Slovak University of Technology in Bratislava
Institute of Information Engineering, Automation, and Mathematics

PROCEEDINGS

of the 18th International Conference on Process Control
Hotel Titris, Tatranská Lomnica, Slovakia, June 14 – 17, 2011
ISBN 978-80-227-3517-9
http://www.kirp.chtf.stuba.sk/pc11

Editors: M. Fikar and M. Kvasnica

Mateljak, P., Petrović, V., Baotic, M.: Dual Kalman Estimation of Wind Turbine States and Parameters, Editors: Fikar, M., Kvasnica, M., In *Proceedings of the 18th International Conference on Process Control*, Tatranská Lomnica, Slovakia, 85–91, 2011.

Full paper online: http://www.kirp.chtf.stuba.sk/pc11/data/abstracts/072.html

Dual Kalman Estimation of Wind Turbine States and Parameters

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Abstract: Modern wind turbines operate in a wide range of wind speeds. Power contained in the wind is proportional to the third power of wind speed and therefore increases rapidly with increase of wind speed. To enable wind turbine operation in such a variety of operating conditions, sophisticated control and estimation algorithms are needed. In this paper, a method for wind turbine state and parameter estimation is proposed. The described estimation is experimentally tested on laboratory wind turbine.

Keywords: Wind turbine, state estimation, parameter estimation, dual Kalman filter.

1. INTRODUCTION

Modern wind turbines operate in a wide range of wind speeds, typically from 3 m/s to 25 m/s. Power contained in wind is proportional to the third power of wind speed and therefore increases rapidly with increased wind speed, Burton et al. (2001). To enable wind turbine operation in such a variety of operating conditions, a sophisticated control system is needed. During weak winds, the control system has to optimise wind energy conversion by using appropriate generator torque. On the other hand, during strong winds, wind turbine power has to be constrained. An efficient way to constrain wind energy capture is pitching the rotor blades around their longitudinal axis, i.e. pitch control.

To employ more complex control algorithms, state estimation is often needed, Simon (2006). Due to wind turbine high nonlinearity and parameters uncertainty, it is not possible to use a linear model for control design and state estimation in the whole operating region. Therefore, Kalman filter for state and parameter estimation is proposed in this paper. The estimation is experimentally verified in Laboratory for Renewable Energy Sources (LARES) on Faculty of Electrical Engineering and Computing, University of Zagreb. Brief description of LARES can be found in Section 2. In Section 3, mathematical model of the wind turbine is given. State and parameter estimation method based on Kalman filter theory is presented in Section 4. Wind speed estimation is described in Section 5. Finally, in Section 6, experimental results are shown with brief conclusion.

2. DESCRIPTION OF THE LABORATORY

Laboratory for Renewable Energy Sources is located at the Faculty of Electrical Engineering and Computing, University of Zagreb. The research in the laboratory is focused on three areas: (i) wind energy, (ii) solar energy and (iii) energy storage using hydrogen fuel cell stack with metal hydride storage. Besides the research of each area independently, their connection into a micro grid is also being investigated, see Perić et al. (2010) for more details. The principle scheme of the laboratory is shown in Figure 1.

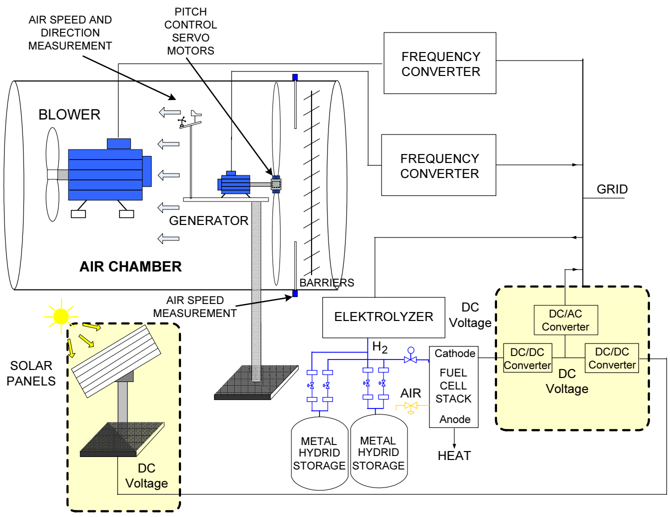

Fig. 1. Principle scheme of the Laboratory for Renewable Energy Sources, Perić et al. (2010).

