International Journal of Control, Automation and Systems 15(3) (2017) 1089-1096
http://dx.doi.org/10.1007/s12555-016-0537-1

ISSN:1598-6446 eISSN:2005-4092
http://www.springer.com/12555

Kalman Filter-based Wind Speed Estimation for Wind Turbine Control

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Abstract: To improve power production and reduce loads on turbine components, exact wind speed information is required in modern wind turbine controllers. However, the wind speed measured on the nacelle is imprecise because of its drawbacks of single point measurement and non-immunity to disturbances. To solve this problem, the EWS (Effective Wind Speed) estimator has been proposed as an alternative. According to the literatures, there are two kinds of EWS estimator, that is, the KF-based estimator and the EKF-based one. Where, the former is applied to estimate the aerodynamic torque, then the EWS is numerically calculated; and the latter directly estimate the EWS. Since the estimate EWS significantly affect the controller's effectiveness, their performance needs to be clarified. To fully investigate the two estimators, there is a need to evaluate their performance on an even platform. In this paper, we present comparative studies on these two methods. Their advantages and drawbacks are investigated on the commercial turbine design software-bladed and compared through detailed simulation results. Finally, we demonstrate some simulation results and differences between the KF-based estimator and the EKF-based one.

Keywords: Extended Kalman filter, Kalman filter, wind speed estimation, wind turbine.

1. INTRODUCTION

An important design goal for modern wind turbine (WT) is to improve power production and reduce loads on turbine components, which can be achieved by tuning the controller. Nevertheless, it is a challenging task. On one hand, the WT aerodynamics presents highly nonlinear characteristics. On the other hand, unlike conventional control objectives, the WT is mainly driven by an external force, that is, wind speed, a stochastic variable varying on both time and space dimensions.

To improve the performance of the WT, there are many researches using advanced control solutions: linear-quadratic-Gaussian (LQG) control [1], nonlinear control [2], fuzzy logic control [3–8], active tolerant control [9], and etc. While research community is carrying out advanced control study, the classical-PID (proportional-integral-derivative) control method continues taking major role in the control applications of wind energy industry. Therein, a dichotomous, single-input single-output architecture is employed, where a torque control and a pitch control are decoupled along the operation trajectory defined by different scheduling parameters [10]. At below rated wind speed, the torque controller functions to extract maximum wind power, while the pitch controller maintains optimal pitch angle. At high wind speed, the pitch controller works to maintain the rotor speed at rated one, while the torque controller keeps the output power constant. Considering the blade's aerodynamic characteristics, the principle to extract maximum wind power is behind that an optimal pitch angle and an optimal TSR (Tip Speed Ratio) are responsible for the maximal aerodynamic power coefficient. Precise wind speed information is required to track the optimal TSR and adjust the optimal pitch angle at below rated wind speed. As for the occasions of high wind speeds, the wind speed signal has been included as an input to participate feedforward pitch control to maintain rotor speed [11, 12]. Consequently, the over-speed shutdowns and over-load risks are reduced. Among these control applications, the wind speed information is useful and indespensable.

However, in current commercial WTs, the wind speed measured on the nacelle is too imprecise to be used in real-time control algorithm. Its drawbacks are single point measurement and non-immunity to disturbances. The alternative solution is to estimate the EWS (Effective Wind Speed) by using the WT itself as a measurement device. When taking advantage of the EWS, the idea controlling

Manuscript received August 27, 2016; revised September 15, 2016; accepted October 4, 2016. Recommended by Associate Editor Do Wan Kim under the direction of Editor Duk-Sun Shim. This work is supported by the National Natural Science Foundation of China under Grant 51677194, the National High-tech R&D Program of China (863 Program) under Grant 2015AA050604, the Project of Innovation-driven Plan in Central South University, the Program for New Century Excellent Talents in University under Grant NCET-13-0599, the Fundamental Research Funds for the Central Universities of Central South University under Grant 2015zzts050, and the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2016R1A6A1A03013567).

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WT could be changed from "blow in the wind" to "make decision on the wind". The EWS has been employed in advanced control algorithm designs [13, 14] and fault diagnosis [15]. Nevertheless, to our best knowledge, the estimation technology is not standard and still under studying.

