Gusts detection in a horizontal wind turbine by monitoring of innovations error of an extended Kalman filter

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Abstract. This paper presents a novel model-based detection scheme capable of detecting and diagnosing gusts. Detection is achieved by monitoring the innovations error (i.e., the difference between the estimated and measured outputs) of an extended discrete Kalman filter. It is designed to trigger a detection/confirmation alarm in the presence of wind anomalies. Simulation results are presented to demonstrate that both operating and coherent extreme wind gusts can successfully be detected. The wind anomaly is identified in magnitude and shape through maximum likelihood ratio and goodness of fit, respectively. The detector is capable of isolating extreme wind gusts before the turbine over speeds.

1. Introduction
This paper focuses on the detection of both operating and coherent extreme wind gusts. The control of a wind turbine is generally designed to deal with normal operating conditions. In practice, the turbine can be subject to anomalous operating conditions such as extreme wind shear or gusts which can trigger wind turbine shut-downs and increase the annual operation and maintenance costs (O&M). A detection scheme is being developed to diagnose these anomalies. Upon detection, the scheme can trigger remedial control actions allowing the wind turbine to ride through these turbulent wind conditions. The developed detection scheme has also being used for the detection of vertical wind shear, mass imbalance and aerodynamic imbalance in [1]. Results on control mitigation are not included in this paper.

Detection of wind gusts has been presented in [8], [9] and references therein. Several control strategies for mitigation of unbalance loads caused by extreme winds have been proposed such as collective blade pitching, individual blade pitching, feedforward pitch control using LIDAR, and more promising strategies such as dynamic variability of rotor speed and power set-points, and constrained rotor over speed on Model Predictive Control. Control strategies for cut-out wind speeds can also be used. To achieve active load mitigation with any of these strategies, a fast anomaly detector combined with very fast actuators is required [10]. This motivates our work presented in this paper.

Wind speed is measured behind the rotor by an anemometer that provides inaccurate measurements of the wind impacting the rotor, making the estimation of wind speed necessary in modern wind turbine controllers. Wind speed estimation with extended Kalman filter (EKF) has been presented in [7] and with Luenberger nonlinear observer in [8]. These results are improved by using the EKF to estimate the wind field impacting on each blade individually. The model used in the EKF is a 3-D wind model which incorporates induced wind turbine unbalanced loads at the turbine rotational frequency, also called 1P. The incorporation of 1P loads allows the detection of various wind anomalies as well as turbine
structural defects. Most anomalies and especially extreme wind gusts, appear at this spectral frequency. The 3-D model can be extended up to 6P to make the detector more sensitive to shared anomalous scenarios but with considerable increase of computational complexity. For instance, the incorporation of 2P loads facilitates the detection of horizontal wind shear and yaw misalignment.

The increase of 1P loads is seen by the EKF through measurements of in-plane and out-of-plane root bending moments of each blade with added Gaussian noise. The EKF state estimates are smoothed using measurements of aerodynamic torque to reduce model mismatch, since they are barely affected by 1P rotational sampling. The 3-D wind model is further improved with the addition of a dynamic inflow model to take into account the effect on the induced flow field due to changes in blade loading.

The EKF is not capable of detecting the effects of gust-like wind events as individual states directly since such events affect the entire wind field. Instead, they can be detected by the increase in model mismatch through a statistical approach. Two scalar statistics are formulated using the EKF innovations error. Decision thresholds are set to identify and isolate extreme wind gusts. Upon the detection and confirmation of a change in variable correlation through the innovations error, the pattern of the measured anomaly is matched through best fit to a given modelled anomalous scenario i.e. extreme operating gusts or extreme coherent gusts. The set of modelled anomalies are derived from models provided at IEC 61400-1 (extreme conditions) [3]. The identified anomaly is introduced in the 3-D model to reduce model mismatch during gusts, thus preserving the EKF stability, and to allow the detection of additional anomalous scenarios. The developed detector is computationally efficient and can be implemented in real wind turbines as an alternative to LIDAR.

