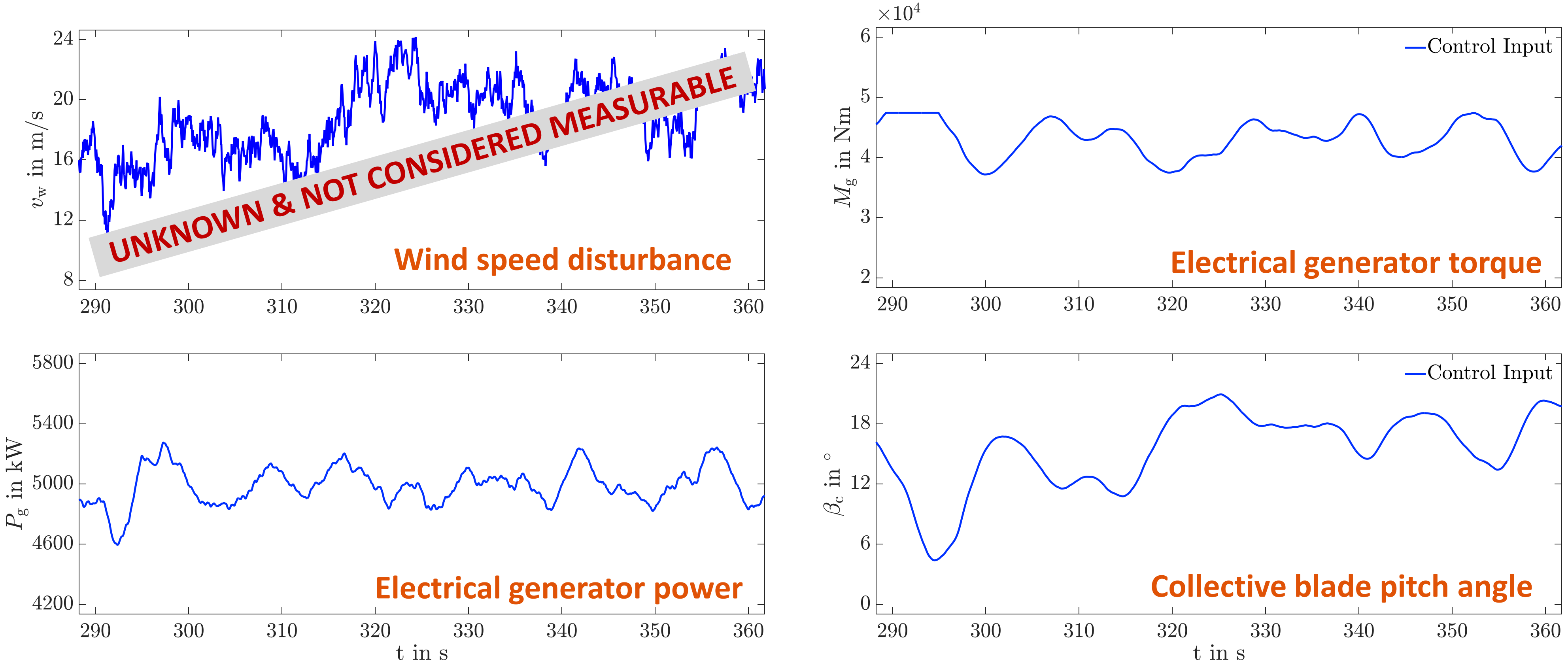
3. Simulation results

Illustrative application to 5-MW reference turbine using FASTv8

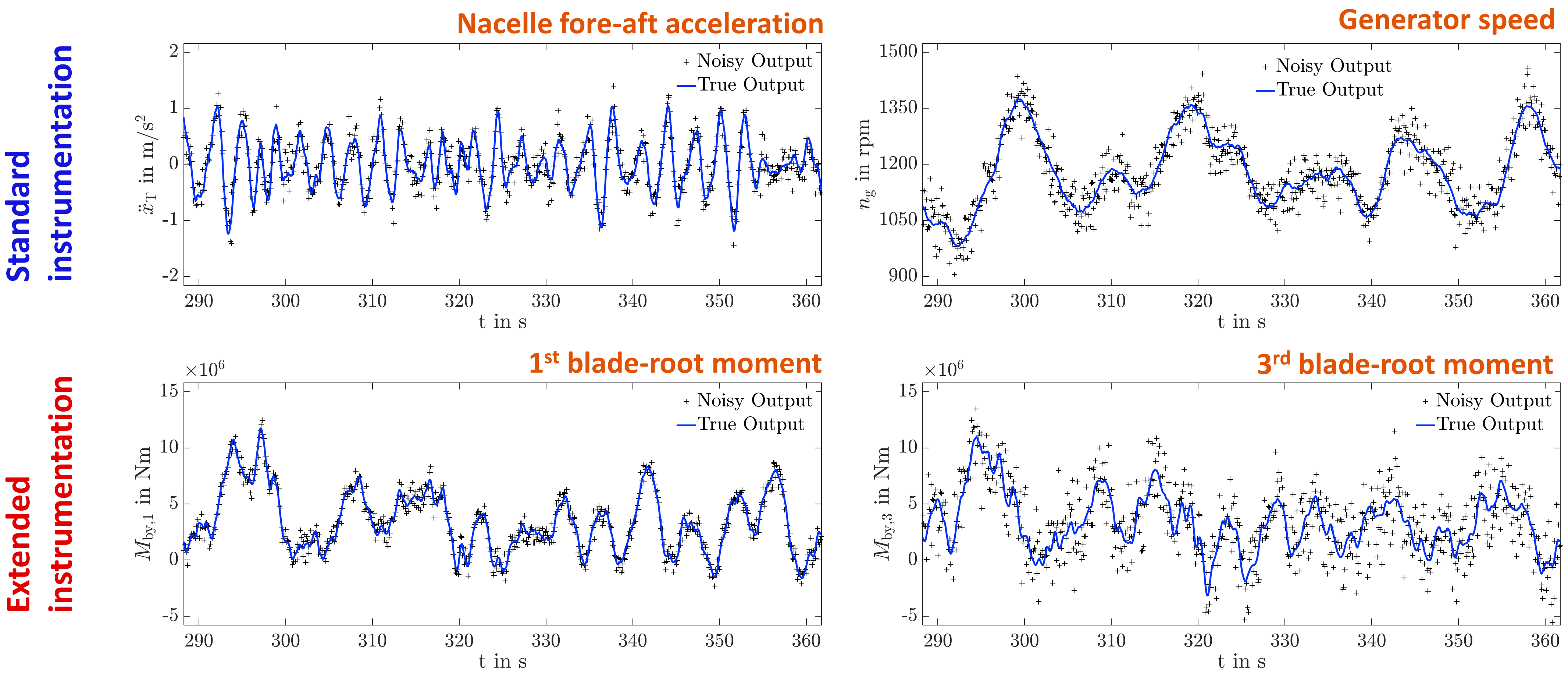
- Disturbance and control inputs



3. Simulation results

Illustrative application to 5-MW reference turbine using FASTv8

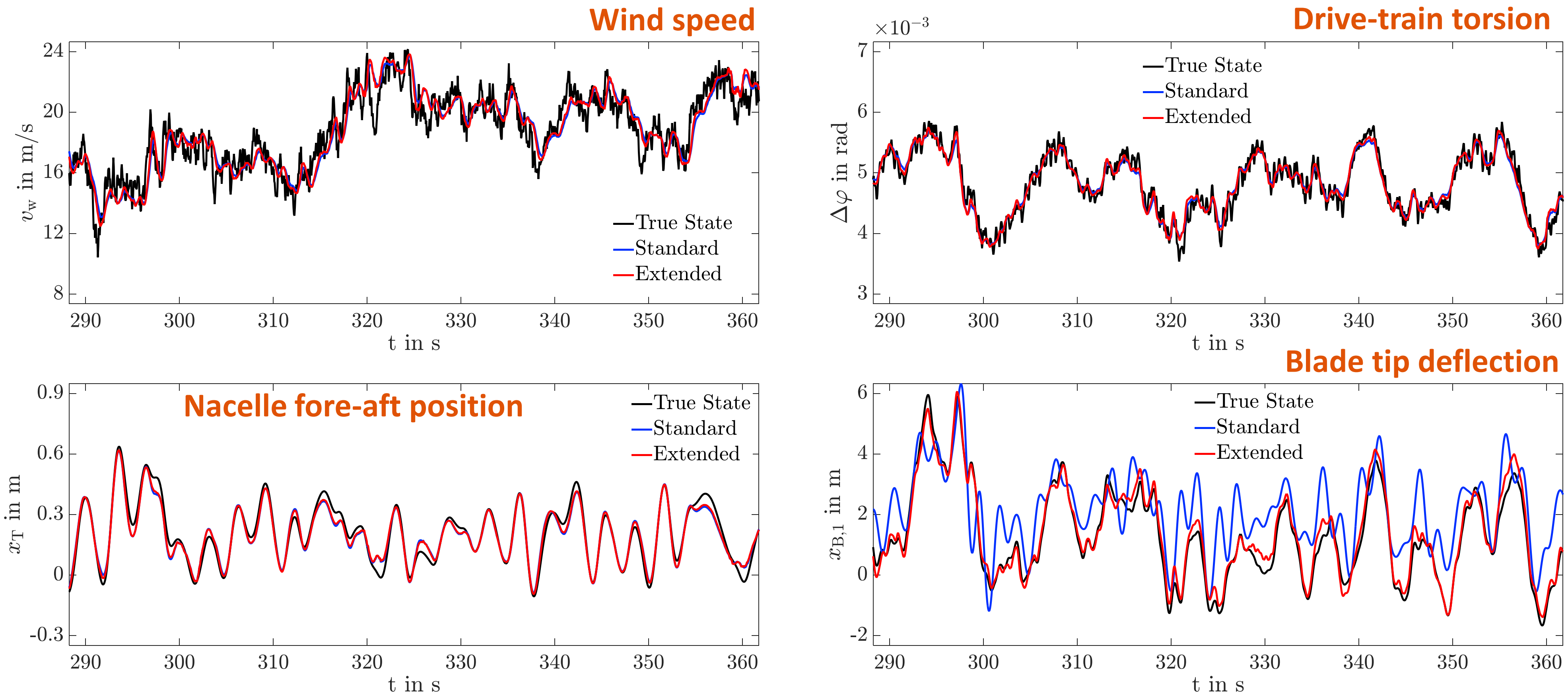
- Measurement outputs/observations



3. Simulation results

Illustrative application to 5-MW reference turbine using FASTv8

- Unknown wind speed and dynamic state estimation (**Standard** vs. **Extended**)



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Central statements

- Sigma-point Kalman filters are **fast, low-cost** and **powerful estimators** (in contrast to error-prone and expensive load sensors)
- **Real-time** study shows feasibility in principle.
- **Distributed architecture** is preferable rather than a monolithic one.
- For basic estimation tasks the **standard instrumentation** is sufficient.
- Additional out-of-plane **blade-root measurements** increase estimate's accuracy of blade dynamic response and certain related parameters.

4. Conclusions

Next steps

→Incorporate filter **adaptation rules** to improve performance in the field

→Explicit consideration of **state** and **parameter constraints** (i.e. by a moving horizon approach)

→**Field testing** with real measurement data

Take-home messages

→Nonlinear state estimation techniques are **ready to use.**

→Since **complete state** information is **on hand**, advanced controllers with **state-feedback** are the right choice for future wind turbine control systems.

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