The laboratory's wind turbine set-up consists of scaled wind turbine placed in air chamber with wind blower for generating wind, as shown in Figure 2.

The laboratory wind turbine is specially constructed so all aerodynamic relations present at MW-scale wind turbines are preserved. Furthermore, construction of laboratory wind turbine tower enables oscillatory fore-aft tower motion. To be able to use the same control strategies as on MW-scale wind turbine, the laboratory wind turbine is equipped with: (i) three servo drives that enable individual pitch control and (ii) synchronous generator with

Fig. 2. The laboratory wind turbine set-up.

frequency converter for torque control. Control algorithms are implemented on PC using LabVIEW (*Laboratory Virtual Instrumentation Engineering* Workbench) platform, Johnson and Jennings (2006). Measurements of the system variables and control signal generation are obtained by a specialized input-output PXI and cRIO circuits, as shown in Figure 3.

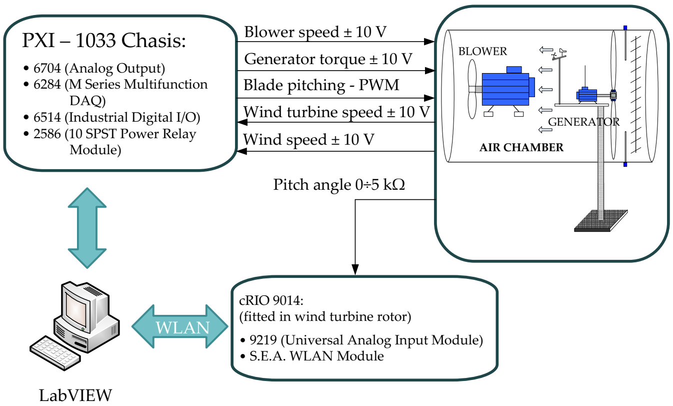

Fig. 3. The basic wind turbine control scheme.

3. WIND TURBINE MATHEMATICAL MODEL

Very common method used for wind turbine modelling is blade element and momentum theory which yields reliable and detailed wind turbine model (Burton et al. (2001)). However, such models describe wind turbine behaviour with implicit equations which are not suitable for controller design. Therefore, a simpler model that uses quasi steady state relations for aerodynamic phenomena is preferred. Such model can easily be used for control and estimator design, but it is still detailed enough to offer necessary insight into physics of the wind turbine.

The motion of the rotor can be described with equation:

$$J_t\dot{\omega} = M_a - M_g, \tag{1}$$

where ω is rotor speed, M_g is generator electromagnetic torque, M_a is aerodynamic torque and J_t is turbine moment of inertia. The aerodynamic torque can be computed as:

$$M_a = \frac{\pi}{2}\rho_a R_b^3 \bar{v}_w^2 C_Q(\bar{v}_w, \omega, \beta), \tag{2}$$

where $\bar{v}_w$ is effective wind speed on wind turbine rotor, R_b is blade length, and ρ_a is air density and C_Q is torque coefficient. Torque coefficient C_Q describes the steady state dependence of aerodynamic torque on wind speed, rotor speed and pitch angle β, Hau (2006).

It should be noted that wind is not uniform and its speed varies over the rotor area. Therefore effective wind speed $\bar{v}_w$ used in this model is not wind speed in any particular point on rotor area. The effective wind speed $\bar{v}_w$ is defined as wind speed of uniform wind that would have the same effect on wind turbine as real nonuniform wind. For most applications, information about effective wind speed is more useful than information about wind speed on any particular point on rotor area, cf. van der Hooft and van Engelen (2003).

