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

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Motivation and objectives

- Accurate knowledge of states and parameters is **the prerequisite** for **advanced wind turbine controllers**, such as **MPC**, to outperform state-of-the-art control schemes for wind turbines.
- Thus, focus is put on **nonlinear estimation techniques,** which provide the required information based on a high-fidelity model and handle most practical challenges satisfactorily.
- Relevant issues treated here: **real-time application**, feasibility and **estimator performance.**

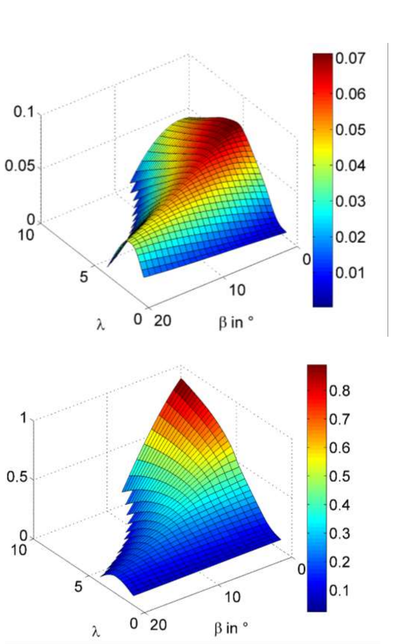
Challenges

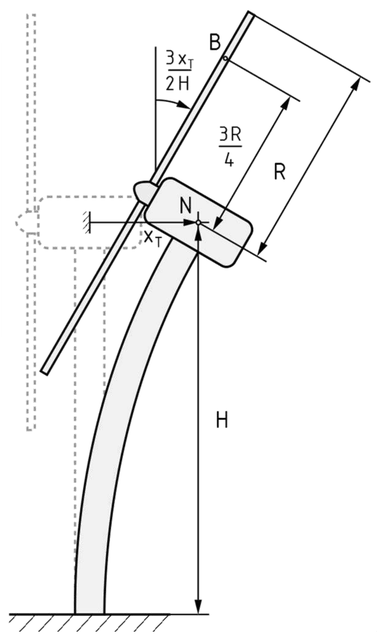
- Check **observability** & **identifiability** properties of nonlinear high-fidelity design model for distinct instrumentation configurations.
- Investigate **benefits from advanced instrumentation** for state and parameters estimation accuracy quantitatively.
- Investigate **nonlinear filter algorithms**, suited for real-time application to derive the best **estimator architecture** for wind turbines.
- Assess **estimator performance** for dynamic states, parameters and mechanical loads at realistic simulation environment.

Advanced nonlinear design model

- High-fidelity nonlinear model captures nacelle/tower & drive-train dynamics as well as blade out-of-plane motion and its coupling to the blade effective wind speed

$$\ddot{x}_\mathrm{T} = f_1(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$
$$\ddot{y}_\mathrm{T} = f_2(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$
$$\ddot{\varphi}_\mathrm{g} = f_3(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$
$$\Delta\ddot{\varphi} = f_4(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$
$$\ddot{x}_{\mathrm{B},1} = f_5(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$
$$\ddot{x}_{\mathrm{B},2} = f_6(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$
$$\ddot{x}_{\mathrm{B},3} = f_7(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{d})$$





Observability and identifiability analysis

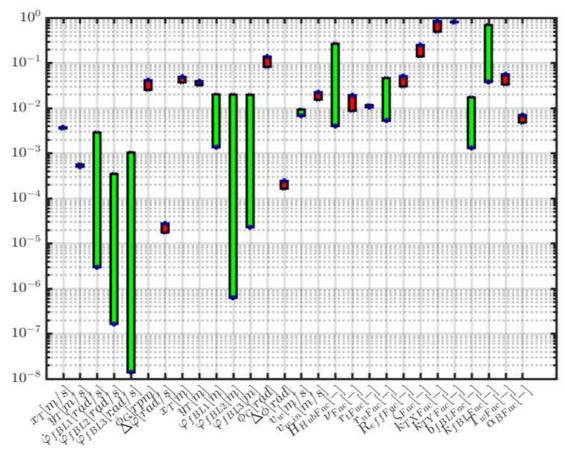
- Analysis conducted for turbulent wind field employing observability gramian to check local observability and identifiability [3,4]
- Results obtained for three instrumentation configurations:

  Standard: Nacelle inertia meas. unit (IMU) & generator speed

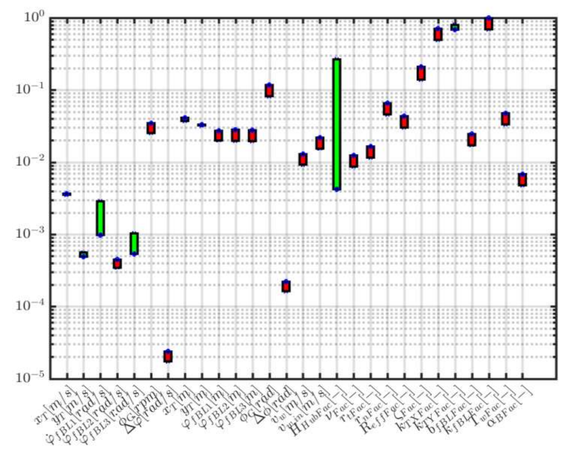
  Extended: Standard + blade-root bending moments (out-of-plane)