The detector scheme is presented in Section 2. Simulation results in Matlab/Simulink (Matlab) are presented in Section 3. Aero-elastic Bladed simulation data from a 2MW Sustainable Power Generation and Supply (Supergen) exemplar wind turbine is used. Conclusions and future work are discussed in Section 4.

2. Detector Scheme

The EKF uses measurements of blade root bending moments (BRBM), aerodynamic torque and rotor speed to estimate deterministic and stochastic components of the 3-D wind field model impacting the wind turbine. The state estimates are accurate for frequencies up to 1P.

2.1. Wind field model

To calculate the loads on each blade, a special kind of wind field generator is used [4]. This generator encompasses effective wind speed and \(n\)P spectral peaks determined by the blade position \((\theta)\) as follows:

\[
V_{b_i}(t) = \hat{V}(t) + \left[a_n + V_{a_n}(t)\right]\cos\left(\theta + \frac{2\pi(i-1)}{3}\right) + \left[b_n + V_{b_n}(t)\right]\sin\left(\theta + \frac{2\pi(i-1)}{3}\right) \quad (1)
\]

\[
\hat{V}_R(t) = \frac{3\pi}{4R} (\hat{V} + V_{a_n}(t)) \hat{V}_R(t) - \left(\frac{3\pi}{4R} + \frac{\pi}{16R} \hat{C}_T(\lambda_R, \beta)\right) (V_{a_n}(t))^2 \quad (2)
\]

\[
\hat{V}(t) = \left[1 + \frac{\pi}{4} \hat{C}_T(\lambda_R, \beta)\right] V_{a_n}(t) \quad (3)
\]

where:

\[
V_{b_i}(s) = F_{b_i} \left(\frac{\gamma R}{V} s\right) u_b(s), \quad V_{a_n} = F_{a_n} \left(\frac{\gamma R}{V} s\right) v_a(s), \quad V_{b_n} = F_{b_n} \left(\frac{\gamma R}{V} s\right) v_b(s),
\]

\[
\hat{V}_b = \frac{V_{b_i}}{s + \frac{d}{\sigma_j}} \quad (4)
\]
Figure 1 3-D wind field model impacting the blades

Figure 1 shows how the wind field $V_i(t)$, impacting at each blade $(i = 1, 2, 3)$, is the sum of the estimated wind speed $\hat{V}(t)$ caused by dynamic inflow, the stochastic wind field components of the turbulence $(V_{i_a}(t), V_{i_b}(t), V_{i_c}(t))$ caused by $nP$ loads, and the deterministic variations in the wind field across the rotor in the horizontal and vertical directions $a_n, b_n$, respectively. $V_R(t)$ is wind speed at the rotor, $\bar{V}$ is the mean wind speed, $\hat{C}_T(\lambda_R, \beta)$ is the rotor torque coefficient that depends on the blade pitch angle $\beta$ and the rotor tip speed ratio $\lambda_R$ given by:

$$\lambda_R = \frac{R \Omega}{V_R}$$  

(5)

$\Omega$ is rotor speed and $R$ is the rotor radius. The model of the dynamic inflow is developed in [5].

The transfer functions $F_{a_n}, F_{b_n}$, and $F_{a_n}$, developed in [4], generate stochastic wind field turbulence components caused by $nP$. They are dependent of rotor radius $R$, the turbulent wind speed decay factor, $\gamma = 1.3$ for $1P$, and mean wind speed $\bar{V}$. $v_{0,a,b}$ is point wind speed calculated from the Dryden spectrum model driven by white noise $\xi_i$. $a_d$ and $b_d$ are coefficients at which the Dryden spectrum best approximates the Von Karman spectrum [6]. Von Karman and Dryden spectra are atmospheric turbulence spectral models capable of generating turbulent winds in all three directions.