Important parts of wind turbine dynamics are tower oscillations. Namely, wind turbine structure is very flexible due to great dimensions of its components and need for their moderate mass. In this paper, only tower flexibility is considered, while blades are assumed to be completely stiff. This assumption is valid for most MW-scale wind turbines that are in use at the present time and for the laboratory wind turbine described in Section 2. However, for larger turbines, (5 MW and more) we should probably take into account flexing of the blades as well. The first harmonic in tower oscillations is the most dominant, so tower dynamics can be approximated by (van Engelen et al. (2007)):

$$M\ddot{x}_t + D\dot{x}_t + Cx_t = F_t, \tag{3}$$

where x_t is the tower top deflection and M, D and C are the modal mass, damping and stiffness, respectively. The aerodynamic thrust force is defined similarly to aerodynamic torque:

$$F_t = \frac{\pi}{2}\rho_a R_b^2 \bar{v}_w^2 C_T(\bar{v}_w, \omega, \beta), \tag{4}$$

where thrust coefficient C_T describes the steady state dependence of aerodynamic thrust force on wind speed, rotor speed and pitch angle, Hau (2006).

Due to tower motion, wind turbine rotor is not influenced by absolute wind speed v_w, but by apparent wind speed that is derived from absolute wind speed and tower top speed:

$$\bar{v}_w = v_w - \dot{x}_t. \tag{5}$$

Tower oscillations are small in magnitude compared to wind speed, but they significantly contribute to wind turbine behaviour and pose main limitation to wind turbine pitch control (Jelavić and Perić (2009)).

For parameter estimation, it is more convenient to have a linear discrete-time state space model of the system. To this end we introduce state vector $x \in \mathbb{R}^3$ and input vector $u \in \mathbb{R}^3$ as follows:

$$x = \begin{bmatrix} \omega \\ x_t \\ \dot{x}_t \end{bmatrix}, \quad u = \begin{bmatrix} v_w \\ \beta \\ M_g \end{bmatrix}. \tag{6}$$

The nonlinear mathematical model (1) – (5) can now be linearised around an operating point (O.P. $\equiv (x^0, u^0)$) and written in the state space form:

$$\dot{x} = Ax + Bu, \tag{7}$$

with matrices $A \in \mathbb{R}^{3\times3}$ and $B \in \mathbb{R}^{3\times3}$ as follows:

$$A = \begin{bmatrix} \frac{M_\omega}{J_t} & 0 & -\frac{M_v}{J_t} \\ 0 & 0 & 1 \\ \frac{F_\omega}{M} & -\frac{C}{M} & -\frac{F_v + D}{M} \end{bmatrix}, \tag{8}$$

$$B = \begin{bmatrix} \frac{M_v}{J_t} & \frac{M_\beta}{J_t} & -\frac{1}{J_t} \\ 0 & 0 & 0 \\ \frac{F_v}{M} & \frac{F_\beta}{M} & 0 \end{bmatrix}, \tag{9}$$

The coefficients M_ω, F_ω, M_v, F_v, M_β and F_β, introduced in (8) and (9), are partial derivatives of aerodynamic torque and thrust force around operating point:

$$\begin{aligned} M_\omega &= \left.\frac{\partial M_a}{\partial \omega}\right|_{O.P.}, \; F_\omega = \left.\frac{\partial F_t}{\partial \omega}\right|_{O.P.}, \\ M_v &= \left.\frac{\partial M_a}{\partial v_w}\right|_{O.P.}, \; F_v = \left.\frac{\partial F_t}{\partial v_w}\right|_{O.P.}, \\ M_\beta &= \left.\frac{\partial M_a}{\partial \beta}\right|_{O.P.}, \; F_\beta = \left.\frac{\partial F_t}{\partial \beta}\right|_{O.P.}. \end{aligned} \tag{10}$$

Partial derivatives (10) and other wind turbine parameters used in this section can be obtained from professional wind turbine simulation tools, e.g., GH Bladed Bossanyi (2009).

Finally, a discrete time model of the wind turbine in the form:

$$x(k+1) = \Phi x(k) + \Gamma u(k), \tag{11}$$

can be obtained from the continuous-time model (7)–(10) with the following approximation (Franklin et al. (1997)):

$$\Phi = e^{AT} \approx I + AT, \tag{12}$$

$$\Gamma = \int_0^T e^{A\tau} B d\tau \approx BT, \tag{13}$$

where T is the sampling time.

