Analysis of Rotor Torque Sensitivity for a Wind Speed Estimator as Applied to an Extreme Scale, Segmented Ultra-light Morphing Rotor

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Abstract

Wind turbines are inherently nonlinear, and with increased size and flexibility of modern turbines, models previously used in the design and synthesis of control systems and estimators may fail to capture the important dynamics of extreme scale turbines (>10MW). Estimation techniques provide a way to predict hard to measure states of a system using readily available signals and a model of the system. It is often the case that a linear model sufficiently captures the important dynamics of a system, providing the framework for the estimator and good signal estimation. In this paper the authors modify a traditional linear torque model used in the design of a wind speed estimator using a systematic study of aerodynamic torque sensitivities, and apply it to a 13.2 MW down-wind, 2 bladed turbine with a Segmented Ultra-light Morphing Rotor (SUMR).

Keywords: *Wind Turbine Modeling, Kalman Filter, Estimation, Observers, Control Systems, Nonlinear Control*

Introduction

Wind energy continues to grow at a record pace with North America accounting for 16% of the added global capacity in 2016 [1], and second only to China on the world stage in terms of national wind energy capacity. With such a hungry market for wind energy, research and industry are continuously growing turbine rotor size [2] and advancing turbine technology. Increases in rotor size and additional actuated degrees of freedom [3] in the turbine rotor are requiring current aerodynamic models to be re-evaluated as applied to large rotors [4] during the design of observers used in state estimation.

Wind turbines are an especially interesting system to model because they are driven by a stochastic disturbance, the wind, which can be difficult to model but a vital part for the design of stabilizing control architectures. Knowledge of wind speed can enhance turbine control. For example, this signal can be used to distinguish which controller to use, say for instance, within a family of linear parameter varying (LPV) controllers designed for optimal operation over a large envelope of design points.

Not only is the wind difficult to model, but it is also difficult to measure in real time operation, requiring expensive LIDARs or meteorological towers to measure. Kalman Filters provide a method in which easily available signals can be used to reconstruct states of interest within a system [5,6]. In this research, we explain how we modify an existing aerodynamic torque model to incorporate sensitivity information from an ultra-scale (13 MW) morphing turbine, then apply the models to a wind speed estimator and compare the results. Our contributions lie in the application to the larger turbine with higher variability in sensitivity in combination with the novel closed-loop, integral error, tip speed ratio (λ) estimator.

I. Methods

The aerodynamic torque on the turbine rotor is given by

$$Q_a = \frac{1}{2}\rho\pi R^2 \frac{U_\infty^3}{\omega_r} c_p(U_\infty, \lambda), \tag{1}$$

where ρ is the air density, R is the blade length, U_∞ is the free stream wind speed, ω_r is the rotor angular velocity, $c_p(U_\infty, \lambda)$ is the rotor power coefficient, and λ is defined as $\lambda = \frac{\omega_r}{U_\infty}$. Using the applied generator torque Q_g to counteract the aerodynamic torque, and accounting for frictional loss, Q_{loss}, the angular acceleration of the rotor can be calculated using (2):

$$J\dot{\omega}_r = Q_a(U_\infty, \omega_r) - Q_g - Q_{loss}, \tag{2}$$

where J is the rotor rotational inertia. The system given by (2) can be linearized and represented in state-space form as shown by (3):

$$\begin{bmatrix} \Delta\dot{\omega}_r \\ \Delta\dot{Q}_a \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{J_{rot}} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\omega_r \\ \Delta Q_a \end{bmatrix} + \begin{bmatrix} -\frac{1}{J_{gen}} \\ 0 \end{bmatrix} \Delta Q_g + \begin{bmatrix} -\frac{1}{J_{gen}} \\ 0 \end{bmatrix} Q_{loss} \tag{3}$$

where Δ represents perturbations about the operating point used for linearization.

The model given by (3) was presented in [5] as part of an observer design for a sub extreme scale turbine. In the coming paper, (3) will be augmented using systematic analyses of a large (5MW) and extreme-scale (13.2MW) rotor torque sensitivity.