Each blade root experiences bending moments caused by angular momentum in the in-plane, $M_{IP,i}$, and out-of-plane $M_{OP,i}$, directions, and gravitational forces as follows:

$$M_{IP,i} = \frac{1}{2} \rho \pi R^3 \left( V_{b,i}(t) \right)^2 C_{M_{IP},i}(\lambda, \beta) - M_{m,i} g \cos(\theta + \varepsilon) \cos(\phi)$$  

(6)

$$M_{OP,i} = \frac{1}{2} \rho \pi R^3 \left( V_{b,i}(t) \right)^2 C_{M_{OP},i}(\lambda, \beta) - M_{m,i} g \sin(\theta + \varepsilon) \sin(\phi)$$  

(7)

$C_{M_{IP},i}$ and $C_{M_{OP},i}$ are moment coefficients, and $\lambda$ is tip speed ratio at the blades. Gravity $g$ acts constantly on the blades always with downwards direction which is preserved by introducing a phase shift $\varepsilon$ to compensate for the initial unknown position of the blades. $M_{m,i}$ is the moment of mass of
each blade and \( \phi \) represents the tilt angle. Better estimates of the stochastic and deterministic wind components are obtained by adding measurements of the aerodynamic torque given by:

\[
T_i = \frac{1}{2} \rho R^3 \left( \bar{V}(t) \right)^2 C_\lambda(\lambda, \beta) \lambda_i
\]  

(8)

At the rotor, the aerodynamic torque is the sum of the in-plane BRMBs of each blade and thus contributions from IP loads cancel each other out. \( C_\lambda(\lambda, \beta) \) is the power coefficient and \( \lambda \) is the tip speed ratio at the rotor. The resulting model from equations (1)-(8) is highly nonlinear.

2.2. Extended Kalman filter

For nonlinear problems, the EKF uses a linearization of the current state estimate. The nonlinear model from Section 2.1. can be discretized at a sampling time of 0.02s, and rearranged as follows:

\[
X_k = f(X_{k-1}, z_{k-1}) + \xi_k
\]

\[
Y_k = g(X_k, \dot{V}_k, C(\lambda, \beta)) + v_k
\]

(9)

where \( X_k \) and \( Y_k \) are state and output vectors, respectively. These vectors include:

\[
X_k = \left[ x_1, \ldots, x_3, V_{h1}, V_{h2}, \ldots, V_{h17}, V_R, a_1, a_2, M_{s1}, \ldots, M_{s9}, M_{y1}, \ldots, M_{y9} \right]^T
\]

\[
Y_k = \left[ T_1, M_{IP1}, \ldots, M_{IP9}, M_{OP1,1}, \ldots, M_{OP9} \right]^T
\]

\( x_1, x_2, \ldots, x_{17} \) are states that represent the dynamics of the turbulence components transfer functions, \( M_{si} \) and \( M_{yi} \) are components to estimate the blade moment of mass and phase shift from the gravitational load such that a trigonometric decomposition can be given by:

\[
M_{si} \cos(\theta + \epsilon) = M_{si} \cos(\theta) - M_{yi} \sin(\theta)
\]

\[
M_{yi} = M_{si} \sin(\epsilon)
\]

\( \epsilon \) denotes noise measurement introduced by the sensors and \( \xi_k \) represents time varying wind turbulence intensity to keep the wind field model quasi-stationary with:

\[
p(\xi_k) = N(0,Q_k)
\]

\[
p(v_k) = N(0,R_m)
\]

(11)

The linearised estimate \( \hat{X}_{k|k-1} \) of \( X_k \) given \( Y_0, \ldots, Y_k \) is generated by:

\[
\hat{X}_{k|k-1} = f(\hat{X}_{k-1|k-1})
\]

\[
P_{k|k-1} = J_{f_k} \left( \hat{X}_{k-1|k-1} \right) P_{k-1|k-1} J_{f_k}^T(\hat{X}_{k-1|k-1}) + J_{f_k}^T(0) P_{k-1} J_{f_k}^T(0)
\]

\[
\hat{X}_{k|k} = \hat{X}_{k-1|k-1} + K_k e_k
\]

\[
K_k = P_{k|k-1} J_{f_k}^T(\hat{X}_{k-1|k-1}) S_k^{-1}
\]

\[
P_{k|k} = \left[ I - K_k J_{f_k} \right] P_{k|k-1} \left[ I - K_k J_{f_k} \right]^T + K_k R K_k^T
\]

(12)