The EWS is defined as the spatial average of the wind field over the rotor shift area with the wind stream being unaffected by the WT [16]. In the literature, a number of algorithms have been dedicated in the estimation of EWS. The EWS is constructed by a model-based estimator, which utilizes measurable information and WT model. Therein, three EWS estimation solutions insist on that they make full use of the knowledge on WT model. Therefore, they are readily accepted by wind energy industry. These three methods are power balance estimator [11], Kalman filter (KF)-based estimator [3, 12, 17], and extended Kalman filter (EKF)-based estimator [18]. Among them, the power balance estimator is the fundemantal one, and the KF-based estimator is an upgrated one. These two estimators are similar in two estimation steps: the first step is to reconstruct the aerodynamic torque, and the second step is to search the TSR solution from an algebraic equation by using numeric iterative Newton-Raphson method. The KF-based estimator potentially outperforms the other for the reason that a better reconstructed aerodynamic torque could be obtained by the KF. Nevertheless, the estimator is linear KF-based. To give optimal estimation results for such a highly nonlinear WT model, nonlinear-based estimator is required. The alternative is to combine a linear model of the drive train with the nonlinear aerodynamic model and use nonlinear algorithms to directly estimate the EWS. In [18], a continuous-discrete EKF was proposed to estimate and predict the EWS at turbine locations in a wind farm, where the estimation of EWS was approached as a standard estimation problem. The wind speed measured on the nacelle was employed in that work under the assumption that the wind measurement is contaminated by Gaussian noise. However, the wind measurement in real-time environments always contains outliers, which disobey the Gaussian noise assumption [19]. Hence, the resulted EWS might not be satifactory. Since the main application of the estimated EWS lies in the real-time control algorithm, the estimate result would directly affect the controller's effectiveness. Before applying them into control application, the performance of the two estimation methods needs to be compared and investigated.

To do this, this paper carries out a comparative study on two estimators based on the KF technology. The main contribution is to provide detailed comparative results of two estimators on an even platform. To make the results reliable, the commercial software of wind turbine design- bladed is used as the simulation tool. Meanwhile, a commercial 1.5MW variable speed WT is chosen as the modelling object, which is manufactured by the CMYWP (China Ming Yang Wind Power). Finally, we demonstrate some simulation results and differences between the two estimators.

The remainder of this work is organized as follows: First, the modelling of a generic wind turbine is described. Then, two EWS estimators with different KF technologies are discussed and presented. This is followed by comparations, which are carried out via simulation tests. Finally, the conclusion is made.

2. THE CONCERNED WIND TURBINE AND ITS MODELING

2.1. The studied wind turbine

In past ten years, the most popular WT in China was with the capacity of 1.5MW. By the end of 2015, their total installation quantity has been more than 75,000 MW, among which the CMYWP contributed near 1/8. The studied WT in this paper is a 1.5MW douly-fed machine with 82m rotor diameter manufactured by the CMYWP. The WT's specifications are shown in Table 1.

2.2. Wind turbine modeling

To design the KF-based etimator, it is necessary to choose a proper model for target system when fully considering available measurements. Otherwise, low observability would make the estimator hard to be stabilized. In the case of an industrial WT, the available measurements include pitch angle, electrical power, rotor speed (or generator speed), and nacelle acceleration speed. Correspondingly, the complete model set should not include more than aerodynamics, pitch system, drive train, converter system and tower models. Considering a general case suitble for both stuided estimators, only the drive train and aerodynamics models are introduced in this paper.

The drive train is described by two inertias interconnected by a spring and a damper. The external forces to this 2-DOF system are the aerodynamic torque on the slow speed shaft and the generator reaction torque on the high speed shaft. The governing motion equation of this model is given by

$$\begin{aligned} J_g\dot{\omega}_g &= T_{sh}/N - T_g, \\ J_r\dot{\omega}_r &= T_a - T_{sh}, \\ T_{sh} &= s_{dt}\gamma + d_{dt}\dot{\gamma}, \end{aligned} \tag{1}$$

where $\gamma = (\theta_r - \theta_g/N)$, θ_r and θ_g are rotor and generator rotational angles, respectively; s_{dt} and d_{dt} are stiffness and damping coefficients of drive train, respectively; J_r and J_g are inertias of blade rotor and generator, respectively; T_a and T_g are aerodynamic torque and generator torque, respectively, and$N$ is gearbox ratio.