The model given by (3) requires empirical tuning in finding the proper value of Q_{loss} for different rotors operating on different scales. One such determining factor of frictional loss on a rotor is the amount of friction generated at the interface of the viscous boundary layer with the free stream wind speed, and with blades at 106 m

(SUMR) in length, and a max chord of 6 m, frictional losses cannot be ignored. For the determination of proper tuning of the model to be used for Q_a estimation, the authors used a study of the aerodynamic torque sensitivity as shown in figure 1.

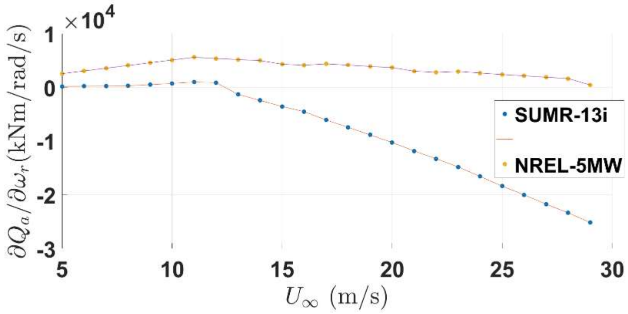

Figure 1-Aerodynamic torque sensitivity with respect to rotor angular velocity as a function of wind speed

The information presented in Figure 1 can be used to augment the model given by (3) as shown by (4).

$$\begin{bmatrix} \Delta\dot{\omega}_r \\ \Delta\dot{Q}_a \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{J_{rot}} \\ \frac{\partial Q_a}{\partial \omega_r}\big|_0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\omega_r \\ \Delta Q_a \end{bmatrix} + \begin{bmatrix} -\frac{1}{J_{gen}} \\ \frac{\partial Q_g}{\partial Q_a}\big|_0 \end{bmatrix} Q_g \qquad (4)$$

where $(\cdot)|_0$ denotes the rotor sensitivity as fit by a 0^{th} order polynomial.

Using (4), Q_a can be estimated using a Kalman filter. With an estimate of Q_a and a monotonic portion of the surface describing c_p as a function of blade pitch (β) and λ available, the wind speed can be reconstructed using (5).

$$Q_a\omega_r = \frac{1}{2}\rho\pi R^2 \frac{R^3\omega_r^2}{\lambda^3} c_p(\beta,\lambda) \Leftrightarrow \frac{2Q_a}{\rho\pi R^5\omega_r^2} = \frac{c_p(\beta,\lambda)}{\lambda^3} \qquad (5a)$$

$$U_\infty = \frac{\omega_r R}{\lambda} \qquad (5b)$$

II. Simulation

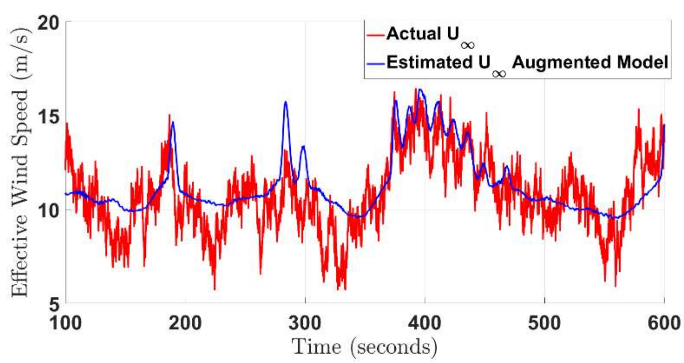

Figure 2 - Actual and Estimated Wind Speed

III. Conclusion

Figure 2 shows a plot comparing the actual wind speed, estimated wind speed using the augmented model (4) and the original model (3). From the plot it can be seen that the augmented estimator captures the low frequency component of turbulent wind speed variation more accurately as compared with the original model providing a wind speed signal which can be used for the selection of a local LPV controller within a family of LPV controllers. The results and methods presented in the above abstract can be more thoroughly presented and discussed given a presentation slot for the conference.

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