Observer design and optimization for model-based condition monitoring of the wind turbine rotor blades using genetic algorithm

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Abstract. In this paper a model based approach for condition monitoring and diagnosis of faults in the wind turbine rotor blades is described. The investigation is focused on creating a fault-free reference system, the design and optimization of the controller/observer based on the Disturbance Accommodating Control theory and the multi-objective genetic optimization algorithm in order to further enhance the condition monitoring and faults diagnosis. Test cases are presented by injecting a parameter change, e.g. pitch angle, as an error to the non-linear wind turbine simulation model in order to demonstrate that the proposed method is able to detect the fault on the blades.

1. Introduction
Over the last ten years, the demand for wind energy has grown exponentially. In recent years, reducing the operation and maintenance costs and improving reliability have become very important in wind turbine operational strategies. Condition monitoring of wind turbines is important to prevent break downs of wind turbines and the loss of power production in case of faults. Therefore, in addition to the design of more reliable wind turbines, the application of condition monitoring techniques offers an approach to detect faults before they get critical and significantly affect the power production.

Different methods for condition monitoring and fault diagnosis exist. These methods can be classified into two categories, namely, the model-based methods and the data driven methods. In the data driven approach, the fault diagnosis is based on different types of measurements and the model that is used to evaluate the measurements [1]. It includes the detection of a mean value and a variance change as well as the change of trends. In general, a physics-based model of a real system is not needed for these methods, but the definition of a healthy status of a real system is required. In the model-based approach, usually an observer or a Kalman filter is designed based on a physics-based model of the nominal behavior of a real system and compared with the measurement on a real system [2]. The difference between the measurement on a real system and the output from the observer is used to generate residuals for faults diagnosis. A fault is diagnosed as a change in the residuals that can be detected using statistical methods.

Both of the methods mentioned above have been employed for condition monitoring of wind turbines [3, 4]. However, the disadvantage of the model-based method is that it requires a model of physics behind the system behavior and a well tuned observer. In this paper, we focus on
the modeling of a wind turbine linearly to be used as fault-free reference system, and keep as much degree of freedom as possible (13 DOFs) and aerodynamic nonlinearities. It couples with a state-space controller/observer based on the Disturbance Accommodating Control (DAC) \[5\] theory in order to perform state estimation for condition monitoring and faults diagnosis. The fault-free reference system is used as the “healthy model” to generate the residuals, and the residuals are analyzed by Cumulative Sum (CUSUM) test \[6\] for detecting faults. Test cases are presented by injecting a pitch angle change on one of the blade to represent an error on blade for showing detection of faults on the rotor blades using the method described in this paper. The NREL 5 MW reference wind turbine \[7\] is used in this study. All simulations are performed in Matlab/Simulink coupled with the aero-elastic software FAST \[8\] from NREL.

2. Overview of the Disturbance Accommodating Control Theory

The continuous-time state-space model of a wind turbine system can be generally described as

\[
\begin{align*}
\Delta \dot{\vec{x}} &= A \Delta \vec{x} + B \Delta \vec{u} + B_d \Delta \vec{u}_d \\
\Delta \vec{y} &= C \Delta \vec{x} + D \Delta \vec{u} + D_d \Delta \vec{u}_d
\end{align*}
\]

where, \( \vec{x} \) is a \( n \times 1 \) vector of all system states; \( \vec{y} \) is the measured output vector with the size of \( q \times 1 \); \( \vec{u} \) is the control input vector with the size of \( p \times 1 \); \( \Delta \vec{u}_d \) is the wind disturbance input with the size of \( r \times 1 \); \( \Delta \) indicates the deviation from the linearization point; \( n \) is the order of the system matrix; \( q \) is the number of measured outputs; \( p \) is the number of control inputs; \( r \) is the number of disturbance inputs; and \( A, B, B_d, C, D, D_d \) are continuous state-space model matrices with appropriate sizes. The wind disturbance input \( \Delta \vec{u}_d \) can be modeled by

