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Effective wind speed estimation for wind turbines in down-regulation

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Abstract. The use of state estimation technique offers a means of estimating the effective wind speed based solely upon the measurements of the turbine. Such wind speed estimations are crucial for turbines to calculate the reserved power for ancillary services. Nonetheless, the system observability or the possibility of estimating the wind speed is influenced by various down-regulation strategies. Thus, this paper investigates the system observabilities of turbines in different down-regulating conditions via the use of the empirical observability Gramian. In addition, wind speed estimators are constructed for each control strategy using an extended Kalman filter approach. Subsequently, each estimation performance is evaluated from the assessments of the Gramians and high-fidelity turbine simulations. The results reveal that it is more difficult to reconstruct the wind estimate from measurements of the turbine operating in torque-based than rotor-speed-based down-regulation strategies.

1. Introduction
Down-regulation is essential for modern large wind turbines and is particularly important in a wind farm. One of the main objectives is to stabilise the power grid. Typically, participation in ancillary services requires the turbine to maintain the proper power flow of the grid by providing the additional reserved power if needed. Such reserved power is calculated based on the difference between the instantaneous power generated by the turbine and the available power from the wind. Thus, the knowledge of the wind speed is crucial to estimating the level of the power reserve for the wind turbine providing the ancillary services.

The problem of wind speed estimation in normal operation has been widely studied over the past two decades. For example, one of the widely used methods in the wind industry and research community is the power balance estimator. This method is based on a static relationship between the generator power and effective wind speed (e.g. [1, 2]). The study by [3] concluded that using dynamic models could improve estimation quality. Later, an increasing number of studies used the concept of model-based state estimation for reconstructing the effective wind speed in normal operation (e.g. [4, 5]).

One of the key questions for state estimation is observability, which relates to the possibility of estimating the system state based on the output. In normal operation, the observability problems have been addressed by several studies (e.g. [6, 7]). In down-regulation, the turbine operates in various fashions dependent on the down-regulation strategies (e.g. [8]). For example, some strategies maintain the rated rotor speed during down-regulation to reserve the maximum rotational kinetic energy, whilst other strategies lower the rotor speed for reducing the fatigue...
of some turbine components and noise reduction [9]. Thus, such various de-rating strategies inevitably influence the system observability.

Therefore, the essence of this paper is to understand the system observability of wind turbines in down-regulation. The contribution is twofold. Firstly, the system observabilities of turbines with various down-regulation control strategies are investigated via the use of the empirical observability Gramian, revealing under what de-rating strategies, the degree of estimating the wind speed is the worst. Secondly, the correlation between the degree of observability derived from the empirical observability matrix and the estimation error based on an extended Kalman filter is studied. From the industrial perspective, the outcome of these studies could demonstrate some inherited drawbacks of some down-regulation strategies in state estimation and justify the need for installing additional sensors.

The remainder of this paper is structured as follows. Section 2 describes the preliminaries on the modelling, basic controller and down-regulation strategies. Section 3 provides the definition of observability and the analysis of the observability measures upon various control strategies, which are the key results in this work. In Section 4, the design of extended Kalman filters is presented. Subsequently, Section 5 demonstrates the simulation results to verify the observability measures. Finally, it is followed by conclusions in Section 6.

2. Background

2.1. Control-oriented modelling

Typically, model-based state estimation requires a simplified model of the nonlinear system. The simplified model needs to capture the key dynamics of the turbine. In this study, a nonlinear turbine system model, that includes the dynamics of the rotor drive-train (1a) and wind speed (1c), is employed.

Firstly, the dynamics of the rotor speed \( \omega(t) \in \mathbb{R} \) is defined as follows:

\[
J \dot{\omega}(t) = \tau_a(\lambda, \theta) - \tau_g(t),
\]

where \( J \in \mathbb{R} \) denotes the moment of inertia of the drive-train, the aerodynamics and generator torques are \( \tau_a : \mathbb{R} \times \mathbb{R} \to \mathbb{R} \) and \( \tau_g(t) \in \mathbb{R} \), respectively, whilst \( \theta(t) \in \mathbb{R} \) is the pitch angle of the blades and the tip-speed ratio \( \lambda(t) \in \mathbb{R} \) is defined as follows:

\[
\lambda(t) = \frac{\omega(t) R}{v(t)},
\]

where \( R \in \mathbb{R} \) denotes the turbine blade length and \( v(t) \in \mathbb{R} \) is the wind speed.

Secondly, the dynamics of the wind speed \( v_k \in \mathbb{R} \) is assumed to be a random walk process and driven by a zero-mean white noise, defined as follows:

\[
v_{k+1} = v_k + n_k, \quad n_k \sim \mathcal{N}(0, \sigma^2_n),
\]

where the subscript \( k \in \mathbb{Z}^* \) denotes the sample time and \( n_k \) is the white Gaussian noise with zero mean and standard deviation \( \sigma_n \in \mathbb{R} \). Notice that the frequency spectrum of a typical wind signal might be different to the spectrum of the output from the random walk model. However, the model (1c) is sufficient to capture the slow dynamics of the wind [10].

