Journal of Physics: Conference Series **753** (2016) 052029 doi:10.1088/1742-6596/753/5/052029

The design of nonlinear observers for wind turbine dynamic state and parameter estimation

B Ritter[1,2], A Schild[3], M Feldt[3] and U Konigorski[1]

[1] Department of Control Systems and Mechatronics, Technische Universität Darmstadt, DE
[2] Industrial Science GmbH, Alexanderstr. 25, 64283 Darmstadt, DE
[3] IAV GmbH, Rockwellstraße 16, 38518 Gifhorn, DE

E-mail: `britter@iat.tu-darmstadt.de`

Abstract. This contribution addresses the dynamic state and parameter estimation problem which arises with more advanced wind turbine controllers. These control devices need precise information about the system's current state to outperform conventional industrial controllers effectively. First, the necessity of a profound scientific treatment on nonlinear observers for wind turbine application is highlighted. Secondly, the full estimation problem is introduced and the variety of nonlinear filters is discussed. Finally, a tailored observer architecture is proposed and estimation results of an illustrative application example from a complex simulation set-up are presented.

1. Introduction

In recent decades the size of wind turbines has increased significantly in order to reach higher nominal power outputs. At the same time the necessity for lowering the costs of energy has promoted the design of more flexible light-weight wind turbines. This development has triggered a lot of research for active vibration and individual pitch control (IPC) to reduce fatigue loads on costly and valuable components [1]. However, more advanced control algorithms [2] demand for more information about the inner state of the turbine which must be provided by additional sensors and/or observers. Since load sensors like strain gauges are often expensive and error-prone, this contribution focuses on observers as inexpensive and powerful alternative to reconstruct unmeasured quantities. These are dynamic states, parameters and/or unknown disturbance inputs.

Although the importance of state and parameter estimation rises with advanced multivariable controllers [3, 4], no profound and complete treatment for wind turbine application has been published yet. Such a complete discussion involves at first the definition of the full-scope estimation problem (Sec. 2). This includes the identification and detailed analysis of all relevant sub-problems. Secondly, the application-proven filter algorithms must be assessed with respect to their underlying concepts and attributes (Sec. 3). Due to the system's nonlinearity, the investigation places the emphasis on available local and global nonlinear algorithms. Section 4 introduces a simplified nonlinear control-relevant wind turbine model and discusses the different components of the observer. A tailored distributed observer architecture is proposed which tackles the full-scope estimation problem completely and as well fulfils the requirements for real-time application. Finally, exemplary results based on data from FASTv8 [5] simulations are presented which include the sub-problems of state, parameter, disturbance and load estimation.

2. The estimation problem for wind turbine control applications

To develop a tailored observer architecture one has first to formulate the estimation problem for the considered system. Such an estimation problem may be static or dynamic, linear or nonlinear, constrained or unconstrained (which depends on the specific application). In any case the problem is related to a mathematical representation describing the system's dynamics adequately. The most general form is the following nonlinear state space model:

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{q}) \tag{1a}$$

$$\boldsymbol{y} = \boldsymbol{h}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}, \boldsymbol{r}) \quad . \tag{1b}$$

Therein, $\boldsymbol{x} \in \mathbb{R}^{n_x}$ is the dynamic state vector, $\boldsymbol{u} \in \mathbb{R}^{n_\mathrm{u}}$ the control input vector, $\boldsymbol{\theta} \in \mathbb{R}^{n_{\boldsymbol{\theta}}}$ the parameter vector, $\boldsymbol{q} \in \mathbb{R}^{n_q}$ and $\boldsymbol{r} \in \mathbb{R}^{n_r}$ the process and measurement noise and $\boldsymbol{y} \in \mathbb{R}^{n_y}$ the output vector. The model consists of the process equation (1a) defined by the arbitrary vector function $\boldsymbol{f} : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_\theta} \times \mathbb{R}^{n_q} \rightarrow \mathbb{R}^{n_x}$ and the measurement/output equation (1b) defined by $\boldsymbol{h} : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_\theta} \times \mathbb{R}^{n_r} \rightarrow \mathbb{R}^{n_y}$. Such a model poses a constraint to the actual estimation problem and permits simultaneously the explicit incorporation of a priori knowledge about the system to improve the estimate's quality. Generally speaking, solving an estimation problem refers to the mission of extracting some kind of desired information from noisy and/or indirect observations $\boldsymbol{y}$ provided by measurement instrumentation. The observation problem often relates to reconstructing the (quickly time varying) dynamic state $\boldsymbol{x}$ of a system. Besides, we are typically faced by unknown or uncertain parameters in real life which do not change at all or vary on a much slower time scale. Likewise, unknown and disturbance inputs can also be considered as (quickly varying) parameters. These quantities are collected in the parameter vector $\boldsymbol{\theta}$. The task of estimating the most likely parameter set $\hat{\boldsymbol{\theta}}$ is termed a parameter estimation problem.

The generalization of the above elucidated tasks is the identification problem [6] which is usually of nonlinear nature since states and parameters are often arbitrarily interrelated. This is especially true in case of wind turbine applications and there are five core estimation sub-problems which comprise

(i) the estimation of rotor effective wind speed and vertical/horizontal shear components,
(ii) the observation of hidden dynamic states and elimination of measurement noise,
(iii) the estimation of process/measurement noise covariances for a good filter parametrization,
(iv) online identification to cope with model mismatches due to deliberate simplifications and
(v) open-loop fatigue load estimation, monitoring of system health or predictive maintenance.

Most of these sub-problems were so far investigated only in an isolated manner which is reasonable since the goal of estimation might have only been focussed on a single task.

For instance, effective wind speed estimation and thus knowledge of the current operating point of the wind turbine is required for gain-scheduling of controller parameters and safety reasons. Since the effective wind speed cannot be measured directly and the wind anemometer provides only insufficient information, various estimators for effective wind speed have been applied and investigated to detect the unknown input to the system [7, 8, 9]. Furthermore, dynamic wind models have been proposed to exploit the a priori knowledge about the stochastic nature of wind systematically [10]. In summary, the estimation of effective wind speed has been treated broadly in literature and is more or less established. Nevertheless, there is still potential for research since dynamic inflow models [11] may provide improved wind estimates and the adaptive design of wind estimators for effective wind, vertical and horizontal shear comes along with benefits compared to static filters.