\[
\begin{align*}
\Delta \dot{\vec{x}}_d &= F \Delta \vec{x}_d \\
\Delta \vec{u}_d &= \Theta \Delta \vec{x}_d
\end{align*}
\]

where, \( \Delta \vec{x}_d \) is the wind disturbance state; \( F \) and \( \Theta \) are the state-space model matrices for the disturbance state, which are specific for each disturbance waveform, for example, here a step waveform is assumed, which means \( \Theta = 1 \) and \( F = 0 \) as discussed in [5]. As it is shown in equation (1), the wind is treated as a disturbance input of the wind turbine system which affects the internal states and the output of the system. One way to account for the wind disturbance is to treat the wind as a disturbance state \( (\Delta \vec{x}_d) \) as it appears in equation (2), and add it to the linearized state-space wind turbine model to get the augmented state-space system to represent the disturbance input. DAC is an extension of the modern state feedback control based on the state observer to reconstruct the disturbance state via an assumed waveform model mentioned above; these disturbance states are used as part of the state feedback control to accommodate or reject any disturbance effects. The detailed description of this method is given in [9]. The augmented state-space model of wind turbine including the disturbance state \( \Delta \vec{x}_d \) is formulated as

\[
\begin{align*}
\begin{bmatrix}
\Delta \dot{\vec{x}} \\
\Delta \dot{\vec{x}}_d
\end{bmatrix} &= 
\begin{bmatrix}
A & B_d \Theta \\
0 & F
\end{bmatrix}
\begin{bmatrix}
\Delta \vec{x} \\
\Delta \vec{x}_d
\end{bmatrix} + 
\begin{bmatrix}
B \\
0
\end{bmatrix} \Delta \vec{u} \\
\Delta \vec{y} &= 
\begin{bmatrix}
C & D_d \Theta
\end{bmatrix}
\begin{bmatrix}
\Delta \vec{x} \\
\Delta \vec{x}_d
\end{bmatrix} + D \Delta \vec{u}
\end{align*}
\]

The control input can be calculated as

\[
\Delta \vec{u} = G_x \Delta \vec{x} + G_d \Delta \vec{x}_d
\]
where, \( G_x \) is the internal state feedback gain to achieve the control task such as stabilization, which can be calculated by the optimal control theory, for example, Linear Quadratic Regulator (LQR); \( G_d \) is the disturbance state feedback gain also called as the disturbance accommodating gain to counteract the disturbance effect on the wind turbine system. The calculation of \( G_x \) and \( G_d \) are explained in the next sections. With the state feedback control based on DAC, the control system can be designed to add damping to the desired flexible modes of the wind turbine, to accommodate the wind disturbance for the purpose of speed regulation, and to estimate the internal states for the purpose of condition monitoring.

3. Implementation of the DAC Based Controller/Observer

Usually not all the internal states can be measured in practical applications. To circumvent this difficulty, \( \Delta \hat{x} \) and \( \Delta \hat{x}_d \) in equation (4) should be estimated via an observer. The observed states \( \Delta \hat{x} \) and \( \Delta \hat{x}_d \) are calculated by

\[
\begin{bmatrix}
\Delta \hat{x} \\
\Delta \hat{x}_d
\end{bmatrix} =
\begin{bmatrix}
A & B_d \Theta \\
0 & F
\end{bmatrix}
\begin{bmatrix}
\Delta \hat{x} \\
\Delta \hat{x}_d
\end{bmatrix} +
\begin{bmatrix}
B \\
0
\end{bmatrix}
\Delta \hat{u}
+ L \left( \Delta y' - \Delta \hat{y} \right)
\]

\[
\Delta \hat{y}' = \begin{bmatrix} C' & D'_d \Theta \end{bmatrix}
\begin{bmatrix}
\Delta \hat{x} \\
\Delta \hat{x}_d
\end{bmatrix} + D' \Delta \hat{u}
\]

(5)

where, \( L \) is the Luenberger observer gain, which can also be calculated by LQR; \( \Delta \hat{y}' \) is the selected measurement with the corresponding system matrices \( C', D', D'_d \) depending on system or application. While this approach allows for arbitrary measurements \( \Delta y' \) to be used for state estimation, we selected to use rotor speed only. It is influenced by all relevant faults, is measured with sufficient accuracy and allows for good demonstration of the methods for fault detection. Additional sensors could improve fault localization. The type and position of additional sensors are part of our ongoing research.