Table 1. Specifications of the studied WT.

Paramters	Value
Rotor diameters	82 m
Number of rotor blades	3
Rated electrical power	1500 kW
Generator speed range	1100–2100.0 rpm
Nominal generator speed	1750.0 rpm
Optimal TSR	9.5
Rotor moment of inertia	4.94×10^6 kg·m^2
Generator moment of inertia	92 kg·m^2
Gearbox ratio	100.48
Drive train stiffness coefficient	1.38×10^8 Nm/rad
Drive train damping coefficient	1.0×10^4 Nms/rad

The model of the aerodynamic torque is expressed as

$$T_a(\lambda,\beta) = \rho\pi R^3 V_e^2 C_q(\lambda,\beta)/2, \tag{2}$$

where ρ is air density, R is rotor radius, V_e is the EWS, and $C_q(\lambda,\beta)$ is aerodynamic torque coefficient which is a nonlinear function of the TSR-λ and pitch angle-β. The λ is defined by

$$\lambda = \omega_r R/V_e. \tag{3}$$

3. KALMAN FILTER-BASED WIND SPEED ESTIMATION

Compared with other estimation solutions, the KF-based approach uses the KF as a fusion tool, where the measurement information from transducers and modeling knowledge are well utilized. Therefore, better results are provided through the fusion of various kinds of information. Nevertheless, KF-based algorithms are only suitable for state estimation rather than input estimation. In this paper, a stochastic input-the EWS, is to estimate. Therefore, to implement the KF algorithm, special technique has to be adopted and will be introduced in this section.

3.1. Wind speed estimation with linear KF

The applied KF-based estimator is based on the algorithm introduced in [3] and [12], where the aerodynamic torque is modelled by using the unknown input as a state variable. But in this paper, we propose not the one-mass drive-train model used in [3] and [12], but a two-mass one to estimate the aerodynamic torque.

3.1.1 KF-based modelling for aerodynamic torque estimation

The two-mass drive-train model given by (2) is further augmented by appending the T_a as an additional state. The complete model including the Gaussian noise is expressed in the form of state space by

$$\begin{bmatrix}\dot{\gamma}\\ \dot{\omega}_r\\ \dot{\omega}_g\\ \dot{T}_a\end{bmatrix} = \begin{bmatrix} 0 & 1 & -1/N & 0\\ s_{dt}/J_r & -d_{dt}/J_r & d_{dt}/(J_rN) & 1/J_r\\ s_{dt}/(J_gN) & d_{dt}/(J_gN) & -d_{dt}/(J_gN^2) & 0\\ 0 & 0 & 0 & 0\end{bmatrix}\begin{bmatrix}\gamma\\ \omega_r\\ \omega_g\\ T_a\end{bmatrix} + \begin{bmatrix}0\\0\\-1/J_g\\0\end{bmatrix} T_g + \begin{bmatrix}w_\gamma\\ w_{\omega r}\\ w_{\omega g}\\ w_{Ta}\end{bmatrix}, \tag{4}$$

where w_γ, $w_{\omega r}$, $w_{\omega g}$ and w_{Ta} are the process noise of γ, ω_r, ω_g and T_a, respectively; ω_r and ω_g are rotor and generator speeds, respectively.

The output equation is defined by

$$y = \omega_g + v_{\omega g}, \tag{5}$$

where the $v_{\omega g}$ is the measurement noise.

For the standard model of target system by (4) and (5), it is convenient to use the Kalman toolbox of Matlab to design the linear Kalman filter. The detail description is not given here for the sake of simplicity. The process and measurement noises are set to 10e-2 and 1000, respectively, determining the estimator performance.