Where the innovations error \( e_k \) and innovations error covariance \( S_k \) are given by:

\[
e_k = Y_k - g(\hat{X}_{k-1|k-1}, \dot{V}_k, C(\lambda, \beta))
\]

\[
S_k = J_{f_k} \left( \hat{X}_{k-1|k-1} \right) P_{k-1|k-1}^T_{f_k} \left( \hat{X}_{k-1|k-1} \right) + R_m
\]

(13)

(14)
\( J_{f_k} \left( \hat{X}_{k|k-1} \right), J_{f_k} \left( \hat{X}_{k|k-1} \right) \) are Jacobian matrices of the nonlinear state and output functions, respectively. \( K_k \) is the Kalman gain, \( P_{k|k-1} \) represents the states error covariance matrix. For simplicity, white noise has been assumed, \( P_{k|k} \) is chosen to be greater than \( \hat{X}_k \hat{X}_k^T \), \( Q \) is assumed to be turbulence intensity and set as a percentage of mean wind speed, and \( R \) is set to be greater than the diagonal matrix formed by the inverse of the sensors variance. In practice, torque measurement variance is calculated by multiplying the variance of the power sensor and the rotor speed sensor, and the variance of the BRBMs is given by the specifications for Fibre Bragg grating sensors.

### 2.3. Anomaly detection

The EKF can be extended to add detection and diagnosis features as a statistical approach [2]. Consider the effects of extreme gusts on the 3-D model as follows:

\[
V_{(\text{anomaly})} = \begin{cases} 
V_{\text{hi}} \left( t \right) & k < T_a \\
V_{\text{hi}} \left( t \right) \pm V_{(\text{gust})} & k \geq T_a 
\end{cases}
\]

Such anomaly can be characterized by an anomaly starting time \( T_a \), a magnitude and its duration. With an appropriate formulation of \( V_{(\text{gust})} \), the anomaly appears at the state estimates. Once a wind anomaly occurs, it influences the expectation of the innovations error \( E \{ e_k \} \). Expanding equation (9) in Taylor series about \( \hat{X}_{k|k-1} \), it follows that:

\[
E \{ e_k | Y_k \} = J_{f_k} \left( \hat{X}_{k|k-1} \right) J_{f_k} \left( \hat{X}_{k|k-1} \right) E \{ \hat{X}_{k|k-1} | Y_{k-1} \}
\]

where \( \hat{X}_{k|k-1} = X_{k-1} - \hat{X}_{k|k-1} \) is the error in the predicted state estimates due to the anomaly. Similarly, the updated state estimates can be calculated using the EKF equations such that:

\[
E \{ \hat{X}_{k|k} | Y_k \} = J_{f_k} \left( \hat{X}_{k|k-1} \right) E \{ \hat{X}_{k|k-1} | Y_{k-1} \} + K_k E \{ e_k | Y_k \}
\]

A linear dependence of \( E \{ \hat{X}_{k|k} | Y_k \} \) on the anomaly features can now be defined as in [2] by the following relation:

\[
E \{ \hat{X}_{k|k} | Y_k \} = H_a \left( k, T_a \right) g_a, \quad k \geq T_a
\]

This relation encompasses the signature matrix of magnitude of the anomaly, \( H_a \left( k, T_a \right) \), affecting the EKF outputs and state estimates, and a signature vector, \( g_a \), representing its behaviour. The signature matrix is time varying to allow the gust-like event to evolve and even change in time.

To measure the drift in standard deviation produced by the anomaly, the squared Mahalanobis distance is calculated on the innovations error as:

\[
\mu_k = e_k^T S_k^{-1} e_k
\]

Equation (19) represents the Anomaly Detection Test (ADT). To avoid false detections caused by noise and since the anomaly can develop in time, an Anomaly Confirmation Test (ACT) is carried out after \( T_c \) time instances following a positive ADT, that is:

\[
\mu_{c,k} = \sum_{k=T_c}^{T_a} e_k^T S_k^{-1} e_k
\]