The disturbance accommodating gain \( G_d \) is calculated based on the linear ideal trajectory of a dynamic system. The system states and the control input are assumed to be linear functions of the disturbance state. The detailed derivation can be found in [10]. This linear relationship can be expressed as

\[
\begin{bmatrix}
\Delta \hat{x} \\
\Delta \hat{y}'
\end{bmatrix} =
\begin{bmatrix} C_1 & C_2 \end{bmatrix}
\begin{bmatrix}
\Delta \hat{x}_d \\
\Delta \hat{x}_d
\end{bmatrix} +
\begin{bmatrix} B_d \Theta \\
D_d \Theta
\end{bmatrix} \Delta \hat{u}
\]

(6)

where, \( C_1 \) and \( C_2 \) are the coefficient matrices of the linear relationship. As it is known that the control objective is to cancel out the disturbance effect on the system output, which means \( \Delta \hat{y}' \) is equal to zero. From equation (1), equation (2) and equation (6), a regulation equation is derived as

\[
\begin{bmatrix} A & B \\
C & D
\end{bmatrix}
\begin{bmatrix} C_1 \\
C_2
\end{bmatrix} =
\begin{bmatrix} C_1 \\
0
\end{bmatrix}
F =
\begin{bmatrix} B_d \Theta \\
D_d \Theta
\end{bmatrix}
\]

(7)

Substituting the equation (6) into equation (4), the disturbance accommodating gain \( G_d \) is computed as

\[
G_d = C_2 - G_x C_1
\]

(8)

where, \( G_x \) is the state feedback control gain associated with the wind turbine internal states \( \Delta \hat{x} \) and has been discussed. \( C_1 \) and \( C_2 \) are included in equation (7), which can be solved by matrix algebra.
After the observer gain $L$, the internal state feedback gain $G_x$ and the disturbance state feedback gain $G_d$ are calculated, the complete closed-loop equation including controller and observer can be expressed as

$$\begin{aligned}
\begin{cases}
\begin{bmatrix}
\Delta \dot{\hat{x}}_f \\
\Delta \dot{\hat{x}}_d
\end{bmatrix} = 
\begin{bmatrix}
A & B_d \Theta \\
0 & F
\end{bmatrix}
\begin{bmatrix}
\Delta \hat{x} \\
\Delta \hat{x}_d
\end{bmatrix} + 
\begin{bmatrix}
B & 0
\end{bmatrix}
(G_x \Delta \hat{x} + G_d \Delta \hat{x}_d) + 
L(\Delta y' - \Delta \hat{y}') \\
\Delta \hat{y}' = 
\begin{bmatrix}
C' & D' \Theta
\end{bmatrix}
\begin{bmatrix}
\Delta \hat{x} \\
\Delta \hat{x}_d
\end{bmatrix} + 
D'(G_x \Delta \hat{x} + G_d \Delta \hat{x}_d)
\end{cases}
\end{aligned}$$

(9)

The Equation (9) shows a typical Lueneberger observer for reconstruction of the internal system states. The measurement $\Delta y'$ from the wind turbine is needed in order to use this equation. The correction term $L(\Delta y' - \Delta \hat{y}')$ ascertains that the estimated system state always tracks actual system behavior. If a fault in the turbine leads to deviations from nominal system behavior, the observer tracks the actual system behavior and reconstructs the system state of the faulty system. For fault detection, comparison with nominal system state without fault is required. This can only be achieved using a fault-free model case as reference. This setup in Matlab/Simulink is described in Section 5.1.

