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# Wind estimation with a non-standard extended Kalman filter and its application on maximum power extraction for variable speed wind turbines

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## HIGHLIGHTS

- Novel non-standard EKF is proposed for EWS estimation solution.
- We provide a detailed description of implementing the proposed solution.
- The MPE is fulfilled by enhancing optimal TSR and pitch angle tracking.
- Application of the EWSE on the MPE increases the AEP by approximately 0.8%.

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## ABSTRACT

To maximize power extraction at below-rated wind speeds, variable-speed wind turbines must be controlled by tracking the optimal TSR (tip speed ratio) and pitch angle, which depend on the wind speed measured by nacelle anemometers or provided by an EWS (effective wind speed) estimator. However, the measured values are imprecise and existing estimators cannot provide qualified estimates. This paper addresses this problem by presenting a novel solution with a non-standard extended Kalman filter. To avoid using imprecise wind speed measurements or other costly measurement devices, the proposed solution employs a virtual measurement that is calculated from related estimated states. In addition, the solution presents an internal EWS model by considering the tower shadow effect, so the obtained model is more general than the statistical model that is difficult to obtain in practice. Compared with existing estimators, the proposed estimator provides more precise estimated results and is suitable for control application. Its application is investigated on the MPE (maximum power extraction) of a variable speed wind turbine, for which an industrial baseline controller is optimized by enhancing the optimal TSR tracking and pitch adjustment. The proposed solutions are validated using both simulation and field testing results. Comparing the proposed estimation solution to two existing methods demonstrates that the former gives the best estimate results. Moreover, its application for the MPE increases annual energy production by approximately 0.8% in comparison with the baseline controller, which is a considerable energy production increment.



## 1. Introduction

To compete with other sources of renewable energy, it is necessary to exploit the best performance for the WT (wind turbine). WT performance is normally evaluated in terms of two indexes: power production and component loads [1]. Because WTs have to be operated in various uncertain environments and their design lifetimes are generally 20 years, WT components are always designed and manufactured with sufficient safety factors [2]. In this regard, power production could be a more crucial performance index in comparison with component loads. Therefore, maximum power extraction (MPE) has been taken as the primary control objective for WTs [3] and related algorithms continue to be addressed by a vast amount of research [4–13].

In the literature, the main algorithm for MPE is maximum power point tracking (MPPT). To maximize the efficiency of a WT, the MPPT algorithm is used to bring the turbine to the MPP

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**Nomenclature**

| | |
|---|---|
| $x$ | state |
| $u$ | input |
| $y$ | output |
| $w$ | process noise |
| $v$ | measurement noise |
| $f(x,u)$ | state transition function |
| $h(x,u)$ | output function |
| $\wedge$ | estimation or prediction |
| $K$ | Kalman gain |
| $P$ | state estimation error covariance |
| $Q$ | process noise covariance |
| $R$ | measurement noise covariance |
| $m$ | output measurement |
| $F, H$ | state space model parameters |
| $\Phi, \Gamma$ | state transition matrix and noise input matrix |
| $\hat{x}_{k-1}$ | state estimate at time k − 1 based on measurement |
| $\hat{x}_k$ | state estimate at time k based on measurement |
| $\hat{x}_{k\|k-1}$ | state prediction at time k − 1 based on state update |
| $T_s$ | sample time |
| $V_e, V_{e1}, V_{e2}$ | effective wind speed, its derivative and its second derivative |
| $N_b$ | blade number |
| $d$ | damping factor |
| $\rho$ | air density |
| $F_a, T_a, P_a$ | aerodynamic thrust, aerodynamic torque and aerodynamic power |
| $C_t, C_q, C_p$ | coefficients of aerodynamic thrust, aerodynamic torque and aerodynamic power |
| $\lambda, \lambda_{opt}$ | tip speed ratio and its optimal value |
| $R$ | rotor radius |
| $\beta, \beta_1, \beta^{set}$ | pitch angle, pitch speed, pitch angle set-point |
| $\omega_\beta, d_\beta$ | natural frequency and damping coefficient of pitch system |
| $\omega_r, \omega_g$ | rotor speed and generator speed |
| $a_r, a_g$ | acceleration speeds of rotor and generator |
| $s_{dt}, d_{dt}$ | stiffness and damping coefficient of drive train |
| $J_r, J_g$ | inertias of blade rotor and generator |
| $T_g^{set}, \dot{T}_g^{set}$ | generator torque set-point and its derivative |
| $N$ | gearbox ratio |
| $x_{fa}, v_{fa}, a_{fa}$ | displacement, speed and acceleration speed of tower for-aft movement |
| $m_t, s_t, d_t$ | mass, stiffness and damping coefficient of tower |
| $k_{opt}$ | the optimal gain of torque control |
| $\omega_g^{cutin}, \omega_g^{rated}$ | cut-in and rated generator speeds |
| $T_g^{rated}, T_g^{\mathrm{limit}}$ | rated generator torque and generator torque limits |
| *set* | setpoint |
| *opt* | optimal |
| max | maximum |
| $T_V, T_\lambda$ | low pass filter time for the EEWS and the TSR |
| EWS | effective wind speed |
| EEWS | estimated EWS |
| EWSE | EWS estimator |
| TSR | tip speed ratio |
| KF | Kalman filter |
| EKF | extended Kalman filter |
| CMYWP | China Ming Yang Wind Power |
| Mx, My, Mz | the rolling, nodding and yawing moments |