In contrast to the wind speed, the estimation of the complete wind turbine state incorporating the relevant system dynamics has so far received only little attention in the research community

Journal of Physics: Conference Series **753** (2016) 052029 doi:10.1088/1742-6596/753/5/052029

[12, 13]. Relevant dynamics comprise the following mechanical degrees-of-freedom: the drive-train dynamics, the nacelle fore-aft and side-side motion and the individual blade dynamics. Such a design model for state estimation purposes must catch the relevant dynamics sufficiently but must not be too detailed to keep the model order (number of states) low and thus computational costs. Preliminary studies for wind turbine state estimation using nonlinear Kalman filters have been presented in [14]. The need for accurate state estimation is also indicated by recent publications based on Model Predictive Control (MPC) schemes [15, 16]. In a nutshell, the significance of high quality state estimates is prominent for advanced wind turbine controllers and a comprehensive treatment is therefore essential for successful application.

The knowledge of process and measurement noise covariances is vital for the performance of estimators. Generally speaking, these covariances represent uncertainties in a priori knowledge of the system. Typical uncertainties are random process noise, disturbances and inaccuracies of measurement instrumentation as well as model mismatches. For instance, the stochastic properties of the wind field entering the wind turbine alter with respect to mean wind speed, wind site and weather conditions. Due to lack of direct access to process and measurement noise covariances in real-world systems, the suitable (usually static) choice of these filter parameters rests with the control designer. However, if the covariances change explicitly or implicitly as function of time, the static choice may be improved by adaptive approaches. In such cases, an adaptation rule (feedback law) is necessary to adjust the filter parameters and thus to guaranty a reliable filter performance. For wind turbine application such approaches were mentioned in [12] and discussed for wind speed estimation based on linear models in [17]. Adaptive filters are one key element of the real-world estimator but the design is a lot more difficult because the feedback character might lead to unwanted and unstable estimator behaviour.

The fourth sub-problem covers the online identification of the wind turbine system. System identification techniques allow for mitigation of uncertainties resulting from model mismatches. Therefore, the problem of finding the best set of system parameters minimizing the deviations between design model and real-world system is addressed. There exist a variety of identification techniques for the parameter identification problem. Typical time domain approaches are the batch processing least-squares estimators (LSE) or recursive Kalman filters. Frequency domain approaches are in general batch processing algorithms for instance applied to wind turbines in [18, 19]. Generally, the task of online identification is essential for practical implementation since larger model mismatches pose a risk for the guaranteed observer performance.

The last sub-problem embraces the ubiquitous wind turbine fatigue loads and the predictive maintenance. As mechanical loads are crucial for design, operation and control of wind turbines it is advantageous to be able to estimate and predict them online. As indicated in [20] this is not a trivial task especially in real-world application. Still, we believe that this can be resolved by a suitable observer architecture. The main requirement for a reliable load prediction poses a nonlinear high-fidelity estimator for the wind speed and the states as well as an accurate and yet simple load model.

Concluding, the full-scope estimation problem includes a broad range of sub-problems to incorporate and handle with care. Treating them separately in the horizon of advanced control schemes is not recommended due to increased complexity of the complete problem and interactions between controller and observer. To benefit from additional information and knowledge of the current system state and thus, to solve the estimation problem in advance, suitable filter algorithms must be selected, designed and tested.

3. Investigation of nonlinear filter algorithms

A filter is a dynamic data processing algorithm employed to solve a given estimation problem or one of its sub-problems. The choice of the right filters and its composition for the estimation problem requires a detailed study of the available algorithms and their properties.

3.1. Properties of estimators

The properties comprise the most relevant questions to be answered before specific application in the field. For the eligible filter choice, these properties must be assessed for the available algorithms. However, making universally valid statements is difficult since there are often several modified versions of the same filter type available [21]. Nevertheless, some generalizations are necessary to handle the great variety. Interesting criteria for filter selection include the following:

(i) the applicability/restriction to linear or nonlinear estimation problems,
(ii) the estimate's accuracy (quality/performance) and the conditions on that,
(iii) computational costs, the curse of dimensionality and real-time capabilities,
(iv) adaptive or static (non-adaptive) filter and suitable adaptation rules,
(v) recursive or batch processing nature,
(vi) convergence issues and filter instability,
(vii) equality and inequality constraints handling,
(viii) a derivative-less approach or required assessment of Jacobians or Hessians,
(ix) requirements for the underlying noise processes (Gaussian/non-Gaussian),
(x) stochastic, deterministic and/or optimization based approach,
(xi) availability of numerically efficient and stable implementations,
(xii) ease of practical realization/numerical implementation and robustness to uncertainties.

The main differentiation has to be conducted between linear and nonlinear, stochastic and deterministic, adaptive and non-adaptive as well as local and global estimators. Linear estimators are e.g. the widely-used and well-known Kalman filter [22] as well as its deterministic counterpart the Luenberger observer [23]. Since both presuppose linear system dynamics, they are only in special cases applicable to wind turbine systems, thus focusing on nonlinear approaches. Secondly, it is distinguished between stochastic estimators (filters), which explicitly incorporate disturbances, and deterministic estimators (observers) which are disturbance-free.

The majority of estimators is assigned to the stochastic framework due to omnipresent uncertainties in real-world systems. Apart from the latter ones, deterministic algorithms such as nonlinear Luenberger observers, immergence and invariance-based observers and moving horizon estimators exist which are excluded from the further discussions due to limited space.

