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Application of Adaptive Extended Kalman Filter Algorithm in Parameter Estimation of Wind Turbine

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Abstract:
Estimates of wind power potential are relevant for decision-making in energy policy and business. Such estimates are affected by several uncertain assumptions, most significantly related to wind turbine technology and land use. Here, we calculate the technical and economic onshore wind power potentials with the aim to evaluate the impact of such assumptions using the case-study area. State estimation provides the best possible approximation for the state of the system by processing the available information. In the proposed work, the state estimation technique is used for the state estimation of wind turbine. Modern wind turbines operate in a wide range of wind speeds. To enable wind turbine operation in such a variety of operating conditions, sophisticated control and estimation algorithms are needed. The theoretical basis of Extended Kalman Filter algorithm is explained in detail and performance is tested with the simulation. The states estimated by using Extended Kalman Filter for wind turbine application includes rotor speed of turbine, tower top displacement and its velocity.

Keywords: Adaptive Extended Kalman Filter, Modelling, state estimation, wind turbine, classical laminate theory etc.

INTRODUCTION

In recent years, sites with low annual average wind speeds have begun to be considered for the development of new wind farms[1]. The majority of design methods for a wind turbine operating at low wind speed is to increase the blade length or hub height compared to a wind turbine operating in high wind speed sites. The cost of the rotor and the tower is a considerable portion of the overall wind turbine cost. This study investigates a method to trade-off the blade length and hub height during the wind turbine optimization at low wind speeds. A cost and scaling model is implemented to evaluate the cost of energy. The procedure optimizes the blades' aero-structural performance considering blade length and the hub height simultaneously. The blade element momentum (BEM) code is used to evaluate blade aerodynamic performance and classical laminate theory (CLT) is applied to estimate the stiffness and mass per unit length of each blade section. Wind energy is renewable and clean, which can help mitigate global climate change. Wind farms with high quality wind resources are limited. The wind farms [2] with low quality wind resources are far more plentiful than high-quality ones and have some advantages such as being closer to the existing electrical grid. The design and development of wind turbines [3] in low wind speed areas faces several technical and financial challenges related to maximizing energy conversion efficiency and minimizing cost of energy (COE). The classical wind turbine literature mainly deals with acquiring ideal blade geometry or structural design and improving structural properties of the tower. The research objective mainly aims to maximize annual energy production (AEP), minimize COE, minimize blades mass, or a combination of these.

State estimation is the process of estimating the values of parameters based on measured data having random component. The parameters explain the underlying physical setting in such a way that the distribution of the measured data is affected by their values. An estimator is used to approximate the unknown parameters by using the values of measurement data. Many types of estimators are available. The commonly used estimator is the Kalman Filter and its types. The Kalman Filter is also known as Linear Quadratic Estimation (LQE). It is an algorithm which uses measurements data taken over time, containing noise i.e. random variations and other inaccuracies. It produces estimates of unknown variables that are more precise than the single measurement alone. It operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state .The Adaptive Extended Kalman Filter (EKF) is known as the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance.

MODEL OF WIND TURBINE

Very common method used for wind turbine[4] modeling is blade element and momentum theory which yields reliable and detailed wind turbine model. However, such models are implicit equations which are not suitable for controller design. Therefore simple model uses quasi steady state relations for controller design. Fig.1 shows a general wind turbine.