4. STATE AND PARAMETER ESTIMATION

As shown in Section 3, wind turbine is a highly nonlinear system. For this reason we have chosen the extended Kalman filter (EKF) as an algorithm for the state and parameter estimation, cf. Simon (2006).

In general, the discrete-time EKF considers the nonlinear system in the state space form:

$$\begin{aligned} x_k &= f_{k-1}(x_{k-1}, u_{k-1}, w_{k-1}), \\ y_k &= h_k(x_k, v_k), \end{aligned} \tag{14}$$

where $x_k \in \mathbb{R}^n$ is the state vector, $u_k \in \mathbb{R}^m$ is the input vector, $y_k \in \mathbb{R}^p$ is the output (measurement) vector, w_k is the process noise, and v_k is the measurement noise at time step k. The process and measurement noise are assumed to be zero-mean stochastic variables with normal distribution, i.e.,

$$\begin{aligned} w_k &\sim (0, Q_k), \\ v_k &\sim (0, R_k), \end{aligned} \tag{15}$$

where Q_k and R_k are corresponding covariances.

The basic idea of the extended Kalman filter is to linearise (i.e., compute the first order Taylor approximation of) the nonlinear system (14) around the Kalman filter estimate of the states. At the same time the Kalman filter estimate of the states is based on the obtained linearised system.

Kalman filter is a recursive estimator that can be decomposed into two phases: prediction and correction, which are performed at every time instant k. In the prediction phase a priori estimation of the state ($\hat{x}_k^-$) is obtained from the system model (14) as if there was no process noise. In the correction phase an improved state estimate is found ($\hat{x}_k^+$) by utilizing the actual measurements. This update is achieved via the so-called Kalman gain matrix, K_k. The quality of the estimation is captured in the error covariance matrix P_k, which is also updated in two phases, i.e., we have a priori value P_k^- and a posteriori value P_k^+.

In the following we give brief summary of the computational steps for discrete-time extended Kalman filter, see Simon (2006) for more details:

(1) Initialize the filter

$$\begin{aligned} \hat{x}_0^+ &= \mathrm{E}(x_0), \\ P_0^+ &= \mathrm{E}\left[(x_0 - \hat{x}_0^+) \cdot (x_0 - \hat{x}_0^+)^T\right], \\ k &= 1. \end{aligned} \tag{16}$$

(2) *Prediction phase*: compute the time update of the state estimate and estimation-error covariance

$$\begin{aligned} \hat{x}_k^- &= f_{k-1}(\hat{x}_{k-1}^+, u_{k-1}, 0), \\ P_k^- &= F_{k-1} P_{k-1}^+ F_{k-1}^T + L_{k-1} Q_{k-1} L_{k-1}^T, \end{aligned} \tag{17}$$

where

$$\begin{aligned} F_{k-1} &:= \left.\frac{\partial f_{k-1}}{\partial x}\right|_{(\hat{x}_{k-1}^+, u_{k-1}, 0)} \\ L_{k-1} &:= \left.\frac{\partial f_{k-1}}{\partial w}\right|_{(\hat{x}_{k-1}^+, u_{k-1}, 0)} \end{aligned} \tag{18}$$

(3) *Correction phase*: compute the measurement update of the state estimate and estimation-error covariance

$$\begin{aligned} K_k &= P_k^- H_k^T \left(H_k P_k^- H_k^T + M_k R_k M_k^T\right)^{-1}, \\ \hat{x}_k^+ &= \hat{x}_k^- + K_k \left[y_k - h_k(\hat{x}_k^-, 0)\right], \\ P_k^+ &= (I - K_k H_k) P_k^-, \end{aligned} \tag{19}$$

where

$$\begin{aligned} H_k &:= \left.\frac{\partial h_k}{\partial x}\right|_{(\hat{x}_k^-, 0)} \\ M_k &:= \left.\frac{\partial h_k}{\partial v}\right|_{(\hat{x}_k^-, 0)} \end{aligned} \tag{20}$$

(4) Increase k and go to step 2.

The estimation process is illustrated in Figure 4.