3.2. Nonlinear filters for estimation purposes

The nonlinear stochastic estimators are distinguished between local and global filters. The first rely on certain approximations like local linearization and/or the assumption of Gaussianity for the random variables (RV). On the contrary, global filters allow for arbitrary probability density functions (pdf) of the RV's. The more important filter types are classified in three categories:

(i) Standard local filters
   (a) the linearized Kalman filter (LKF)
   (b) the extended Kalman filter (EKF) and its second-order versions
   (c) the iterated extended Kalman filter (IEKF)
(ii) Derivative-less local filters or sigma-point/cubature point filters
   (a) the unscented Kalman filter (UKF)
   (b) the spherical simplex Kalman filter (SSKF)
   (c) the central difference or divided difference Kalman filter (CDKF/DDKF)
   (d) the Gauss-Hermite Kalman filter (GHKF)
   (e) the cubature Kalman filter (CKF)

(iii) Global filters
  (a) the Gaussian sum filter (GSF)
  (b) the point mass algorithm (PM)
  (c) the particle filter (PF) or sequential Monte Carlo filters (SMCF)

First, the standard local filters are discussed. The LKF is the simplest nonlinear filter with the least computational effort since it computes the necessary linearization of Eq. (1) only once as initialization step. As a consequence, the accuracy reduces with increasing distance to the linearization point. The EKF addresses this inaccuracy effectively by a recursive linearization procedure. However, due to this feedback character the risk of filter instability and divergence rises [24, 25]. The accuracy is improved by an iterative linearization procedure within each recursion step of the original EKF [26]. Thereby, the IEKF attempts to minimize the difference between a priori and a posteriori estimate iteratively though with an unreasonable increase in computation time compared to EKF. In contrast, the second-order EKF allows for significantly improved estimation quality which is dearly bought with the need for Jacobians as well as second-order partial derivatives (Hessians). Concluding, all standard local filters use approximations of the nonlinear model, even if the model is accurately known, which is an unattractive approach. Fortunately, these types of local filters are obsolete due to today's powerful alternatives.

The newer types of derivative-less local filters eliminate the necessity to evaluate partial derivatives completely [27, 28]. Instead they employ so-called sigma-points (or cubature points for the GHKF and CKF) which are deterministically chosen representative vector points for the assumed Gaussian multivariate density distributions. They are summarized in the class of sigma-point Kalman filters (SPKF) [25, 29]. Their development started in 1997 with the UKF introducing a new approach to Kalman filtering [27]. It uses a set of $2n_x+1$ sigma-points to approximate the complete multivariate probability density of the n_x random variables. This set is propagated through the nonlinear model and then the new statistics of the propagated points are computed which is known as Unscented Transform (UT). The SSKF is quite similar to the UKF since both employ the UT but with a reduced number n_x+2 of sigma-points for the SSKF and thus lower computational effort [30]. The CDKF is very similar to the UKF as it is derivative-less but interestingly also related to the second-order EKF since it approximates the nonlinear model by a second-order Stirling polynomial interpolation. Therefore, no analytical derivatives are required like with the EKF. Instead it uses just a finite number of functional evaluations of the nonlinear function and remains thus derivative-less. The GHKF uses orthogonal Hermite polynomials to approximate the multi-dimensional distribution [29]. Unfortunately, this comes along with 3^{n_x} cubature points as samples and thus the GHKF suffers from the curse of dimensionality [21] (and is yet only feasible for $n_x < 6$). The CKF being the latest derivative-less local filters has been developed just a few years ago [31]. Contrary to the GHKF, the CKF is proposed to be well-suited for higher order systems and to be even superior to the UKF [28]. It requires computation of only $2n_x$ cubature points to support the random variable's statistic properties. Hence, computational costs are comparable to the UKF and CDKF. In summary, the framework of SPKF offers several advantages compared to standard local filters and for most of them filters exist already numerically efficient square-root algorithms.

The third category of global filters tackles the assumption of Gaussianity which is inevitable for all local filters. The price to be paid is a comparable vast increase in computational effort for high-dimensional systems. A detailed treatment of these global filters is excluded from this paper because derivative-less local filters are often sufficient for nonlinear Gaussian problems.

4. Nonlinear observer architecture and design

The prerequisites for a successful application of nonlinear filters to the wind turbine estimation problem comprise

(i) the nonlinear high-fidelity model of the wind turbine with different granularities,
(ii) the local/global observability and identifiability given a measurement configuration,
(iii) the suitable choice of nonlinear filters and its architecture, as well as the estimator design including adaptation rules for filter parameters.

The nonlinear model used in this paper was properly introduced and analysed in [32, 4] following a white-box modeling approach. It incorporates the nacelle motion as well as the drive-train dynamics which yields the state vector

$$\boldsymbol{x} = \begin{bmatrix} \dot{x}_\mathrm{T} & \dot{y}_\mathrm{T} & \dot{\varphi}_\mathrm{g} & \Delta\dot{\varphi} & x_\mathrm{T} & y_\mathrm{T} & \varphi_\mathrm{g} & \Delta\varphi \end{bmatrix}^\mathrm{T} \tag{2}$$

with eight mechanical states (Tab. 1 provides a list of all variables and parameters). Hence, the dynamics of onshore horizontal axis wind turbines with $b=3$ individual blades are governed by the following set of nonlinear second-order differential equations:

$$m_\mathrm{T}\ddot{x}_\mathrm{T} + b_\mathrm{x}\dot{x}_\mathrm{T} + k_\mathrm{x}x_\mathrm{T} = \frac{\rho}{2}\frac{\pi R^2}{3}\sum_{b=1}^{3}\Big(1+\zeta r_\mathrm{n}\cos\psi_b\Big)C_\mathrm{T}(\lambda_b,\beta_b)v_b^2 \quad , \tag{3a}$$

$$-m_\mathrm{T}\ddot{y}_\mathrm{T} - b_\mathrm{y}\dot{y}_\mathrm{T} - k_\mathrm{y}y_\mathrm{T} = \frac{\rho}{2}\frac{\pi R^3}{3\,r_\mathrm{t}}\sum_{b=1}^{3}\cos\psi_b\, C_\mathrm{M}(\lambda_b,\beta_b)v_b^2 + \zeta i_\mathrm{gb}M_\mathrm{g} \quad , \tag{3b}$$

$$\Theta_\mathrm{r}(\ddot{\varphi}_\mathrm{g} + \Delta\ddot{\varphi}) + \Theta_\mathrm{g}\ddot{\varphi}_\mathrm{g} = \frac{\rho}{2}\frac{\pi R^3}{3}\sum_{b=1}^{3}C_\mathrm{M}(\lambda_b,\beta_b)v_b^2 - i_\mathrm{gb}M_\mathrm{g} \quad , \tag{3c}$$

$$\Theta_\mathrm{r}(\ddot{\varphi}_\mathrm{g} + \Delta\ddot{\varphi}) + b_\varphi\Delta\dot{\varphi} + k_\varphi\Delta\varphi = \frac{\rho}{2}\frac{\pi R^3}{3}\sum_{b=1}^{3}C_\mathrm{M}(\lambda_b,\beta_b)v_b^2 \quad . \tag{3d}$$