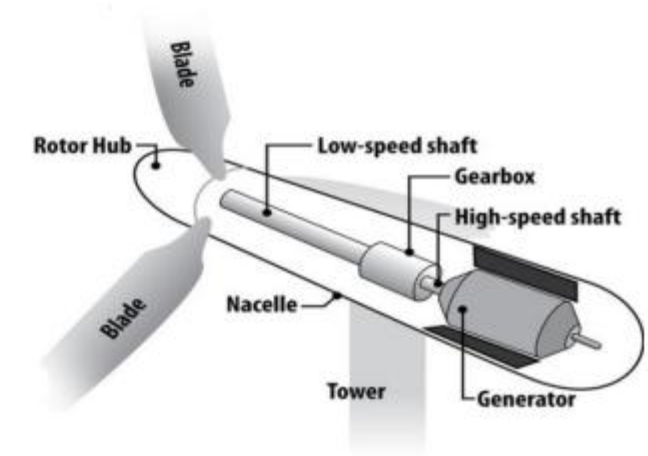

Fig.1 General wind turbine diagram

As wind turbines grow in size, so do their blades— from about 8m in 1980 to more than 40m for many land-based commercial systems. Improved blade designs have enabled the weight growth to be kept to a much lower rate than simple geometric scaling, as already described. Today's blade designs are subjected to rigorous evaluation using the latest computer analysis tools so that excess weight can be removed. Designers are also starting to work with lighter and stronger carbon fiber in highly stressed locations to stiffen the blade and improve fatigue resistance while reducing blade weight. However, carbon fiber must be used judiciously because the cost is about 10 times that of fiberglass. Typically, a turbine will cut-in and begin to produce power at a wind speed of about 5.4 m/s (12 mph). It will reach its rated power at about 12.5 m/s to 13.4 m/s (28 to 30 mph), where the pitch control system begins to limit power output and prevent overloading the generator and drive train. At around 26.8 m/s (60 mph), the control system pitches the blades to stop rotation (which is referred to as feathering the blades) to prevent overloads and damage to the turbine's components. All of the energy present in a stream of moving air cannot be extracted; some air must remain in motion after extraction or no new, more energetic air can enter the device. Building a brick wall would stop the air at the wall, but the free stream of energetic air would just flow around the wall. On the other end of the spectrum, a device that does not slow the air is not extracting any energy either. The solution for the optimal blockage is generally attributed to the German Physicist Albert Betz and is called the Betz limit. At best, a device can extract a theoretically maximum 59% of the energy in a stream with the same area as the working area of the device. The aerodynamic performance of a modern wind turbine has improved dramatically over the past 20 years. The rotor system can be expected to capture about 80% of the theoretically possible energy in the flow stream. This has been made possible through the design of custom airfoils for wind turbines. In fact, it is now commonplace for turbine manufacturers to have special airfoil designs for each individual turbine design. These special airfoils attempt to optimize low-speed wind aerodynamic efficiency and limit aerodynamic loads in high winds. These new airfoil designs also attempt to minimize sensitivity to blade fouling, due to dirt and bugs that accumulate on the leading edge and can greatly reduce efficiency. Although rotor design methods have improved significantly, there is still room for improvement.

Table1.Paremeters of wind turbine

S.No	Parameters	Values
1.	M_ω	0.08268 Nms/rad
2.	M_v	1.26910 Ns
3.	F_ω	19.664 Ns/rad
4.	F_v	5.0541 Ns/m
5.	F_β	19.784 N/rad
6.	J_t	3.8Nm
7.	M	2.421 Ns/m
8.	D	4.572 Ns/m
9.	C	8.564 N/m

These parameters are used by adaptive extended kalman filter to estimate the states of wind turbine.

ADAPTIVE EXTENDED KALMAN FILTER ALGORITHM

The Kalman filter is well-known for solving the problem of the target location. To overcome the nonlinear problems, the extended Kalman filter (EKF) estimates the state through a linearization process. The EKF uses priori guess to estimate the process and measurement noise covariance. As the circumstances change at different times, it's difficult to track the position precisely when the priori values are estimated with too much error from the real values. In this section, we propose an adaptive extended Kalman filter for precise position tracking. Using the adaptive factor, the process and measurement error covariance can be modified to approach the real values. The Kalman filter performs remarkably in calculation and location estimation. However, the estimation error can be large when the priori noise covariances are assumed with improper values. Therefore, we offer an adaptive extended Kalman filter (AEKF) to update the noise covariance at every measurement and estimation process to find proper noise covariance at each steps. The AEKF reduces the position error effectively and improves the accuracy of target tracking greatly. The extended Kalman filter (EKF) for target tracking is widely used in the position estimation of nonlinear system. However, the divergence of estimated results caused by a modeling error is considered to be a crucial weakness. Generally, the dynamic properties and errors are considered together in Kalman filter. The EKF algorithm uses a fixed priori estimates for the process and measurement noise covariances during the whole estimation process. It becomes difficult to apply the EKF method to track the accurate position with the past static priori values during the target's fast movement. As a solution to prevent the divergence of extended Kalman filter, the adaptive extended Kalman filter (AEKF) is proposed to update the covariance of process noise and measurement noise in current states.