As already mentioned, besides estimation of the signals, the extended Kalman filter can be used for parameter

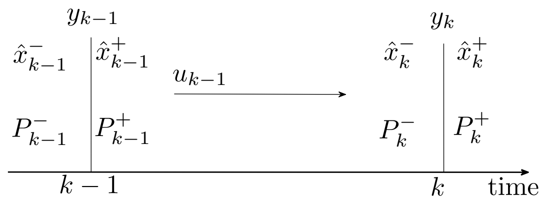

Fig. 4. Kalman filter estimation process.

estimation as well, cf. Wan and Nelson (2001). Basic idea is to define state vector with parameter values and perform estimation procedure.

In control systems one usually assumes that the parameter changes are slow, i.e., that one can write:

$$p_{k+1} = p_k + \delta_k, \tag{21}$$

where p_k is the parameter vector and δ_k is the parameter uncertainty at discrete time step k. The parameter uncertainty δ_k is defined as a stochastic variable with a zero mean value and standard deviation Q_δ.

In case of a wind turbine, the parameter changes cannot be observed as in (21), because parameter values depend on wind speed. So, mathematical model, given in (12) and (13) is used to obtain expected parameter values. In this paper, both of these approaches are used in order to obtain a priori estimation as it is proposed in following equation:

$$p_k^- = \alpha \cdot p_{k-1}^+ + (1-\alpha) \cdot \tilde{p}_k, \tag{22}$$

where p_k^- is a priori parameter estimation at discrete time step k, p_{k-1}^+ is a posteriori parameter estimation at discrete time step $(k-1)$, $\tilde{p}_k$ is expected parameter value based on mathematical model and α is tuning coefficient.

It must be noted that a posteriori estimation is calculated using Kalman gain matrix as in case of state estimation.

Wind turbine is a highly nonlinear system whose dynamics strongly depend on wind speed, so its parameters are changing in time. The goal of this paper is to estimate the changing parameters and use obtained estimates to improve estimation of the system states. To this end we employ extended Kalman filter, which is suitable for parallel estimation of the system states and parameters, see Wan and Nelson (2001) for more details.

To carry out the dual task of state and parameter estimation it is necessary to enable synchronous operation of two Kalman filters as it is shown in Figure 5. This is achieved using the state estimator and available measurements, which will converge towards the correct estimation values. Furthermore, these values will be used as an input data to parameter estimator. Finally, calculated values are returned in the first estimator using feedback. In this way, one gets two estimators, which interact with each other, and thus provide two types of data from the process, state and parameters values. These data are usually hard or even impossible to measure. It is necessary to point out that possible estimation problems are expected because of limited number of signals that are actually measurable.

Note that, in general, the algorithm is able to calculate all parameters and state values. However, the obtained

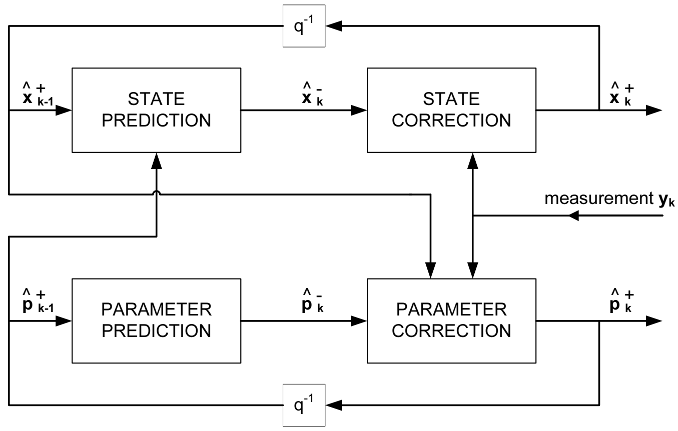

Fig. 5. Dual Kalman filter scheme.

solution may not be accurate, because estimated values may be only one of possibly many solutions that satisfy system dynamics and initial conditions. So, there are limitations to the number of signals which can be reliably estimated.