4. Description of the Optimization Algorithm: NSGA-II

Based on the above mentioned DAC based controller/observer design method, it is necessary to select four weighting matrices ($Q_c, R_c, Q_o, R_o$) in order to solve the Algebraic Riccati Equations to get the control feedback gain $G_x$ and the observer gain $L$. The empirical method is typically used in the selection of the weighting matrices to get a good performance and robustness. This manual selection of the elements of the matrices is not straightforward and therefore evolutionary algorithms such as genetic algorithms can be used to automate the searching process for the best values of the weighting matrices that meet the design requirements. In this work, a multi-objective optimization algorithm called NSGA-II [11] based on a genetic algorithm is used for the optimization. NSGA-II is inspired by evolutionary processes. An initial population is created based on the feasible range of design variables. Then, an iterative process starts. During each iteration, called generation, fitness of each individual is checked. Individuals are selected, combined and mutated using simulated binary crossover [12] and polynomial mutation [13] operators. In the end, a new population is formed. This process converges towards the global optimum, or, for multi-objective problems, towards the Pareto front. The Pareto front includes all individuals, i.e. all parameter combinations, for which a given objective can only be improved at the cost of other objectives. The detailed description of the NSGA-II algorithm can be found in [11].

To apply NSGA-II on the DAC controller/observer design and optimization procedure, the genetic representation of the feasible design variables (individuals) and the fitness functions (objective functions) are required. They are explained in the following:

1. **Individual:** The diagonal elements of four weighting matrices ($Q_c, R_c, Q_o, R_o$) are considered to compose an individual, namely the chromosome. For simplification of the problem, in this work, only two weighting matrices ($Q_c, Q_o$) are considered as the design variables, the other two weighting matrices ($R_c, R_o$) are selected as identity matrices.

2. **Population:** The population is composed by a group of the individuals mentioned before with a size that remains constant in every generation.

3. **Fitness functions:** The fitness functions, also called the objective functions, are used to evaluate the fitness of each feasible DAC controller/observer in the optimization algorithm. The fitness functions are based on the system response to the turbulent wind field and an optimal
performance index. The optimal performance index used here is considered as the time Averaged Integral of the Squared Error multiplied by Time (AISET). It is expressed as

\[ AISET = \frac{\int_0^t \tau (e(\tau))^2 d\tau}{t} \]  

(10)

where, \( e(\tau) \) is the error of a signal in time domain; \( t \) is the total integration time; \( \tau \) is the integral variable. In this work, two fitness functions related with the output errors in generator speed and estimated wind speed are defined as

\[
\begin{align*}
    f_1 &= \frac{\int_0^t \tau (\omega_g(\tau) - \omega_{ref}(\tau))^2 d\tau}{t} \\
    f_2 &= \frac{\int_0^t \tau (v_{est}(\tau) - v_{ref}(\tau))^2 d\tau}{t}
\end{align*}
\]

(11)

where, \( \omega_g(\tau) \) and \( \omega_{ref}(\tau) \) are the generator speed and the generator speed reference; \( v_{est} \) and \( v_{ref} \) are the estimated wind speed and the actual wind speed.

(4) Selection operator and genetic operator: The selection operator chooses the best individuals of the current generation based on the value of the fitness functions which is calculated from the simulation on a wind turbine system. The genetic operators, namely the simulated binary crossover and polynomial mutation, are applied on the selected individuals to produce the offspring for the next generation.

5. Simulation Setup and Results

5.1. Description of the Model-based Condition Monitoring System

To evaluate the performance of the implemented fault-free reference system together with the DAC based controller/observer in terms of the fault diagnosis, the NREL 5 MW wind turbine [7] is used in this study as a reference turbine. As discussed in Section 3, the Matlab/Simulink model is constructed in the way that the fault-free reference system does not depend on any measured signal from the real wind turbine except the wind disturbance. The Simulink model of the model-based condition monitoring system used for the simulation test is shown in the Figure 1. The upper block represents the real wind turbine and provides the required estimated actual system states. In the lower block, a real-time capable locally linearized wind turbine model is used to simulate nominal system behavior. In order to provide reference states for fault detection, the same DAC controller/observer is used to estimate the fault-free reference states. Using this setup, the fault-free reference system only receives the wind as the disturbance input, no other inputs are needed.