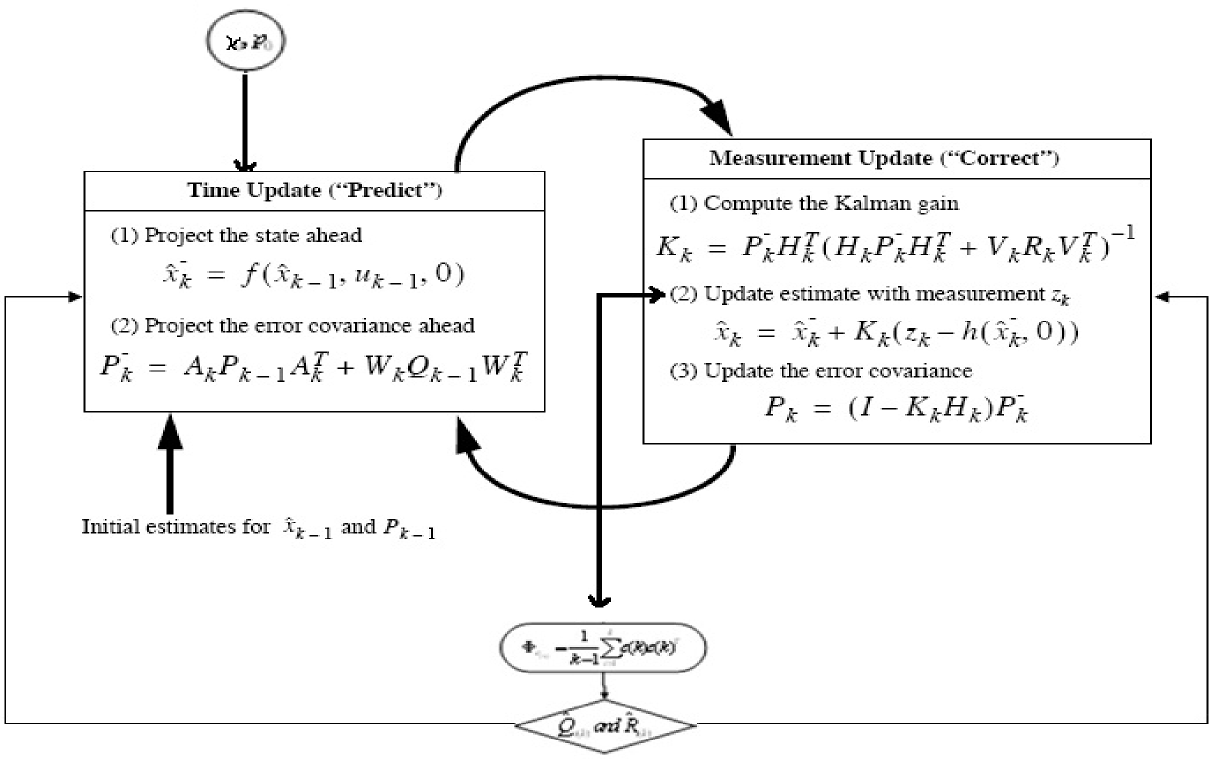

Fig.2 Adaptive Extended kalman filter algorithm

As the AEKF algorithm uses the recent covariance values in the process and measurement state, it is effective to overcome the disturbance problem.

The summary for EKF algorithm consists of two parts and is given as

1. Time update (prediction part)

(a)The state projection:

$$\widehat{x}(k+1) = f(\hat{x}(\mathrm{k}), \mathrm{u}(\mathrm{k}), \mathrm{w}(\mathrm{k})), \qquad (1)$$

(b)The error covariance projection:

$$P^-(k) = A(k)P(k-1)A(k)^T + W(k)Q(k)W(k)^T, \qquad (2)$$

2) Measurement update (correcting part)

(a) Kalman gain update:

$$K(k) = P^-(k)H(k)^T[H(k)P^-(k)\,H(k)^T + V(k)R(k)V(k)^T]^{-1} \qquad (3)$$

(b) The error covariance update:

$$P(k) = [I - K(k)H(k)]P^-(k), \qquad (4)$$

The estimate update with measurement z (k):

$$\hat{x}(k) = \hat{x}^-(k) + K(k)[z(k) - \hat{z}(k)] \qquad (5)$$

Here $\hat{x}$ (k) is the predicted estimate of state at k-th step, $\hat{x}$ (k) $-$ is a posteriori estimate of state at *k-th* step, u (k) is the control input with a velocity of a moving target, P $(k)^-$ is the error covariance of $\hat{s}$ $(k)^-$, A (k) is the state transition matrix, K (k) is the gain matrix, and Q (k) and R (k) represent the process and measurement noise covariance, respectively.

The initial condition is x_0 designed to be a zero-mean Gaussian random variable with a covariance p_0 ($p_0 > 0$) , and w(k) and v(k) are independent zero-mean white Gaussian noises.