5. WIND SPEED ESTIMATION

As it can be seen in (6), wind speed is one of process inputs and it can be shown that it contributes significantly to wind turbine behaviour. Although it would be possible to use the wind speed measurement in the Laboratory, such information about wind speed on the rotor is typically not available on a MW-scale wind turbines. Namely, anemometers are placed on wind turbine nacelle, so wind speed measurement has a significant time lag. Also, wind measured by the anemometer on a MW-scale turbine is deformed due to passing through the wind turbine rotor. Therefore, wind speed estimation is used in this paper instead of the real wind speed measurement.

Furthermore, in Section 4, it is mentioned that there may be a limit on a number of states and parameters one could estimate sufficiently well depending on the number of measured outputs. Therefore, instead of augmenting EKF from Section 4 to estimate wind speed, another approach is used. As it is shown by van der Hooft and van Engelen (2003), the effective wind speed can be estimated from (1) that describes the wind turbine rotor motion. By using expression for aerodynamic torque (2), one can readily form the following nonlinear function:

$$f_w(\hat{v}_w) = \frac{\pi}{2}\rho_a R_b^3 \hat{v}_w C_Q(\hat{v}_w, \omega, \beta) - M_g - J_t\dot{\omega}. \tag{23}$$

Pitch angle β and electromagnetic torque M_g can be easily measured, while rotor speed ω can be obtained from Kalman filter described in Section 4. The torque coefficient C_Q is based on the aerodynamic characteristics of the turbine, and can be calculated using professional simulation tools, e.g. GH Bladed, Bossanyi (2009). Clearly, when the estimated wind speed $\hat{v}_w$ is equal to the effective wind speed on the wind turbine rotor $\bar{v}_w$ then the function (23) has a zero value. Therefore, the wind speed estimation can be done by numerically solving the nonlinear equation:

$$f_w(\hat{v}_w) = 0. \tag{24}$$

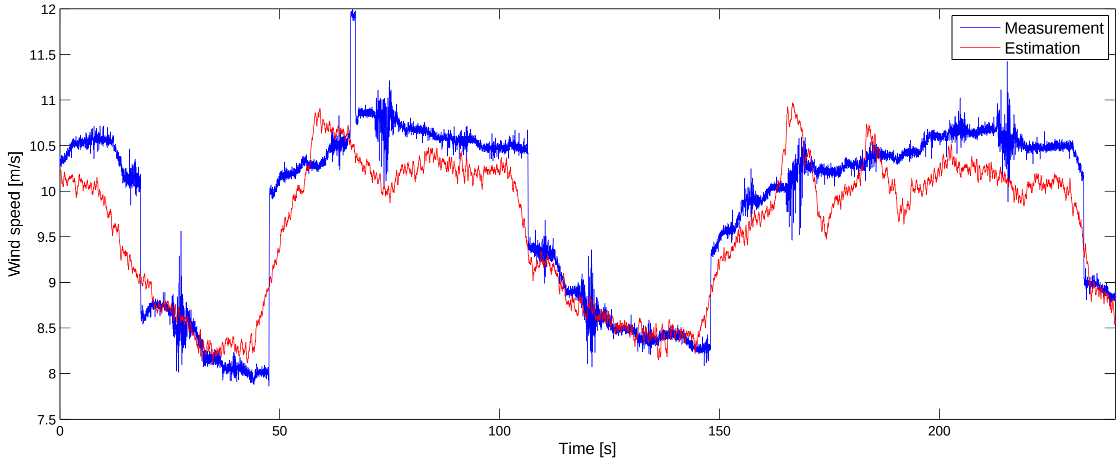

Fig. 6. Comparison between wind speed estimation and wind speed measurement.

Figure 6 shows comparison between wind speed estimation and measurement.

6. EXPERIMENTAL RESULTS

The state and parameter estimation method described in Section 4 was experimentally tested in Laboratory for Renewable Energy Sources (LARES) at the Faculty of Electrical Engineering and Computing, University of Zagreb. The wind turbine in question has the following parameters:

$$\begin{aligned} J_t &= 4\,\mathrm{Nms}^2, \\ M &= 2.321 \cdot 10^4\,\mathrm{Ns}^2/\mathrm{m}, \\ D &= 4.672 \cdot 10^3\,\mathrm{Ns/m}, \\ C &= 8.468 \cdot 10^5\,\mathrm{N/m}. \end{aligned}$$

In the Laboratory setup the control system comprises two separated control loops. First controller is used below rated wind speed to set up the moment reference. The second controller is used above rated wind speed to obtain pitching of the rotor blades around their longitudinal axis in order to constrain the capturing of wind energy. The goal of the experiment was to verify the state and parameter estimation based on the Kalman filter theory.