ADT follows a central \( \chi^2 \) distribution with \( N \) degrees of freedom and \( \alpha_d \) level of significance. ACT follows the same distribution but with \( N \times (T_c + 1) \) degrees of freedom, \( \alpha_c \) level of significance. The stopping rules will therefore be given by:
\[ ADT_{(\text{alarm})} = \left\{ k > 0, \quad \mu_k > \chi^2_{N,\alpha_k} \right\} \]
\[ ACT_{(\text{alarm})} = \left\{ k > 0, \quad \mu_k > \chi^2_{N(T_k + 1),\alpha} \right\} \]

(21)

In practice, \( \alpha_d \) is smaller than \( \alpha_c \) since the ACT is of higher priority. A suitable period of time \( T_c \), for a positive ACT, is chosen as half of the EKF convergence time.

To isolate a particular type of anomaly upon positive detection/confirmation alarms, the signature matrix from equation (18) is obtained. The estimate \( \hat{H}_a(k, T_k) \) is given by the maximum likelihood ratio of the probability density function between the innovations error and the error caused by a modelled anomaly as follows:

\[ \hat{H}_a(k, T_k) = \begin{bmatrix}
\mathbf{g}_d^T 
\mathbf{J}_{f_i}
(\hat{\mathbf{X}}_{j,k-1})
\mathbf{J}_{f_i}^T
(\hat{\mathbf{X}}_{j,k-1})
\mathbf{S}_k^{-1}
(\mathbf{J}_{f_i}
(\hat{\mathbf{X}}_{j,k-1})
\mathbf{J}_{f_i}^T
(\hat{\mathbf{X}}_{j,k-1}))^{-1}
\end{bmatrix}^{-1}
\begin{bmatrix}
\mathbf{g}_d^T 
\mathbf{J}_{f_i}
(\hat{\mathbf{X}}_{j,k-1})
\mathbf{J}_{f_i}^T
(\hat{\mathbf{X}}_{j,k-1})
\mathbf{S}_k^{-1}
(\mathbf{J}_{f_i}
(\hat{\mathbf{X}}_{j,k-1})
\mathbf{J}_{f_i}^T
(\hat{\mathbf{X}}_{j,k-1}))^{-1}
\end{bmatrix}\mathbf{g}_a^{-1} \]

(22)

Since the anomaly has evolved in time for \( T_c < k < T_c \), goodness of fit is used to select the signature vector for this interval. At this point, the data set for anomaly isolation is relatively small and if there is a positive percentage of goodness of fit, it would be small. Detection and isolation are repeated until the goodness of fit is closed to 100%. In reality, goodness of fit cannot reach full percentage since the modelled anomaly does not account for the turbulence intensity present in the measured anomaly. The isolated anomaly can be added to the EKF state estimates using equation (16) to both preserve the detector stability and allow new anomalies to be detected. When the model mismatch increases considerably, the dynamic inflow model struggles to adapt quickly.

In practice, gust-like events can have any form, thus updating the estimate of the magnitude of the anomaly during the entire anomaly, helps at accommodating any unknown form of the anomaly. If an anomaly cannot be isolated appropriately, that is the percentage of goodness of fit is never positive, the data is stored and used when another anomaly appears. A set of diagnostic actions can be determined to counteract the anomaly in the turbine control. Proposed control approaches are Individual pitch control (IPC) or open loop control. Results on control will be presented in a future paper.

3. Simulation Results

Both extreme operating gusts and extreme coherent gusts are tested using DNV-GL Bladed offline data of a 2MW Supergen exemplar wind turbine with added Gaussian noise. Such data is available in real wind turbines but the noise is not necessarily Gaussian. The detector is implemented in Matlab and runs for 400s.

An extreme operating gust (Mexican hat) is simulated in Bladed at 120s. BRBMs extracted from Bladed are used as EKF inputs. Figure 2 shows the results of ADT and ACT with confidence limits 0.75 and 0.92, respectively, and Bladed hub wind speed. ADT shows several positive alarms during the simulation. ACT then becomes useful to filter out alarms produced by noise. Positive ACT alarms are triggered twice during this simulation interval: one alarm at 64.9s and another one at 121.3s. Since the first alarm does not remain up to \( T_c \), the detector rules it out as false alarm. If the alarm would have persisted during the confirmation interval and the detector could not identify it as a known anomaly, it is classified as an unmodelled anomaly and the data is stored. The second alarm is persistent up to \( T_c \) and extreme operating gust is initially isolated with 19.8% model fit.