The standard measurement instrumentation of such turbines provides the output vector $\boldsymbol{y} = \begin{bmatrix}\ddot{x}_\mathrm{T} \; \ddot{y}_\mathrm{T} \; n_\mathrm{g} \; \varphi\end{bmatrix}^\mathrm{T}$. Moreover, the turbine's controller accesses today with $\boldsymbol{u} = \begin{bmatrix}M_\mathrm{g} \; \beta_1 \; \beta_2 \; \beta_3\end{bmatrix}^\mathrm{T}$ at least four independent inputs to Eq. (3). The uncontrollable and yet desired wind input v_w has a direct impact on the blade effective wind speed v_b and the tip speed ratio λ_b defined by

$$v_b = \Big(1 + H^{-1}R^*\cos\psi_b\Big)^\nu v_\mathrm{w} - \Big(1 + \zeta R^*\cos\psi_b\Big)\dot{x}_\mathrm{T} \quad , \tag{4a}$$

$$\lambda_b = \Big(\dot{\varphi}_\mathrm{g} + \Delta\dot{\varphi}\Big)R\,v_b^{-1} = \Omega R\,v_b^{-1} \quad . \tag{4b}$$

which both together with the blade pitch angles β_b determine the aerodynamic forces acting on the wind turbine. The azimuth angle for the blades $b = 1, 2, 3$ denotes:

$$\psi_b = \varphi_\mathrm{g} + \Delta\varphi + 2\pi/3\,(b-1) \quad . \tag{5}$$

The above model has been successfully validated against the high-fidelity aeroelastic simulator FASTv8 [5]. Since some inputs and parameters are unknown or uncertain, they are gathered in the parameter vector which for instance denotes $\boldsymbol{\theta} = \begin{bmatrix}v_\mathrm{w} \; k_\mathrm{x} \; R^* \; \zeta\end{bmatrix}^\mathrm{T}$.

4.1. Observer architecture and design

Prior to estimation, the observability check of the design model is crucial but practically often unmindfully neglected. Since global observability is often hard to prove, preliminary studies focussed on local observability which has been successfully verified based on a complete set of linearized models. Therefore, the state vector $\boldsymbol{x}$ is observable given the measurements $\boldsymbol{y}$ and the

Table 1. Nomenclature

$\boldsymbol{x}$	dynamic state vector	R	blade tip radius	H	hub height
$\boldsymbol{u}$	control input vector	R^*	power-effective radius	ζ	Beam coupling coefficient
$\boldsymbol{y}$	system output vector	r_n	effect. normal radius	ρ	air mass density
$\boldsymbol{\theta}$	parameter vector	r_t	effect. tangential radius	k_x	equivalent fore-aft stiffness
$\boldsymbol{q}$	process noise vector	$\ddot{x}_\mathrm{T}$	nacelle fore-aft acc.	k_y	equivalent side-side stiffness
$\boldsymbol{r}$	observation noise vector	$\ddot{y}_\mathrm{T}$	nacelle side-side acc.	b_x	equiv. fore-aft damping coeff.
M_g	generator torque	$\dot{x}_\mathrm{T}$	nacelle fore-aft velocity	b_y	equiv. side-side damping coeff.
β_b	blade pitch angle	$\dot{y}_\mathrm{T}$	nacelle side-side velocity	m_T	equiv. tower top mass
λ_b	blade tip speed ratio	x_T	nacelle fore-aft position	i_gb	drive-train gear-box ratio
v_w	hub-height wind speed	y_T	nacelle side-side position	n_g	measured generator speed
v_b	blade effect. wind speed	$\dot{\varphi}_\mathrm{g}$	generator angular speed	Θ_r	combined rotor and blade inertia
ν	vertical shear exponent	$\Delta\dot{\varphi}$	drive-train angular speed	Θ_g	generator low-speed inertia
ψ_b	blade azimuth angle	φ_g	generator azimuth angle	M_By	blade-root out-of-plane moment
C_T	thrust coefficient	$\Delta\varphi$	drive-train torsion	M_Tx	tower base roll moment
C_M	torque coefficient	Ω	rotor angular speed	M_Ty	tower base pitch moment

control inputs $\boldsymbol{u}$. Further investigations showed that the parameter vector $\boldsymbol{\theta}$ is well identifiable provided a sufficient system's excitation. Hence, the second prerequisite for observer application is assumed to be fulfilled. Thus, only a suitable architecture and the filter design are missing.

The simplest approach to conduct the estimates $\hat{\boldsymbol{x}}$ and $\hat{\boldsymbol{\theta}}$ is to employ a monolithic estimator with an augmented state vector $\boldsymbol{x}_a^\mathrm{T} = \left[\boldsymbol{x}^\mathrm{T}\ \boldsymbol{\theta}^\mathrm{T}\right]$. Therefore, the sub-problems of state/parameter estimation as well as the unknown wind estimation are covered in a joint estimation approach. This works fine as long as the augmented system's dimension remains small and the investigation is conducted only within numerical simulation. Considering the real-time applicability as one key requirement, it must be the goal to focus on efficient, robust and elegant implementation strategies. Moreover, it makes sense to develop a distributed architecture because

(i) the system's nonlinearity is predominantly related to the unknown wind speed input v_w,

(ii) the elastodynamics are purely linear which can be exploited systematically,

(iii) global filters (for higher estimation quality) are only applicable to low-order sub-problems since high dimensions pose unreasonable computational costs and

(iv) slowly-varying parameters need no update on the same time scale as the states.

Thus, it is highly recommended to use a well-composed distributed observer architecture (DOA) rather than a monolithic structure as indicated in Fig. 1. Within this architecture, all relevant estimation sub-problems from Sec. 2 are included and in the following these are discussed and matched to the specific properties of the filter algorithms previously discussed in Sec. 3.2.