  Advanced: Extended + tower-base bending moments (pitch/tilt)

Standard vs. **Extended**

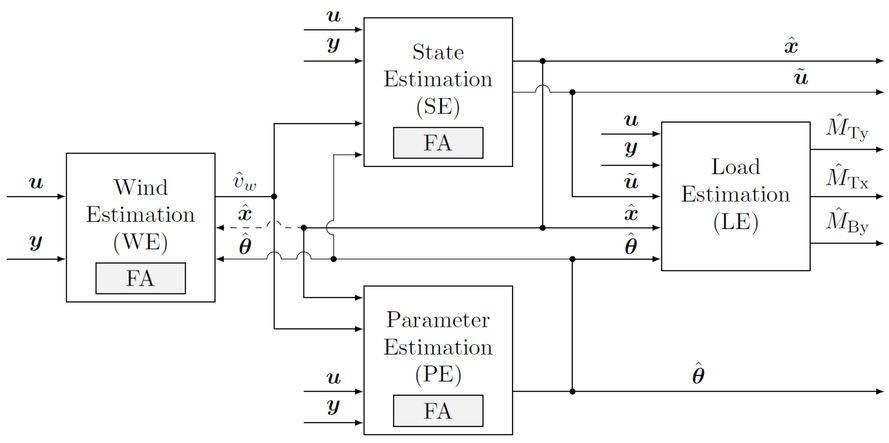


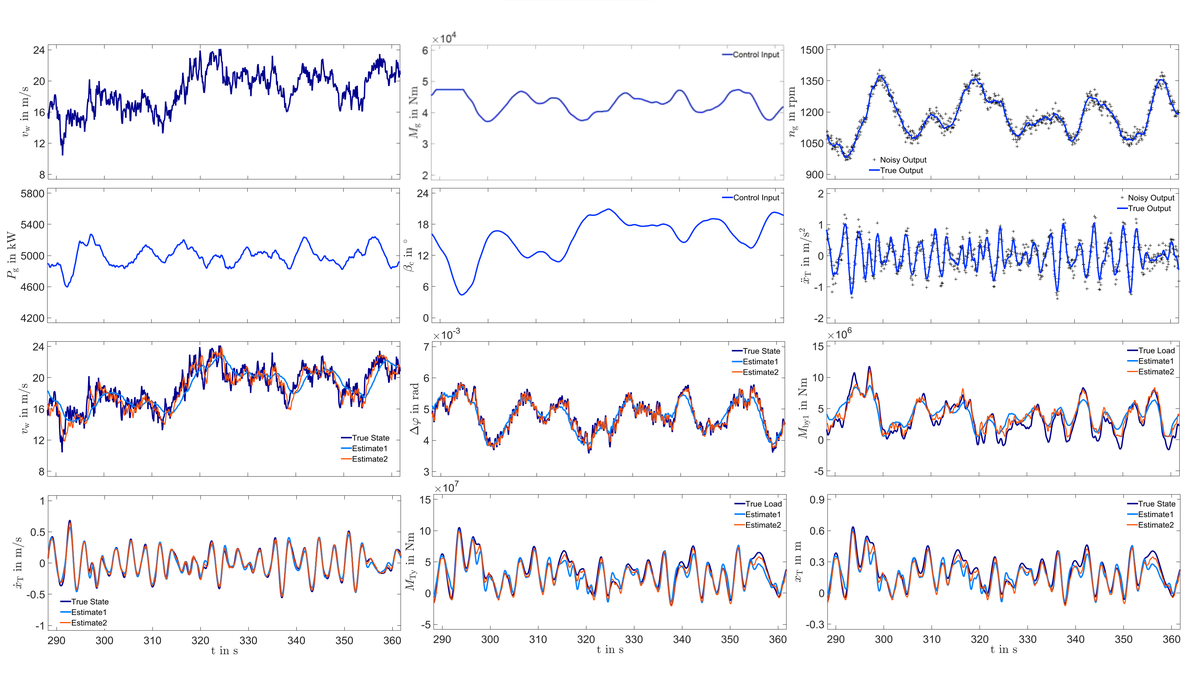
Extended vs. **Advanced**



Testing and evaluation of estimator performance

- Distributed architecture addressing **real-time application** [1]
- Evaluated with realistic **FASTv8**-data & **sigma-point Kalman filters** [2]





Conclusions and take-home messages

- Sigma-point Kalman filters are **real-time feasible**, **low-cost** and **powerful estimators** for wind turbines → **ready to be used** for advanced state-feedback control.
- **Distributed architecture** is paramount, if real-time execution, online filter adaptation and practical implementation are of concern.
- **High estimation quality** of dynamic nacelle/drive-train states and mechanical loads with **standard measurement** equipment.
- **Non-standard blade-root measurements** show significant potential for improving estimation quality of blade states & blade parameters.
- Remaining challenges: integration of Sigma-point Kalman filters into an industry-ready platform & **field-testing** on multi-MW turbines.

References

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2. R. **van der Merwe**: “Sigma-point Kalman Filters for Probabilistic Inference in Dynamic State-Space Models”, PhD-Thesis, OGI University, 2004
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4. H. **Miao et al.**: ”On identifiability of nonlinear ODE models and applications in viral dynamics”, SIAM review, 2011