Two series of experiments were made. In the first set of experiments the state and parameter estimation is performed below rated wind speed. In that case the blade pitch angle is constant and the moment controller is active. In the second set of experiments, during strong winds above rated wind speed, generator torque is on its rated value and pitch controller is active.

Estimated wind speed and rotor speed in the experiment below rated wind speed are shown in Figure 7 and Figure 8, respectively. Initial values of parameters in (10) are

$$\begin{aligned} M_\omega &= -0.082663\,\mathrm{Nms/rad}, \\ F_\omega &= -19.774\,\mathrm{Ns/rad}, \\ M_v &= 1.26908\,\mathrm{Ns}, \\ F_v &= 5.06419\,\mathrm{Ns/m}, \\ M_\beta &= 0.048625\,\mathrm{Nm/rad}, \\ F_\beta &= -19.774\,\mathrm{N/rad}, \end{aligned}$$

and initial continuous-time model (7) with

$$A = \begin{bmatrix} -0.0207 & 0 & -0.3173 \\ 0 & 0 & 1 \\ -8.55 \cdot 10^{-4} & -36.627 & -0.2023 \end{bmatrix},$$

$$B = \begin{bmatrix} 0.3173 & 0.012156 & -0.25 \\ 0 & 0 & 0 \\ 2.19 \cdot 10^{-4} & -6.364 \cdot 10^{-4} & 0 \end{bmatrix},$$

is discretized with the sampling time of 20 ms to get a discrete-time model (11).

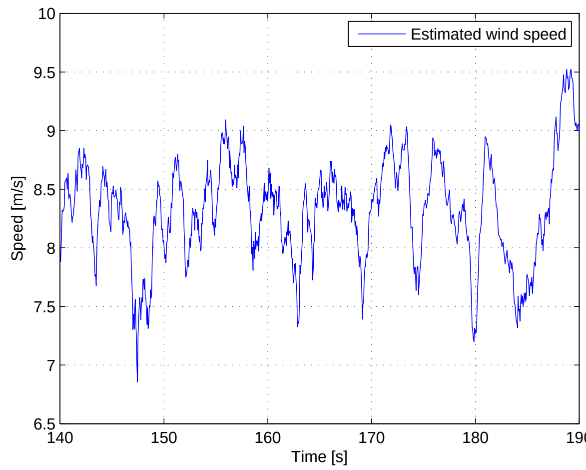

Fig. 7. Wind speed estimation below rated wind speed.

Representative results in experiments above rated wind speed are reported in Figure 9 (estimated wind speed) and Figure 10 (estimated rotor speed).

Estimation results show that the measurement noise is suppressed and estimation error is negligible in both cases – both below and above rated wind speed.

For illustration, in Figure 11 we report one representative sample of the parameter estimation results: estimation of parameter $\Gamma_{1,1}$. The blue line represents the expected value of $\Gamma_{1,1}$ based on the mathematical model (13). A posteriori estimation using the extended Kalman filter is plotted with a red line.

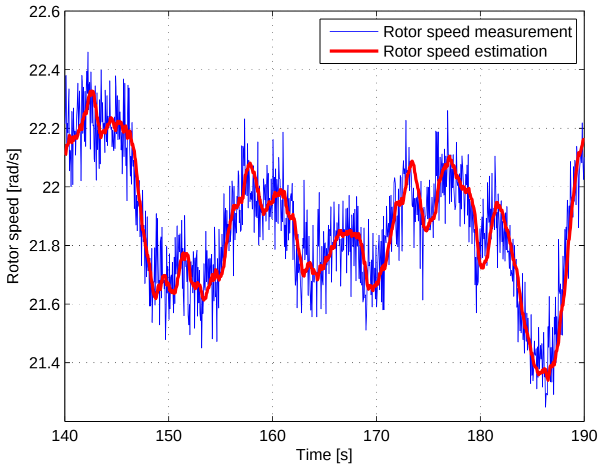

Fig. 8. Rotor speed estimation below rated wind speed.