5.2. Description of the Fault-free Reference System

FAST [8] is used to create the fault-free reference system with appropriate number of Degree of Freedoms (DOFs) to get the state-space model described by equation (1) for on-line simulation and for the DAC controller/observer design. As it is shown in Table 1, the fault-free reference system contains 7 operational points above rated wind speed; at each operational point, it contains 13 DOFs. The azimuth averaged system matrices \((A, B, B_d, C, D, D_d)\) are calculated for each operating points to obtain a linear time invariant model that contains 7 operational points. This represents the fault-free reference system for the condition monitoring. For the purpose of DAC controller/observer design, the Coleman transformation [14] is applied on the azimuth averaged system matrices to obtain the state-space system needed by the DAC controller/observer design. In addition, the generator azimuth state is eliminated but the generator speed state is included in the state-space model for the collective pitch control design because if we retain the generator azimuth state, but only measure the generator speed, the resulting state-space system is not observable.
Table 1: Linearization points and the selected DOFs of the fault-free reference system

| Linearization Points                          | Selected DOFs                                      |
|-----------------------------------------------|----------------------------------------------------|
| Wind speed (m/s)                              | Generator rotation angle  On                       |
| Generator speed (rpm)                         | Blade 1, 2 and 3 first flap-wise mode  On          |
| Generator torque (Nm)                         | Blade 1, 2 and 3 second flap-wise mode  On         |
| Pitch angle (deg)                             | Blade 1, 2 and 3 first edge-wise mode  On          |
|                                               | First drive train torsional deflection angle  On   |
|                                               | tower first fore-aft and side-to-side mode  On     |

5.3. Design and Optimization Results of the DAC Controller/Observer

The following set of parameters are used in NSGA-II algorithm: population size of 200; distribution index for simulated binary crossover and polynomial mutation are \( \eta_c = 20 \) and \( \eta_m = 20 \); the crossover probability of 90 % and the mutation probability of 10 %; the maximum number of generation of 100. No further investigation on finding the best parameters is carried out. The population is initialized randomly based on the physical range of the weighting matrices. In this case the minimum value of each element is zero and the maximum value of each element is selected based on a preliminary design of the DAC controller/observer. The optimization loop is stopped if the maximum number of generation is reached, or if there is no change on the individuals if the current generation is compared with the previous generation. A turbulent wind field with a mean wind speed of 14 m/s and turbulent intensity of 16.1 % is used. The fault-free reference system created above is used to calculate the system response for evaluating the two fitness functions defined in equation (11) in order to avoid the large total
computational time.

Figure 2a and Figure 2b show the initial values of the fitness functions at zero generation and the search process of the NSGA-II algorithm starting from the 1\textsuperscript{st} generation. It is found out that the difference of the fitness functions between the 80\textsuperscript{th} generation and the 85\textsuperscript{th} generation becomes very small. This shows that the algorithm has converged to the Pareto front.

5.4. Verification of the Fault-free Reference system

After the optimization, the design variables associated with the Pareto front are selected based on the compromise between the fitness function $f_1$ and $f_2$ in order to achieve both good speed regulation performance and wind speed estimation performance. Simulations are performed at different turbulent wind fields, 14 m/s, 16 m/s, 18 m/s and 20 m/s, using the optimized DAC controller/observer on both the fault-free reference system and the FAST non-linear wind turbine model in order to evaluate the performance of the fault-free reference system at full load operational region. Simulation time is 100 second, and the first 10 seconds are removed from the plot to get rid of the transition period of the simulation. The actual turbulent wind fields

used by FAST non-linear simulation are compared with the estimated effective wind speeds calculated by the DAC controller/observer in Figure 3. It shows that the observer tracks the
actual wind speed and corrects for some measurement errors at different wind speeds correctly. This good agreement is of major importance since the estimated effective wind speed is used for controlling the rotor speed by disturbance accommodating control (feedforward control). Figure 4 shows that the disturbance accommodating control based on the estimated effective wind speed is able to regulate the rotor/generator speed at different wind speeds. The quality of the rotor speed in the fault-free reference system is slightly worse than the one in the FAST non-linear model. This is because the fault-free reference system used in the simulation is a time averaged model, and it is only valid at certain linearization points mentioned above.