The wind estimator (WE) in Fig. 1 tackles the first (nonlinear) sub-problem of estimating the unknown rotor effective wind speed. A reduced second-order nonlinear model is sufficient for this purpose. If the nacelle fore-aft velocity remains small in relation to the wind speed (which applies most of the times for non-floating wind turbines) there is no need for direct coupling to the state estimator (SE). Hence, the WE design is conducted independently which makes it more robust. Typical sample times for wind turbine control systems go from 20 to 100 ms. The low-order model allows for testing of arbitrary nonlinear filters. Derivative-less local filters are in general a good choice when starting from scratch and assuming Gaussian pdf's. Global filters like PF show only substantial benefits in estimation accuracy for non-Gaussian distributed noise. Finally, a square-root CDKF was chosen as wind estimator as the best trade-off between accuracy and computation time.

The state estimator (SE) fulfils the main task to provide high quality estimates of the wind turbine state using the model from Eq. (3). Due to the aerodynamic forces interacting with the rotor and tower, the filter usually needs to be nonlinear. However, there is a more elegant way

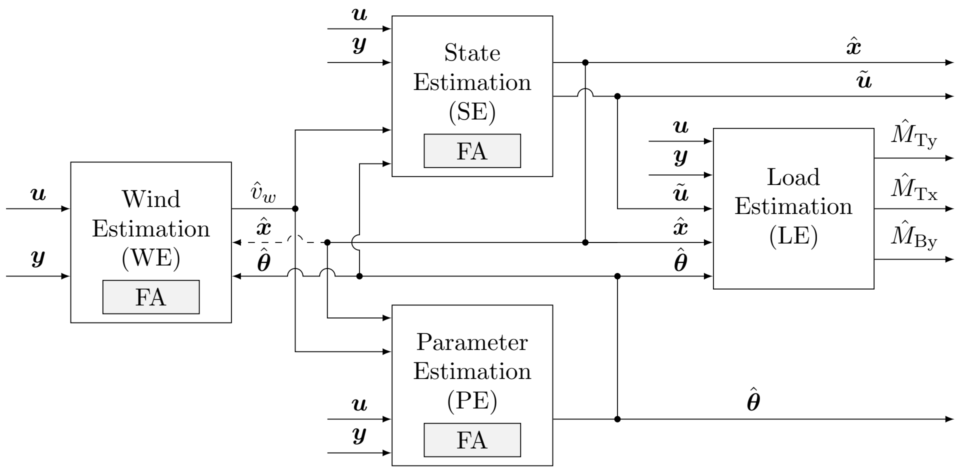

Figure 1. Structural sketch of the proposed observer architecture

to resolve this sub-problem by exploiting the mainly linear mechanical dynamics. Considering all nonlinear influences as fictitious (linear) inputs $\tilde{\boldsymbol{u}} = \tilde{\boldsymbol{u}}(\boldsymbol{u}, \hat{\boldsymbol{x}})$ to the system, the estimation sub-problem reduces to a purely linear one. Hence, a simple discrete-time Kalman filter is used involving a tremendously reduced computational effort. The single drawback to this approach is the need for the current state vector $\hat{\boldsymbol{x}}$ to compute $\tilde{\boldsymbol{u}}$. The simple and yet practical solution is to use the previous estimate (which makes no significant difference for fast sample rates).

The parameter estimator (PE) in Fig. 1 focuses as third observer component on model mismatches. It must address the accuracy of the internal models of the WE, SE and LE. Required intervals for parameter updates are in contrast to the latter rather slow and go from 2 to 10 s. Therefore, the real-time feasibility is not critical and either batch processing algorithm like MHE (which can easily incorporate parameter constraints) or simple recursive local filter types are sufficient. The structural decoupling allows for much lower sample times and reduced computational cost. Moreover, the separate PE can simply be by-passed in case of low parameter identifiability in certain situations.

Finally, the load estimator (LE) employs all the information provided by the other observer components to predict mechanical turbine loads online. Since the majority of operating wind turbines is not equipped with load sensors, turbine loads are not considered directly measurable and the LE is implemented as a trivial open-loop observer (simulator). Yet, a high-fidelity model is crucial for this type of online load assessment which the PE must assure.

The filter adaptation (FA) plays a major roll from a practical point of view. In this contribution the estimator's use only static filter parameter configurations to obtain the desired quantities. Due to its complexity the adaptive design will be discussed in a separate paper.

4.2. Simulation results and evaluation of observer performance

The above DOA has been implemented and tested with realistic simulation data obtained from FASTv8 [5] and the well-known 5-MW reference wind turbine [33]. The performance is compared to a monolithic observer architecture (MOA) using square-root CDKF. The illustrative estimation results are shown in Fig. 2. These imply a reasonable performance of the nonlinear observer compositions. Despite the corrupted noisy measurements and model errors, the distributed filter architecture provides high-fidelity estimates for the hidden dynamic states. The effective wind speed is accurately reconstructed even without incorporation of the nacelle wind anemometer measurement. In addition, the online estimation of relevant wind turbine loads as tower-base bending roll and pitch moments M_{Tx} and M_{Ty} shows reliable results.

However, apart from the subjective impression, objective criteria are required to assess the