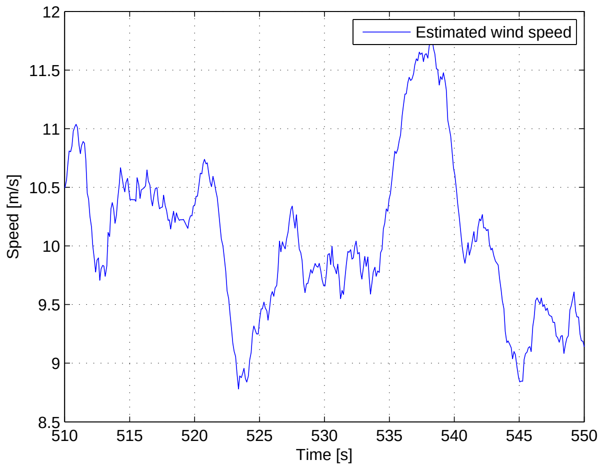

Fig. 9. Wind speed estimation above rated wind speed.

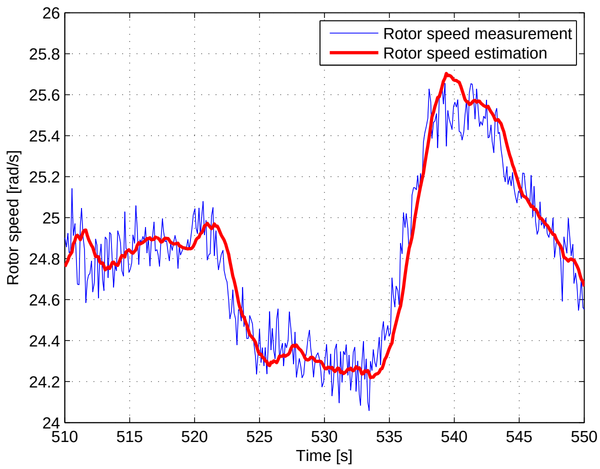

Fig. 10. Rotor speed estimation above rated wind speed.

7. CONCLUSION

In this paper, wind turbine state and parameter estimation based on a dual Kalman filter theory is implemented and

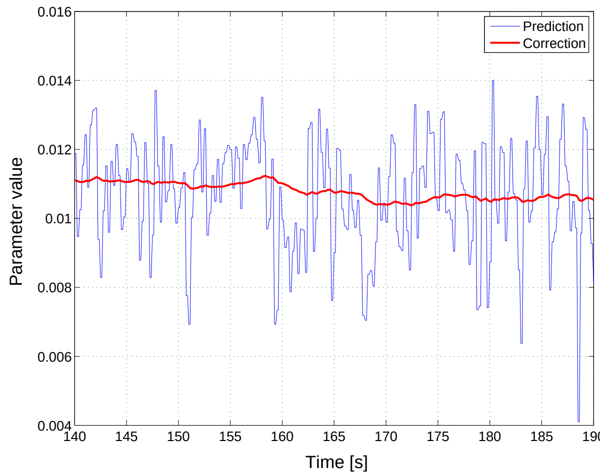

Fig. 11. Parameter estimation below rated wind speed, parameter $\Gamma_{1,1}$.

experimentally tested in Laboratory for Renewable Energy Sources. A modification of the parameter estimation is used to improve a priori estimation of the state vector.

We report results for wind speed estimation and rotor speed estimation. Experiment is performed in two different operating modes, below and above rated wind speed. It is shown that the rotor speed can be estimated with a high quality in both cases. It is also possible to implement this estimation method for other states, e.g. tower top deflection.

ACKNOWLEDGEMENTS

This research has been financially supported by the Ministry of Science, Education and Sports of the Republic of Croatia under grant No 036-0361621-3012; by the National Foundation for Science, Higher Education and Technological Development of the Republic of Croatia; and by Končar - Electrical Engineering Institute. This support is gratefully acknowledged.

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