over a full wind speed range. In a recent study [5], MPPT algorithms were categorized into indirect power controller (IPC) and direct power controller (DPC). The IPC maximizes the captured mechanical wind power, whereas the DPC directly maximizes the output electrical power. These two types of MPPT algorithms have the following features:

- The DPC, which mainly refers to hill climbing search [6], does not require WT knowledge and locates the MPP by analysing the power variation based on a pre-obtained system curve. In theory, the DPC can provide better performance than the IPC because a priori knowledge for WTs may not be precise. However, typical DPCs always take a long time to converge. Moreover, a robust performance may not be guaranteed, for instance, when there is oscillation around the MPP.
- Under the IPC, there are three types of MPPT algorithms: the tips speed ratio (TSR) algorithm [7], power signal feedback (PSF) [8], and optimal torque (OT) MPPT algorithm [9,10]. The IPC aims at tracking the optimal TSR, which depends on precise information about the wind speed. Because the wind speed measured by the anemometers equipped in commercial WTs is too imprecise to be used in real-time control algorithms [11], the direct TSR algorithm is difficult to use, and therefore, the latter two algorithms were developed as alternative methods.

In current commercial WTs, the PSF and OT algorithms are commonly used due to their mature technology and robust performance. However, these two methods are not optimal for exploiting energy production of WTs. They can be further improved by adding a feed-forward term to assist in acceleration or deceleration [12] or adopting adaptive control to determine the accurate gain parameter [13]. For the wind dynamics not considered by them, the PSF and OT algorithms are internally less accurate than the direct TSR method [4,5]. Meanwhile, the MPP refers to the optimal pitch angle, in addition to the optimal TSR. For a typical blade, there is an optimal pitch angle and optimal TSR corresponding to the maximal aerodynamic power coefficient. Therefore, to maximize power extraction, it is necessary to obtain precise information about the wind speed. Currently, it is possible to measure precise wind information using advanced measurement devices, such as lidar [14], but these devices are normally costly. The alternative solution is to use the estimated wind speed. When using a WT as a measurement device, the effective wind speed (EWS) can be estimated, and consequently, both the optimal TSR and pitch angle can be obtained and tracked using control technology. Compared with the discussed MPPT technologies ignoring optimal pitch tracking, such technology using the estimated EWS (EEWS) is a more general MPE solution. However, this technology requires a reliable EWS estimate solution, but the estimation technology is not standard and is still under study.

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 [11,15]. Despite some research efforts on advanced control algorithms [16,17] and fault diagnosis algorithms [18] using the EEWS as an input, studies on improvements to the estimation solution and real application of the EEWS are lacking. In the literature [19–29], a number of algorithms have been used to estimate the EWS, in which the EEWS has generally been constructed by a model-based estimator that uses available measured information and the WT model. Because WTs are highly nonlinear and ANNs (artificial neural networks) are in effect broadly connected to different zones to overcome the issue of nonlinear connections and expectations [20], ANN-based soft computing models have been proposed to calculate the EEWS by the research community