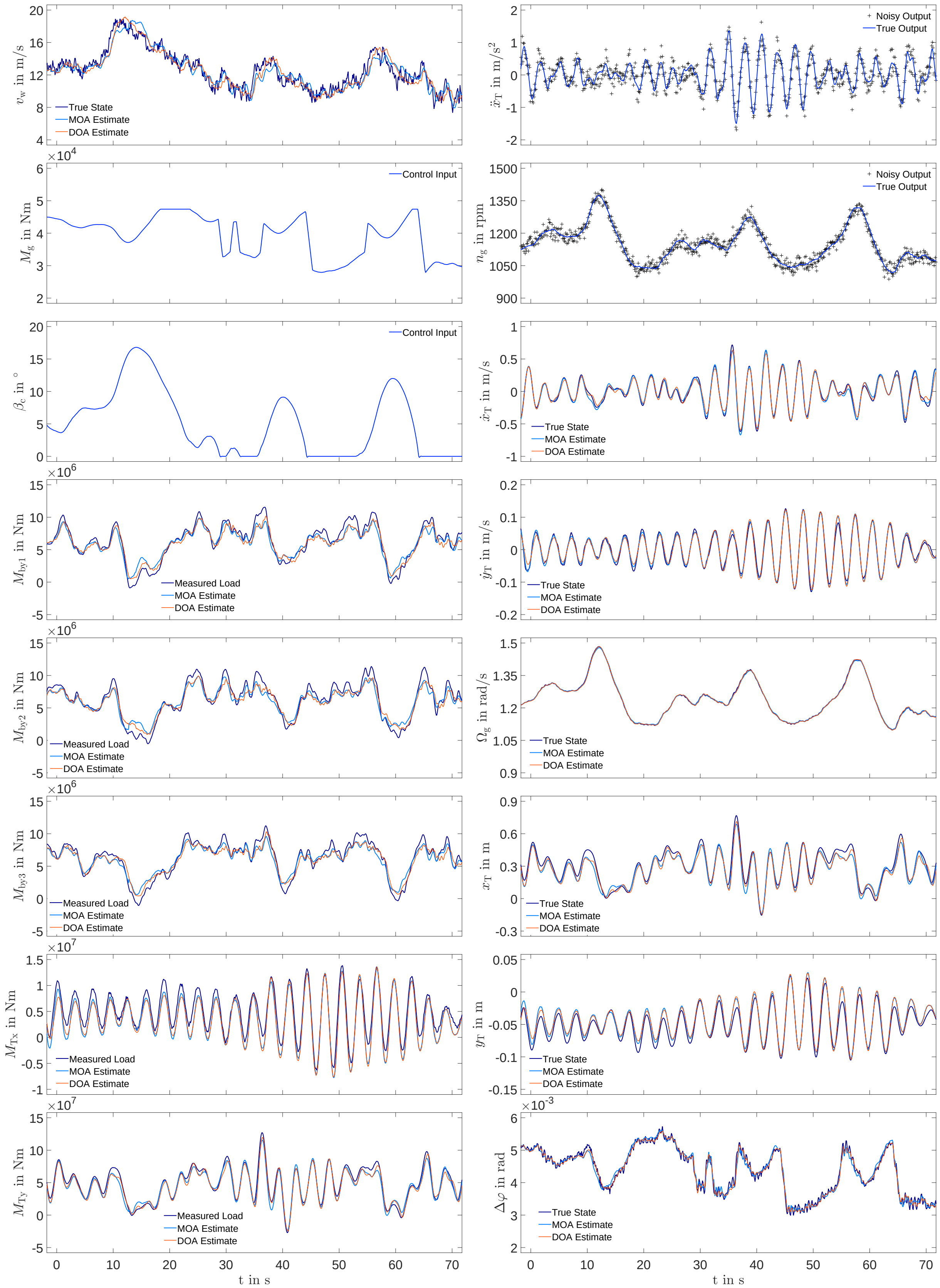

Figure 2. Illustrative estimation results with monolithic and distributed observer architecture

estimation accuracy and thus observer performance on a quantitative basis. In order to develop such measures, the Kalman filter's update equation [26]

$$\hat{\boldsymbol{x}}_k^+ = \hat{\boldsymbol{x}}_k^- + \mathbf{K}_k(\boldsymbol{y}_k - \hat{\boldsymbol{y}}_k) = \hat{\boldsymbol{x}}_k^- + \mathbf{K}_k\boldsymbol{v}_k \tag{6}$$

is a good starting-point because it is identical for all linear and nonlinear discrete-time Kalman filters. It comprises the posterior estimate $\hat{\boldsymbol{x}}_k^+$, the a priori estimate $\hat{\boldsymbol{x}}_k^-$, the Kalman gain $\mathbf{K}_k$, the predicted $\hat{\boldsymbol{y}}_k$ and measured output $\boldsymbol{y}_k$, as well as the innovation $\boldsymbol{v}_k$. The vector $\boldsymbol{x}_k$ denotes the true value and $x_{k,i}$ is its i-th element. The performance is then assessable by the following:

(i) the estimation error $e_{k,i} = x_{k,i} - \hat{x}_{k,i}^+$ which is though unknown in reality due to the unknown true state $x_{k,i}$. It is the main performance indicator but only applicable in simulation.

(ii) the relative estimation error $\tilde{x}_{k,i} = \hat{x}_{k,i}^+ - \hat{x}_{k,i}^-$ between posterior and a priori estimate which either indicates a high-fidelity of the model and/or a low confidence in the measurement.

(iii) the innovation $v_{k,j} = y_{k,j} - \hat{y}_{k,j}$ of the j-th output which is a good measure for model accuracy. It remains small if predicted and measured observation match each other.

(iv) the predicted $\mathbf{P}_k^-$ and updated $\mathbf{P}_k^+$ error covariances can be used for filter evaluation since they provide confidence intervals for the estimates $\hat{\boldsymbol{x}}_k^-$ and $\hat{\boldsymbol{x}}_k^+$.

(v) the analysis of the Kalman gain which indicates the filter's confidence whether to trust the model or the observation.

For sake of simplicity, the focus rests in this paper on the first two items. Thus, the following measures are conducted and applied:

$$\bar{e}_i = \frac{1}{N}\sum_{k=1}^{N}\left(x_{k,i} - \hat{x}_{k,i}^+\right) = \frac{1}{N}\sum_{k=1}^{N} e_{k,i} \tag{7a}$$

$$\mathrm{MSE}(e_{k,i}) = \frac{1}{N}\sum_{k=1}^{N}\left(x_{k,i} - \hat{x}_{k,i}^+\right)^2 = \left[\mathrm{RMSE}(e_{k,i})\right]^2 \tag{7b}$$

$$\mathrm{MSE}(\tilde{x}_{k,i}) = \frac{1}{N}\sum_{k=1}^{N}\left(\hat{x}_{k,i}^+ - \hat{x}_{k,i}^-\right)^2 = \left[\mathrm{RMSE}(\tilde{x}_{k,i})\right]^2 \tag{7c}$$

These include the mean estimation error, as well as the mean-squared (MSE)/root mean-squared errors (RMSE). The criteria have been evaluated for both architectures (Tab. 2). Generally, the estimates are very accurate. The RMSE($\tilde{x}_{k,i}$) is often strongly reduced in relation to the RMSE($e_{k,i}$). Thus, the update step only applies minor corrections to the a priori estimates. The RMSE($e_{k,i}$) indicates the high estimation quality since it is for many quantities $x_{k,i}$ much lower than its min/max-range. Concluding, the estimation performance is similar for the investigated observer compositions with greatly reduced computational effort (by one magnitude order) for the DOA due to its tailored architecture. The PE and the filter adaptation have been identified as a crucial components of the architecture especially for real-world wind turbine systems.