3.1.2 The KF-based wind speed estimator

Based on (3), we know that the EWS can be calculated by using the TSR and the rotor speed. The TSR is derived based on the reformulation of (2) by

$$T_a(\lambda,\beta)/(\rho\pi R^5\omega_r^2) - C_q(\lambda,\beta)/(2\lambda^2) = 0. \tag{6}$$

Since the only unknown variable in (6) is λ, it can be obtained through searching the algebraic solution by using numeric iterative Newton-Raphson method. In order to solve (6), the $C_q(\lambda,\beta)$ has to be expressed by mathematic formulations. In this paper, it is approximated by

$$C_q(\lambda,\beta) = k_3\lambda^3 + k_2\lambda^2 + k_1\lambda + k_0, \tag{7}$$

where $\lambda \in (\lambda_i, \lambda_{i+1}), \beta = const.$

3.2. Wind speed estimation with nonlinear EKF

The applied EKF-based estimator is based on the algorithm introduced in [18]. To keep consistent with the model described in Section 2.2, we propose a two-mass drive-train model rather than the one-mass one used in [18]. Moreover, the EWS is modelled by an internal wind model in this paper, therefore the utilization of statistic wind information required in [18] is avoided.

3.2.1 The EKF-based modeling

To design the EFK-based EWS estimator, the concerned system model has to be modelled in the following nonlinear form:

$$\dot{x} = f(x,u) + w,$$

$$y = h(x,u) + v. \tag{8}$$

The turbine model refers to the two-mass drive train model by (2), which is reformulated as follows:

$$\begin{aligned}
\dot{\omega}_r &= a_r + w_{\omega r},\\
\dot{a}_r &= [\dot{T}_a - s_{dt}(\omega_r - \omega_g/N)\\
&\quad - d_{dt}(a_r - a_g/N)]/J_r + w_{ar},\\
\dot{\omega}_g &= a_g + w_{\omega g},\\
\dot{a}_g &= [s_{dt}(\omega_r - \omega_g/N)/N\\
&\quad + d_{dt}(a_r - a_g/N)/N - \dot{T}_g^{set}]/J_g + w_{ag},
\end{aligned} \tag{9}$$

where w_{ar} and w_{ag} are the process noises of a_r and a_g, respectively; a_r and a_g are acceleration speeds of rotor and generator, respectively.

The EWS model is not standard. In [18], it was modelled through using statistical information of wind conditions. However, it is in practice not an easy task to obtain such priori knowledge. In this paper, the EWS model is set up by taking the tower shadow effect into consideration and given by

$$\begin{aligned}
\dot{V}_e &= V_{e1} + w_{Ve},\\
\dot{V}_{e1} &= V_{e2} + w_{Ve1},\\
\dot{V}_{e2} &= -N_b^2\omega_r^2 V_{e1} - 2N_b d_v \omega_r V_{e2} + w_{Ve2},
\end{aligned} \tag{10}$$

where V_{e1} and V_{e2} are the EWS' derivative and the derivative of its derivative, respectively; w_{Ve}, w_{Ve1} and w_{Ve2} are the process noises of V_e, V_{e1} and V_{e2}, respectively. The tower shadow effect is embodied as a function of the rotor speed and blade number N_b. Meanwhile, the tower shadow effect is damped by the factor d_V.

Besides the state model set, the measurement part is also required. Considering the fact that performance of the EKF-based estimator could be enhanced by more measured information, it would be better to define more measurements through indirect calculations. In this paper, the measurement parts include

$$\omega_r^m = \omega_r + v_{\omega r}, \tag{11a}$$
$$\omega_r^m = \omega_r + v_{\omega r}, \tag{11b}$$
$$a_r^m = a_r + v_{ar}, \tag{11c}$$
$$\omega_g^m = \omega_g + v_{\omega g}, \tag{11d}$$
$$V_e^m = V_e + v_{Ve}. \tag{11e}$$

By integrating (9)-(11), the whole model is in the same form as that in (8), where the state x, input u and output y are given by

$$x = (V_e\ \ V_{e1}\ \ V_{e2}\ \ \omega_r\ \ a_r\ \ \omega_g\ \ a_g)^T, \tag{12a}$$
$$u = (T_g^{set}\ \ \beta^{set})^T, \tag{12b}$$
$$y = (V_e^m\ \ \omega_r^m\ \ a_r^m\ \ \omega_g^m\ \ a_g^m)^T, \tag{12c}$$

Based on (12), it is not difficult to apply the standard EKF algorithm to estimate the EWS. The interesting readers can refer to [20, 21] for the EKF implementation.