We assume the process and measurement noise as,

$$E[w(i)w(k)^T] = \begin{cases} Q(k), i = k \\ 0, i \neq k \end{cases}$$

$$E[v(i)v(k)^T = \begin{cases} R(k), i = k \\ 0, i \neq k \end{cases}$$

$$E[w(i)v(k)^T = 0, \text{ for all k and i.} \qquad (6)$$

In figure, with initial values of x_0 , p_0 in time update process, we evaluate the estimate of system state by time flow and we calibrate the state estimation by comparing the differences between a real measurement and an estimate through a system modeling in measurement update process. The implementation of Kalman filter requires a priori statistical knowledge of the process noise and measurement noise. Poor knowledge of the noise values may seriously degrade the function of Kalman filter and the divergence problem in the filtering process may happen. To fulfill the accuracy requirement, the adaptive extended Kalman filter can be utilized as the noise-adaptive filter to estimate the process and measurement noise covariance matrices, Q(k) and R(k).

An innovation sequence utilizes the correlation and covariance matching techniques to estimate the noise covariance. Here, the maximum-likelihood estimation for the multivariate normal distribution approach is to make the actual value of the covariance consistent with its theoretical value. From the incoming measurement and the optimal prediction z(k) and the optimal prediction $h(\hat{x}^{-}(k), u(k), v(k))$ obtained in the previous step ,the innovation sequence is defined as $e(k) = z(k) - \hat{z}(k)$.

The innovation sequence can be written as:

$$e(k) \approx H(k)\big(x(k) - \hat{x}^{-}(k)\big) + v(k) \quad (7)$$

The covariance can be obtained by taking the variance on both sides of the eq.(7)

$$\emptyset_{e(k)}=H(k)P^{-}(k)H(k)^{T} + R_{v(k)} \quad (8)$$

The covariance of e(k) can be written as

$$\emptyset_{e(k)}=E[e(k)e(k)^{T}] \quad (9)$$

According the maximum-likelihood estimation for the multivariate normal distribution approach ,the statistical sample variance of $\emptyset_{e(k)}$:

$$\emptyset_{e(k)}=\frac{1}{k}\sum_{i=1}^{k} e(k)e(k)^{T} \quad (10)$$

From equation (8), the estimate of the measurement noise covariance is as

$$\hat{R}_{v(k)}=\hat{\emptyset}_{e(k)} - H(k)P^{-}(k)H(k)^{T} \quad (11)$$

The estimate of the process noise covariance is

$$\hat{Q}_{w(k)}=\frac{1}{k}\sum_{i=1}^{k}(x(k) - \hat{x}^{-}(k)(x(k) - \hat{x}^{-}(k))^{T} + P(k) - A(k)P(k-1)A(k)^{T}$$
$$\approx K(k)\hat{\emptyset}_{e(k)}K(k)^{T}. \quad (12)$$

Two important values for the process and measurement noise covariance are modified adaptively by using the Eqs. (11) and (12).

SIMULATION RESULTS

Adaptive Extended Kalman Filter provides the estimates of wind turbine [5] such as rotor speed, tower top displacement and its velocity. The estimated outputs for wind turbine are shown in Fig 3, 4 and 5.