5. Conclusions and future work

This contribution has presented the full-scope estimation problem for wind turbine control applications with its five sub-problems and discussed the relevant existing publications for each of them. The variety of nonlinear filters to solve the specific sub-problems has been discussed including a detailed treatment of their main attributes. With the fully defined estimation problem and the overview of available algorithms in mind, a well-composed observer architecture has been proposed to tackle all sub-problems at once. Therefore, the estimation of dynamic

Table 2. Performance comparison of observer architectures

		$\dot{x}_{\mathrm{T}}$ in m/s	$\dot{y}_{\mathrm{T}}$ in m/s	$\dot{\varphi}_{\mathrm{g}}$ in rad/s	$\Delta\dot{\varphi}$ in rad/s	x_{T} in m	y_{T} in m	φ_{g} in rad	$\Delta\varphi$ in rad
	$\max(x_{k,i})$	0.771	0.205	1.48	0.00513	0.769	0.0538	6.28	0.00577
	$\mathrm{mean}(x_{k,i})$	-4.979e-04	3.285e-06	1.22	1.746e-06	0.295	-0.0475	3.14	0.00424
	$\min(x_{k,i})$	-0.706	-0.207	0.897	-0.00427	-0.153	-0.146	0.00129	0.00191
MOA	$\bar{e}_i$	-8.236e-04	9.445e-05	5.964e-05	6.311e-06	-0.0289	0.00598	-7.749e-04	-1.109e-05
DOA	$\bar{e}_i$	-2.956e-04	2.914e-05	1.850e-05	-2.194e-04	-0.0277	0.006	-7.822e-04	-3.786e-06
MOA	$\mathrm{RMSE}(e_{k,i})$	0.0423	0.00763	0.0161	0.00157	0.0502	0.00792	0.0608	1.554e-04
DOA	$\mathrm{RMSE}(e_{k,i})$	0.0447	0.0108	0.0278	0.0213	0.0426	0.00867	0.0609	0.00189
MOA	$\mathrm{RMSE}(\tilde{x}_{k,i})$	0.011	8.223e-04	0.016	2.274e-04	0.00706	9.871e-04	0.0608	3.357e-05
DOA	$\mathrm{RMSE}(\tilde{x}_{k,i})$	0.00447	8.285e-05	0.0142	0.00382	0.00743	4.301e-04	0.0595	0.00128
		v_{w} in m/s	$M_{\mathrm{By},1}$ in MNm	$M_{\mathrm{By},2}$ in MNm	$M_{\mathrm{By},3}$ in MNm	M_{Tx} in MNm	M_{Ty} in MNm	k_{x} in MN/m	ζ in 1/m
	$\max(x_{k,i})$	18.9	13.4	13	12.2	20.3	127	1.7	0.018
	$\mathrm{mean}(x_{k,i})$	12	6.26	6.22	6.23	4.6	47.9	1.51	0.0171
	$\min(x_{k,i})$	5.09	-0.891	-0.562	-1.06	-11.6	-27.1	1.49	0.0133
MOA	$\bar{e}_i$	-0.178	-0.36	-0.324	-0.353	-1.3	-3.26	0.131	-7.191e-04
DOA	$\bar{e}_i$	-0.166	-0.34	-0.31	-0.318	-1.3	-3.07	0.118	6.385e-04
MOA	$\mathrm{RMSE}(e_{k,i})$	0.944	0.986	0.957	1.18	1.57	7.36	0.0442	3.431e-04
DOA	$\mathrm{RMSE}(e_{k,i})$	0.897	0.914	0.923	0.901	1.67	6.05	0.0392	3.925e-04
MOA	$\mathrm{RMSE}(\tilde{x}_{k,i})$	0.159	0.986	0.957	1.18	1.57	7.36	0.00322	2.612e-05
DOA	$\mathrm{RMSE}(\tilde{x}_{k,i})$	0.143	0.914	0.923	0.901	1.67	6.05	0.00287	3.143e-05

states, of uncertain parameters and disturbance inputs, as well as the online estimation of wind turbine fatigue loads were addressed. The simulation results confirm the validity of the presented approach. The estimate's accuracy for monolithic and distributed structure indicates comparable results. The accurate reconstruction relies yet on a nonlinear high-fidelity model as well as the suitable choice of filter algorithms and their systematic design. The presented DOA reveals its main benefits insofar as real-time applicability as key requirement for higher order estimation problems is concerned. Only by splitting-up the problem it is possible to employ a nonlinear low-order filter for wind speed with high accuracy as well as a higher order linear filter for the dynamic tower and drive-train states with the least computational effort.

Future work will focus on adaptation rules for the different observer components to manage changing wind and site conditions by automated filter parameter update. Moreover, nonlinear Moving Horizon estimators (NMHE) as optimization based batch processing algorithms will be reviewed for wind turbine application for instance to tackle the parameter estimation problem. Additionally, practical issues for design and implementation in real-world wind turbines like robustness, numerical stability and constraints need to be addressed explicitly.

Concluding, the full-scope estimation problem includes a broad range of sub-problems to handle with care. It is in general multiobjective and not trivial due to increased complexity and interactions between controller and observer. Nevertheless, nonlinear observers for state and parameter estimation offer substantial improvements for future wind turbine operation and control. Yet, a thorough understanding of nonlinear filters and their specific properties is essential to harvest this potential and to design improved closed-loop controllers.

References

[1] Bossanyi, E. A.: *Individual Blade Pitch Control for Load Reduction.* Wind Energy J., (6):119–128, 2003.

[2] Gros, Sébastien: *An economic NMPC formulation for wind turbine control.* IEEE Conference on Decision and Control, pages 1001–1006, 2013.