3.2.2 The EKF-based wind speed estimator

To develop the EKF-based estimator, it is necessary to linearize the nonlinear model, and tune the initial state, initial state prediction covariance, process and measurement noise covariances. Since the EKF algorithm is to solve the nonlinear system by online linearization, the $C_q(\lambda,\beta)$ has to be defined as a mathematic equation so that its derivatives with respect to λ and β can be obtained. In this paper, $C_q(\lambda,\beta)$ is induced in the following form:

$$C_q(\lambda,\beta) = \begin{bmatrix} 1\\ \lambda\\ \ldots\\ \lambda^m \end{bmatrix}^T \begin{bmatrix} a_{0,0} & a_{0,1} & \ldots & a_{0,n}\\ a_{1,0} & a_{1,1} & \ldots & a_{1,n}\\ \ldots & \ldots & \ldots & \ldots\\ a_{m,0} & a_{m,1} & \ldots & a_{m,n} \end{bmatrix} \begin{bmatrix} 1\\ \beta\\ \ldots\\ \beta^n \end{bmatrix}, \tag{13}$$

where $a_{i,j}(i = 0..m, j = 0..n)$ are the parameters to be specified.

The intial state and prediction covariances are given by

$$\hat{x}_0 = (8\ \ 0\ \ 0\ \ \omega_r^m\ \ a_r^m\ \ \omega_g^m\ \ a_g^m)^T, \tag{14}$$
$$P_0 = diag(0.1, 0.1, 0.1, 1e-3, 1e-3, 1e-2, 1e-2). \tag{15}$$

The process and measurement covariances are given by

$$\begin{aligned} Q = diag(&1e-1, 1e-2, 1e0, 1e-4, 1e-8, 1e-2,\\ &1e-2), \end{aligned} \tag{16}$$
$$R = diag(1e-1, 1e-8, 1e-6, 1e-6, 1e-4). \tag{17}$$

Besides above parameters, the damping factor d_V defined in (10) has to be predefined. In this paper, it is set to 0.8.

3.3. Assessment of two KF-based estimators

For the linear KF-based EWS estimator, the estimate procedure is divided into two steps: the first step is to estimate the aerodynamic torque, and the second step is to search the TSR solution from an algebraic equation. Therein, the aerodynamic torque is an input. To counter this, the aerodynamic torque is modelled with the unknown input as a state variable [3, 12], or observed by a PI tracking controller [17]. Since the measurement information is only used to estimate the aerodynamic torque, the estimate result would heavily depend on accuracy of the modeling. Meanwhile, the final EWS is provided by the solution to the algebraic equation. When there are invalid solutions, the resulted EWS would be out of expection.

As for the EKF-based EWS estimator, the EWS is directly estimated by the nonlinear algorithm. However, the EWS model and its measurement are required. In the literature, there is no standard EWS model. Meanwhile, the wind speed measured on the nacelle is used as the measurement part. By comparison to the linear KF-based estimator, this kind of estimator makes better use of wind speed measurement and its modeling. Moreover, the nonlinear part is solved by online linearization. Theoretically speaking, the EKF-based estimator would give better estimate result than the other. But the wind speed measurement in real-time environments always contains outliers, which disobeys the Gaussian noise assumption. Therefore, its performance has to be intensively investigated.

Although a basic assessment has been obtained based on analyses of the characterstics of two estimation methods, it is indispensable to performance a detailed performance comparison through nonlinear simulations, which is important to give designers reliable data to choose suitable estimator according to their requirement.

4. COMPARATION OF TWO METHODS

4.1. Simulation results and discussion

To test the proposed two estimators, the industry-standard software for the WT performance and loading calculations, Garrad Hassan's Bladed [22] WT software package, is used to carry out simulations. The source codes of the two estimators are developed and included in the external DLL(Dynamic Link Library) to the model of the concerned WT.

3D turbulent winds defined in Bladed are chosen in the simulations. To check performance of the two developed estimators, the most severe wind turbulence is taken from the extreme turbulence model defined in IEC (International Electro-technical Commission)-standard [23]. The mean wind speed is set among 4-20m/s with increasing amplitude of 2m/s. For the sake of simplicity, four representative simulation results are shown in Figs. 1-4, which are from mean wind speed of 4 m/s, 8 m/s, 12 m/s and 16 m/s, respectively. Among numerous simulation data obtained from Bladed, rotor average longitudinal wind speed is chosen as the baseline EWS. Meanwhile, the nacelle wind speed is also included. Besides, estimated results based on the two estimators are gathered. The simulation results for the nacelle wind speed, the baseline EWS, the two estimated EWSs from the linear KF-based estimator and from the EKF-based estimator are plotted in black, red, blue and green, respectively.