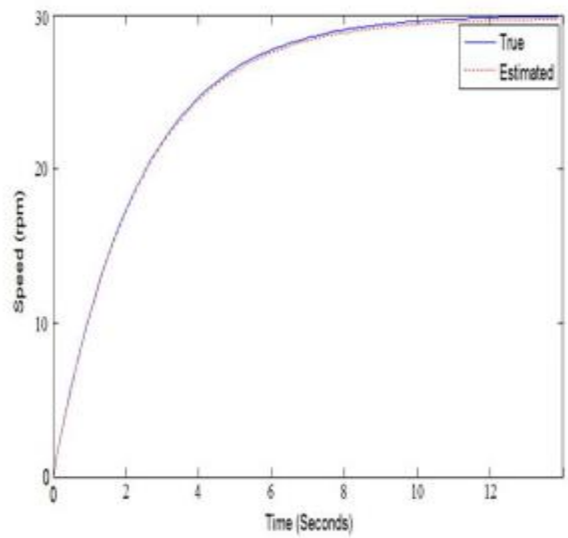

Fig 3.Plot of estimated and true value of rotor speed

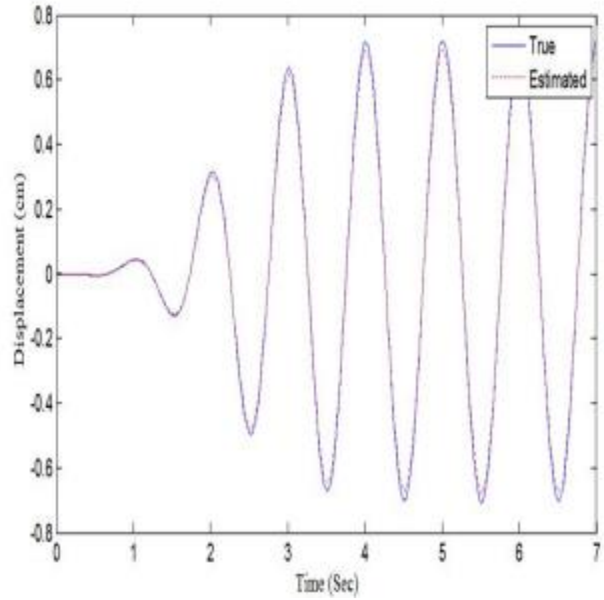

Fig 4.Plot of estimated and true value of tower top displacement

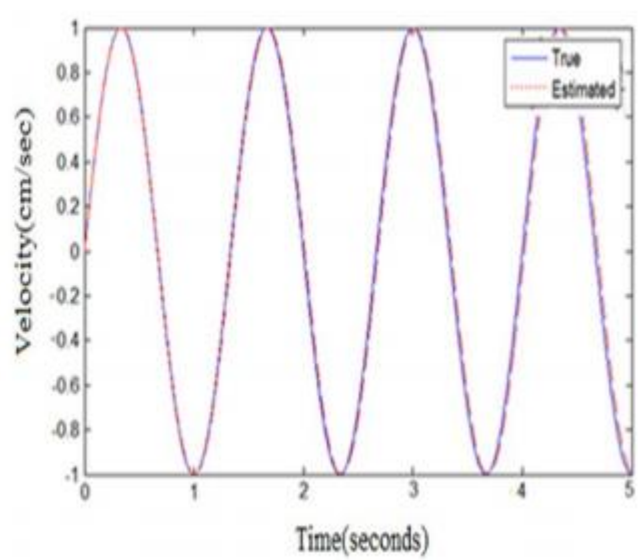

Fig 5.Plot of estimated and true value of tower top velocity

From the above estimated plots it is observed that Adaptive Extended Kalman Filter provides best estimates of wind turbine, highly non linear system.

CONCLUSION

The application of wind turbine [6] is very useful nowadays and the state estimation provides to have better understanding of the behavior of the system. Rotor speed, tower top displacement and its velocity are estimated using Adaptive Extended Kalman Filter algorithm and it is shown that AEKF provides best accuracy for highly non linear systems. It is possible to implement this estimation method for all other wind turbine states such as position of each blade tip, pitch velocity, velocity of each blade tip along blade [7] coordinate system and so on. During weak winds, the control system has to optimize and minimize wind energy conversion by using appropriate generator torque and during strong winds, wind turbine has to be constrained.

REFERENCES

1. W. Short, N. Blair, D. Heimiller and V. Singh, V, Modeling the Long-Term Market Penetration of Wind in the United States, NREL/CP-620-34469. Golden, CO, National Renewable Energy Laboratory (2003).

2. U.S. Department of Energy, 20% Wind Energy by 2030: Increasing Wind Energy's Contribution to the U.S. Electricity Supply, DOE/GO-102008-2567 (May 2008).

3. R. Wiser and M. Bolinger, Annual Report on U.S. Wind Power Installation, Cost, and Performance Trends: 2006 (2007).

4. D.A. Griffin, WindPACT Turbine Design Scaling Studies Technical Area 1 -- Composite Blades for 80- to 120-Meter Rotor. NREL /SR-500-29492, Golden, CO, National Renewable Energy Laboratory (2001).

5. European Wind Energy Technology Platform for Wind Energy, Strategic Research Agenda – Market Deployment Strategy from 2008 to 2030, Synopsis – Preliminary Discussion Document., TPWind Secretariat Brussels, Belgium (2008).

6. D.E. Berg and J.R. Zayas, Aerodynamic and Aeroacoustic Properties of Flatback Airfoils, 46th AIAA Aerospace Sciences Meeting and Exhibit, 27th ASME Wind Energy Symposium, Reno, Nevada (January 2008).

7. A.D. Wright and L.J. Fingersh, Advanced Control Design for Wind Turbines: Part I, Control Design, Implementation, and Initial Tests. NREL /TP-500-42437, Golden, CO, National Renewable Energy Laboratory (2008).