Results of initial anomaly isolation and rotor speed are shown in figure 3. The identification has been achieved at the initial decrease in wind speed of the Mexican-hat-like shape. Rotor speed variation is minimum during this range. The estimate \( \hat{H}_a(k, T_k + T_c) \) is calculated and added to the EKF. Comparison between the original EKF model and the compensated model are shown in figure 4.

Extreme coherent gust is simulated in Bladed as a sudden cosine-shaped increase in wind speed from 14m/s to 24m/s. The wind magnitude is sustained at the latter value for the rest of the simulation. To generate this type of data set in Bladed, a simulation of 2000s is used. The EKF runs in Matlab only
for 400s. This time interval allows the introduction of a discrepancy in mean wind speed during the extreme coherent gust.

**Figure 2.** (a) Anomaly detection test with $\alpha_d = 0.75$, (b) Anomaly confirmation test with $\alpha_c = 0.92$ and bladed hub wind speed for extreme operating gust.

**Figure 3.** (a) Rotor speed for extreme operating gust, (b) Zoomed identification interval for operating gust, achieved anomaly fit: 19.8%
Figure 4. (a) Estimated wind component $V_0(t)$ before and after EKF state estimates compensation. (b) Estimated wind component $V_{B1}(t)$ seen by blade 1 before and after EKF state estimates compensation vs Bladed hub wind speed for extreme operating gust.

Figure 5. (a) Anomaly detection test with $\alpha_d = 0.75$. (b) Anomaly confirmation test with $\alpha_c = 0.92$ and Bladed hub wind speed for extreme coherent gust.
Figure 6. (a) Rotor speed for extreme coherent gust. (b) Zoomed identification interval 1 for coherent gust, achieved anomaly fit: -27.1%. (c) Zoomed identification interval 3 for coherent gust, achieved anomaly fit: 5.86%.

Figure 7. (a) Estimated wind component $V_0(t)$ before and after EKF compensation. (b) Estimated wind component $V_{B_i}(t)$ before and after EKF compensation vs Bladed hub wind speed.

Figure 5 shows Bladed hub wind speed and results of ADT and ACT with confidence levels of 0.75 and 0.9, respectively. $\alpha_c$ is reduced intentionally to test the sensibility of the detector against the mean wind speed value discrepancy. Again the ADT shows several alarms. Three alarms in ACT are ruled
out as false alarms at 43.48s, 74.22s and 74.48s. The anomaly is detected at 74.88s. Several alarms occur while wind speed remains with coherent gusts. The detector rules them out as false alarms. Nonetheless with further information about mean wind speed, the detector could be able to classify them as model mismatch.

Initial isolation shows a negative goodness of fit of -27.1%. Since the ACT alarm is persistent, the detector performs further isolation tasks and achieves a model fit of 5.86%. The algorithm decides that the anomaly resembles a coherent gust like shape. Figure 6 shows the two significant isolation tasks and rotor speed. Compensation of the EKF state estimates is carried out and shown in figure 7. If the compensation is unsuccessful, the goodness of fit will reduce and the detector keeps updating its isolation feature. A decrease in goodness of fit can signify either new anomalies happening (known or unknown) or the presence of anomalies with shared effects. These issues will be address in the future.

4. Conclusions
The detector is capable of detecting and isolating extreme gusts before rotor speed reaches the turbine shut down threshold. Percentages of goodness of fit increase as the anomaly evolves and are subject to change if new anomalies are detected. Compensation of the EKF estimates is necessary to allow the detection scheme to detect new upcoming anomalies. Diagnostic actions for extreme gusts can be applied based on open loop control or IPC. In the future, the improvement of anomaly isolation and anomalies with shared effects will be considered as a Bayesian Inference problem where Particle filtering or Ensemble Kalman filter can provide better results than EKF.

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