As shown in Figs. 1-4, there are similar trends among four kinds of wind speeds, but the differences are obvious. The baseline EWS (red curves) is much smoother than the nacelle wind speed (black curvers). The reason is that the wind speed measured on the nacelle is only a single-point measured value, which is packed with high frequency disturbance and other outliers, whereas the baseline EWS is an averaged longitudinal wind speed faced by the whole blade rotor. As for two estimated EWSs, it is distinguishable in that the KF-based estimated EWS is almost closer to the baseline EWS at all wind speeds than the other. The EKF-based estimated EWS varies by following the nacelle wind speed, while the other does not vary that much. Therefore, it is shown that the KF-based estimator outperforms the EKF-based one. This result is out of expectation but acceptable for the reason that as the input of EKF-based estimator, the wind measurement contains outliers and disobeys the Gaussian noise assumption.

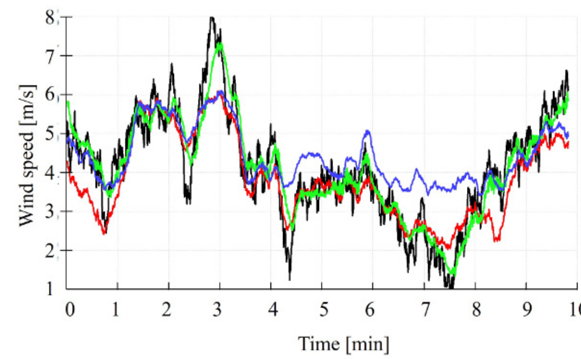

Fig. 1. Simulation results of the nacelle wind, the baseline EWS and two estimated EWSs at 4 m/s mean wind speed.

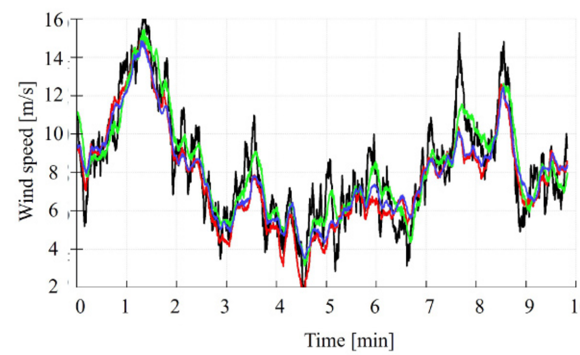

Fig. 2. Simulation results of the nacelle wind, the baseline EWS and two estimated EWSs at 8 m/s mean wind speed.

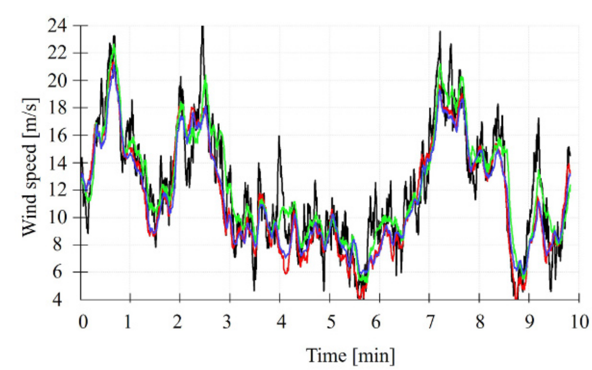

Fig. 3. Simulation results of the nacelle wind, the baseline EWS and two estimated EWSs at 12 m/s mean wind speed.