[3] Kolås, Steinar, Bjarne Foss and Tor Steinar Schei: *State estimation IS the real challenge in NMPC*. Int. Workshop on Assessment and Future Directions of NMPC Pavia, Italy, September 5-9, 2008.
[4] Ritter, Bastian and Ulrich Konigorski: *Advanced Multivariable Control Design for Modern Multi-MW Wind Turbines*. Proceedings of the 11th EAWE PhD Seminar on Wind Energy in Europe, 2015.
[5] Jonkman, J and B. Jonkman: *NWTC Information Portal (FAST v8). https://nwtc.nrel.gov/FAST8*, 2015.
[6] Besançon, Gildas: *Nonlinear Observers and Applications*. Springer, 2007.
[7] Østergaard, K Z, P Brath and J Stoustrup: *Estimation of effective wind speed*. Journal of Physics: Conference Series 75 (2007). The Science of Making Torque from Wind, 75, 2007.
[8] Ortega, R., F. Mancilla-David and F. Jaramillo: *A Globally Convergent Wind Speed Estimator for Windmill Systems*. IEEE Conf. on Decision and Control and European Control Conf. (CDC-ECC), 2011.
[9] Soltani, M. N., T. Knudsen, M. Svenstrup, R. Wisniewski, P. Brath, R. Ortega and K. Johnson: *Estimation of Rotor Effective Wind Speed: A Comparison*. IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY, 21(4):1155–1167, 07 2013.
[10] Knudsen, Torben, Thomas Bak and Mohsen Soltani: *Prediction models for wind speed at turbine locations in a wind farm*. Wind Energy, 14:877–894, 2011.
[11] Henriksen, L. C., M. H. Hansen and M. K. Poulsen: *A simplified dynamic inflow model and its effect on the performance of free mean wind speed estimation*. Wind Energy, (16):1213–1224, 2013.
[12] Bottasso, C. L. and A. Croce: *Cascading Kalman Observers of Structural Flexible and Wind States for Wind Turbine Control*. Technical Report DIA-SR 09-02, Politecnico di Milano, 2009.
[13] Bottasso, C.L., A. Croce, C.E.D. Riboldi and G.S. Bir: *Spatial estimation of wind states from the aeroelastic response of a wind turbine*. The Science of Making Torque from Wind, 2010.
[14] Ritter, B., N. Chrysalidis and U. Konigorski: *Application of Nonlinear Kalman Filters to Wind Turbine State Observation*. 12th EAWE PhD Seminar on Wind Energy in Europe, DTU Lyngby, 2016.
[15] Gros, Sébastien, Milan Vukov and Moritz Diehl: *A Real-time MHE and NMPC Scheme for Wind Turbine Control*. IEEE Conference on Decision and Control, 2013.
[16] Kumar, A. A., P. J. Rainey and E. A. Bossany: *LIDAR Assisted Model Predictive Control of a Next Generation Wind Turbine for Tower Fatigue Load Reduction and Improved Speed Control*. EWEC, 2015.
[17] Bourlis, Dimitris and J.A.M. Bleijs: *A Wind Speed Estimation Method Using Adaptive Kalman Filtering For A Variable Speed Stall Regulated Wind Turbine*. IEEE, 2010.
[18] Jasniewicz, Boris and Martin Geyler: *Wind turbine modelling and identification for control system applications*. Fraunhofer IWES, Division Control Engineering and Energy Storages, 2010.
[19] Geyler, M. and B. Jasniewicz: *Parameter estimation for control design models based on operational modal analysis techniques*. DEWEK, 2010.
[20] Jasniewicz, B.: *Online estimation of mechanical loads for wind turbines*. Technical Report, Fraunhofer IWES, 2011.
[21] Daum, Fred: *Nonlinear Filters: Beyond the Kalman Filter*. IEEE Aerospace and Electronic Systems Magazine, 20(8):57–69, 08 2005.
[22] Kalman, R. E.: *A New Approach to Linear Filtering and Prediction Problems*. Trans. ASME - Journal of Basic Engineering, 82(D), 1960.
[23] Luenberger, D. G.: *Observing the State of a Linear System*. Military Electronics, IEEE Transactions on, 8(2):74–80, 1964.
[24] Merwe, R. van der and E. A. Wan: *The square-root Unscented Kalman Filter for state and parameter-estimation*. IEEE International Conference on Acoustics, Speech, and Signal Processing, 2001. Proceedings. (ICASSP '01). 2001, 6:3461–3464, 2001.
[25] Merwe, Rudolph van der: *Sigma-Point Kalman Filters for Probabilistic Inference in Dynamic State-Space Models*. PhD thesis, OGI School of Science & Engineering at Oregon Health & Science University, 2004.
[26] Simon, D.: *Optimal State Estimation. Kalman, H_∞, and Nonlinear Approaches*. John Wiley & Sons, 2006.
[27] Julier, Simon J. and Jeffrey K. Uhlmann: *A New Extension of the Kalman Filter to Nonlinear Systems*. 11th International symposium on Aerospace/Defence Sensing, Simulation and Control, 1997.
[28] Arasaratnam, I. and S. Haykin: *Cubature Kalman Filters*. IEEE Transactions on Automatic Control, 54(6):1254–1269, June 2009.
[29] Haug, Anton J.: *Bayesian Estimation and Tracking: A Practical Guide*. John Wiley & Sons, Inc., 2012.
[30] Julier, Simon J.: *The Spherical Simplex Unscented Transformation*. Proceedings of the 2003 IEEE - American Control Conference, 3:2430–2434, 2003.
[31] Arasaratnam, I.: *Cubature Kalman Filtering: Theory & Applications*. PhD thesis, McMaster Univ., 2009.
[32] Ritter, B., H. Fürst, M. Eichhorn and U. Konigorski: *Multivariable Model for Simulation and Control Design of Wind Turbines*. Proceedings of the 12th German Wind Energy Conference (DEWEK), 2015.
[33] Jonkman, J., S. Butterfield, W. Musial and G. Scott: *Definition of a 5-MW Reference Wind Turbine for Offshore System Development*. Technical Report NREL/TP-500-38060 February, 2009.