Figure 4: Fault free case: comparison of rotor speed.

Figure 5: Fault free case: comparison of Blade 2 out-of-plane tip deflection.

Figure 5 shows the comparison between the “measured” (simulated by FAST non-linear model)
blade 2 out-of-plane tip deflection and the same one calculated by the fault-free reference system for the fault-free cases. The results show a good agreement between the FAST non-linear model and the fault-free reference system for the blade out-of-plane tip deflection at different turbulent wind speeds in terms of both the mean value and the amplitude. The estimated system state of the fault-free reference system and the FAST non-linear wind turbine model is compared in Figure 6. It indicates that the fault-free reference system can be used for the condition monitoring and fault detection on the rotor blades.

![Figure 6: Fault free case: comparison of system internal state.](image)

### 5.5. Fault Detection on Rotor Blades

As mentioned before, the residual vector is created based on the estimated system state from the FAST non-linear wind turbine model and the one from the fault-free reference system. Afterward, the residual vector is evaluated using the sequential change detection algorithm so called the CUSUM test in order to diagnose the faults. In this section, simulations are performed for checking the ability of the presented method in terms of fault detection. During the simulation, a fault is introduced to the FAST non-linear simulation which represents the faults as if it would happen on the real wind turbine. The fault is triggered at forty seconds simulation time to mimic that the pitch actuator on blade 2 is broken and the blade 2 pitch angle is stuck at the current pitch angle position. Figure 7a shows the comparison of estimated system state from both systems at 14 m/s when the fault is triggered. The result indicates that, when the fault is triggered, the estimated system state from the FAST non-linear wind turbine model deviates from the system state estimated from the fault-free reference system. Figure 7b shows the CUSUM control chart. The highlighted circle at the sample point around 4000 indicates the cumulative sum drifts more than the target mean. This shows that the presented approach is able to detect the fault.

![Figure 7: Fault case: comparison of system internal state.](image)
6. Conclusions
In this paper a model-based approach for condition monitoring and fault diagnosis on the wind turbine rotor blades is described. A DAC controller/observer that estimates the internal turbine states and thus allows additional insights into turbine behavior is developed. Additionally, a fault-free reference system is designed to provide a fault-free reference state estimation. Comparison between both state estimation allows for fault detection and condition monitoring. Verification results show that the fault-free reference system coupled with the DAC controller/observer has a good agreement on estimated state and the blade out-of-plane tip deflection compared with the FAST non-linear wind turbine model for the fault free cases at different wind speeds. Test cases are presented to show the ability of the presented method in terms of the fault detection on the wind turbine blades when a dummy fault represented as a pitch error on blade 2 is triggered. The CUSUM control chart shows that the proposed method catches the fault. Further more, the dummy fault used in the test cases can also represent other real faults that would occur on the wind turbine, for example, aerodynamic unbalance due to the iced blade. At this time, the only measurement that is input into the DAC controller/observer to estimate the system states is rotor speed. This only allows for limited fault localization, since many faults change the rotor speed in similar manner and cannot be distinguished. To compensate for this, the approach presented in this paper allows for extension of the DAC controller/observer input. Possible sensor signals are blade root bending moments, blade tip displacements or accelerations, and similar measurements closer to actual fault locations. The evaluation of possible additional sensors and their positioning is part of our ongoing research. Beside this, the sensitivity study of the fault-free reference system to the uncertainty in the measurement of wind speed is also part of our ongoing research.

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