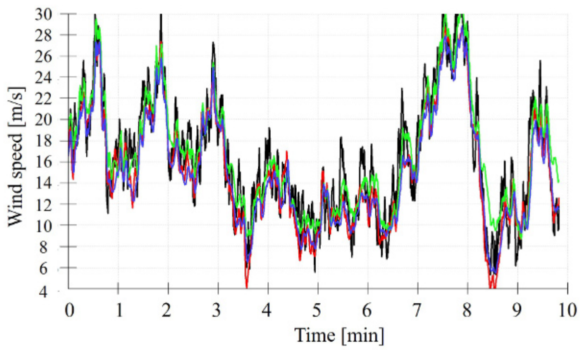

Fig. 4. Simulation results of the nacelle wind, the baseline EWS and the estimated Kalman filer-based WES at 16 m/s mean wind speed.

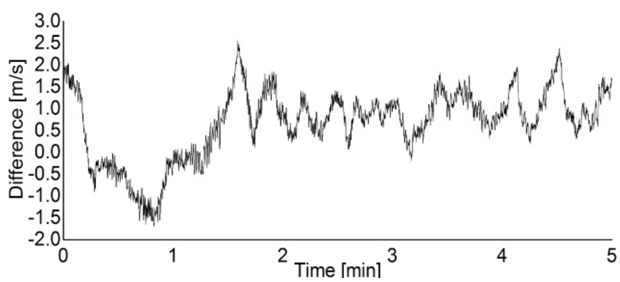

Fig. 5. Difference between the nacelle wind speed and the baseline EWS at 8 m/s mean wind speed.

To further investigate the impact of the measurement noise mixed in the nacelle wind speed on the estimate result of the EKF-based estimator, the difference between the nacelle wind speed and the baseline EWS, and the one between the baseline EWS and the EKF-based estimated EWS based on Fig. 2 are calculated. The results are plotted in Fig. 5 and Fig. 6, respectively. Both differences in similar trends reveal the fact that there is an obvious impact from the measurement noise on the estimate EWS. From Fig. 5 and Fig. 6, it is very clear that the difference between nacelle wind speed and the baseline EWS is stochastic but not a Gaussian noise. Since the baseline EWS is an averaged wind speed experienced by the whole rotor, it can be concluded that the difference is caused by the measurement noise of the nacelle wind speed.

Performance of the KF-based estimator is still unsatisfactory, which can be seen by enlarging trajectories of the Fig. 4. Fig. 7 shows trajectories of the baseline EWS (black curve) and the KF-based estimated EWS (red curve). As seen from Fig. 7, there is obvious difference between the two EWSs at some high wind speeds. There are two reasons for this difference: the first one is that for the KF-based estimator, the invalid TSR solution would be obtained when the WT goes into stalled operation; the other is that the aerodynamic torque cannot be well estimated when there is an intensive pitch action.

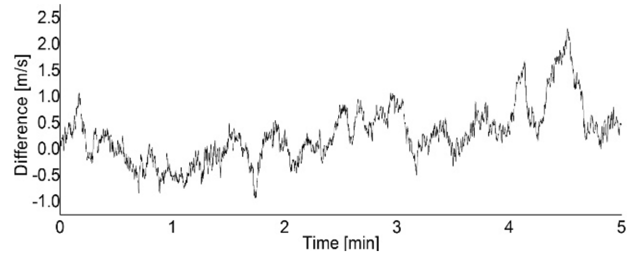

Fig. 6. Difference between the baseline EWS and the EKF-based estimated EWS at 8 m/s mean wind speed.

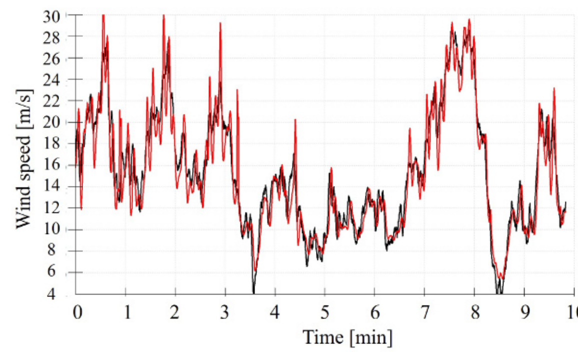

Fig. 7. Comparisons between the baseline EWS and two estimated EWSs at 16 m/s mean wind speed.

4.2. Comparative results

In order to evaluate performance of the two proposed etimators in detail, their statistical properties are used to compare. The statistical properties include the mean estimation error $E[\varepsilon]$, the standard deviation of the estimation error σ_ε, the mean square of the error$E[\varepsilon^2]$, and the CC (Correlation Coefficients) between the baseline and the estimated EWS defined by [24]:

$$CC(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i - E(A)}{\sigma_A}\right)\left(\frac{B_i - E(B)}{\sigma_B}\right), \quad (18)$$

where $E[A]$ and σ_A are the mean and standard deviation of A, respectively, and $E[B]$ and σ_B are the mean and standard deviation of B, respectively.

The statistical results between the baseline and the linear KF-based EWSs, and between the baseline and the nonlinear EKF-based EWSs are summarized in Tables 2 and 3, respectively.

The statistical data in two tables show that: nearly all $E[\varepsilon]$, σ_ε and $E[\varepsilon^2]$ obtained from Table. 2 are smaller than those from Table 3, and all results of the CC from Table 2 are bigger than those from Table 3. When checking the $E[\varepsilon]$, almost each mean error between the baseline and the EKF-based estimated EWS is more than 0.6m/s. This statistical property reveals that the EKF-based estimator results in a big estimate error. The reason is that the

Table 2. Statistical comparisons between the baseline and the linear KF-based EWS.

	$E[\varepsilon]$	σ_ε	$E[\varepsilon^2]$	CC
4m/s	0.401	0.382	0.306	0.950
6m/s	0.443	0.524	0.471	0.990
8m/s	0.251	0.534	0.348	0.992
10m/s	0.176	0.762	0.611	0.987
12m/s	-0.039	0.761	0.581	0.983
14m/s	-0.106	1.274	1.633	0.959
16m/s	-0.277	2.075	4.380	0.911
18m/s	-0.395	2.417	6.933	0.910
20m/s	-0.579	2.974	9.180	0.909

Table 3. Statistical comparisons between the baseline and the nonlinear EKF-based EWS.

	$E[\varepsilon]$	σ_ε	$E[\varepsilon^2]$	CC
4m/s	0.381	0.561	0.476	0.851
6m/s	0.618	0.632	0.751	0.963
8m/s	0.660	0.791	1.055	0.970
10m/s	0.623	0.911	1.273	0.964
12m/s	0.905	1.387	2.389	0.939
14m/s	0.993	1.295	2.532	0.957
16m/s	1.079	1.275	2.719	0.961
18m/s	1.114	1.417	2.817	0.805
20m/s	1.202	1.985	2.884	0.797

tolerance of wind speed measured on the nacelle is not a Gaussian noise. By comparison, the values of$E[\varepsilon]$between the baseline and the linear KF-based estimated EWSs are much smaller. Similarly, smaller standard deviation and mean square appear in the estimation error between the baseline and the KF-based estimated EWSs. Again, the outweighing performance of the KF-based estimator is confirmed by the fact that almost all values of the CC in Table 2 are much closer to 1.0 than the ones in Table 3.

In Table 2, another trend for the KF-based results is pronounced, that is, when the wind speed is getting higher from 12m/s to 20m/s, the $E[\varepsilon]$, σ_ε and $E[\varepsilon^2]$ are increasing, and the CC is decreasing. This trend well agrees the results in Fig. 6. Both results expose the fact that the KF-based estimator's performance becomes unsatisfactory at high wind speeds.

5. CONCLUSIONS AND FUTURE WORK

In this paper, two Kalman filter-based EWS estimators have been developed, that is, the linear KF-based estimator and the EKF-based one. Then, we have demonstrated some simulation results and differeces between the developed two estimators. The results have shown that the performance of the EKF-based one is inferior to the other for the reason that the measurement noise of wind speed seen on the nacelle disobeys the Gaussian noise assumption in the EKF technology. Although better results are achieved by the KF-based estimator, the estimated results are unsatisfactory at high wind speeds. Since the simulation tests are carried out based on industry-standard turbine design software, the obtained results can be used as a guide to choose suitable estimated EWS solution.

Regarding that the WT is a highly nonlinear system and the EKF is nonlinear system oriented, the EKF-based estimator could be potentially improved by overcoming its drawback. Our future work will be toward two optimal solutions to the EKF-based estimator. One is to design a robust estimator which is immune to the presence of outliers, and the other is to replace the contaminated measurement with a reliable one. Besides, further studies could be also carried out in the presence of model uncertainties.

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