Finally, the discrete-time nonlinear turbine model can be constructed based on (1a) and (1c):

\[
\begin{align*}
x_{k+1} &= f(x_k, u_k) + w_{n,k}, \\
y_k &= h(x_k, u_k) + v_{n,k},
\end{align*}
\]

where \( x_k = [\omega_k, v_k]^T \in \mathbb{R}^{n_x} \) denotes the system state vector, whilst \( u \in \mathbb{R}^{n_u}, y \in \mathbb{R}^{n_y} \) are the system input and output vectors. The state transition and output functions are denoted as \( f : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \to \mathbb{R}^{n_x}, h : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \to \mathbb{R}^{n_y} \). The process and measurement noises are linearly added to the system and denoted as \( w_{n,k} \in \mathbb{R}^{n_x}, v_{n,k} \in \mathbb{R}^{n_y} \), respectively.
2.2. Turbine controller and down-regulation strategies

2.2.1. Basic turbine controller  Basic wind turbine controllers are typically consisted of the generator torque and blade pitch controllers. The generator torque control law is defined as follows:

\[ \tau_g(t) = \begin{cases} K_{\text{opt}} \omega(t)^2, & \text{if } \theta(t) \leq \theta_s, \\ \frac{P_{\text{rated}}}{\omega(t)}, & \text{if } \theta(t) \geq \theta_s, \end{cases} \]  

(3a)

(3b)

(3c)

\[ \tau_g(t) \in [\tau_g^\text{min}, \tau_g^\text{max}], \]

The operating conditions are dependent on the switching parameter of the pitch angle \( \theta_s \). In below-rated wind condition (3a), the generator torque controller maximises the turbine power by tracking the optimal tip-speed ratio with the optimal gain \( K_{\text{opt}} \in \mathbb{R} \), whilst in the above-rated wind condition (3b), the controller maintains the power at the rated value \( P_{\text{rated}} \in \mathbb{R} \). The generator torque is constrained by the minimum and maximum limits denoted as \( \tau_g^\text{min}, \tau_g^\text{max} \in \mathbb{R} \).

For brevity, the aspects of how the controller (3) handles transitions around the start-up and the rated rotor speed are omitted from this paper and more details can be found in [11].

The blade pitch controller is typically designed as a gain-scheduled proportional-integral (PI) controller, defined as follows:

\[ \theta(t) = f_{\text{PI}}(\omega(t) - \omega_{\text{rated}}), \quad \theta \in [\theta_{\text{min}}, \theta_{\text{max}}], \]

(4)

The PI control law \( f_{\text{PI}} : \mathbb{R} \rightarrow \mathbb{R} \) drives the rotor speed to the rated value \( \omega_{\text{rated}} \in \mathbb{R} \) and typically, it is gain-scheduled by the pitch angle (e.g. [11]), whilst the pitch angle is limited by \( \theta_{\text{min}}, \theta_{\text{max}} \in \mathbb{R} \).

2.2.2. Down-regulation strategies  The power produced by a turbine is the generator torque times the generator speed. Down-regulation can be achieved by either manipulating the generator torque or rotor speed set-point [8]. Therefore, two types of methods are considered in this work: torque-based and rotor-speed-based down-regulation strategies.

Definition 2.1  Torque-based down-regulation strategy  The torque-based strategy performs turbine down-regulation by changing the generator torque input solely. One of the benefits of such a strategy is that during power curtailments, the rotor speed is operating at rated and thus reserving the maximum amount of spinning energy for providing fast frequency response support to the grid [12]. To implement the torque-based strategy, a new maximum torque limit \( \bar{\tau}_g^{\text{derated}} \in \mathbb{R} \) is imposed on the generator torque in (3c), defined as follows:

\[ \bar{\tau}_g^{\text{derated}} = \frac{P_{\text{derated}}}{\omega_{\text{rated}}}, \]

(5)

where \( P_{\text{derated}} \in \mathbb{R} \) denotes the derated power set-point.

Definition 2.2  Rotor-speed-based down-regulation strategy  In this strategy, down-regulation is performed by defining the rotor speed set-point and the generator torque is updated accordingly. There are numerous advantages to this strategy. For example, the turbines operating in lower rotor speed produce lower noise and also lower fatigue loads on the tower [9]. To perform the rotor-speed-based strategy, the original rated rotor speed and generator torque limit needs to be modified as follows:

\[ \omega_{\text{derated}} = \sqrt[3]{\frac{P_{\text{derated}}}{K_{\text{opt}}}}, \quad \bar{\tau}_g^{\text{derated}} = \frac{P_{\text{derated}}}{\omega_{\text{derated}}}, \]

(6)
Figure 1: Operational steady-states of various control strategies on the $C_p$ surface.

Figure 2: Comparison of the simplified nonlinear turbine model with HAWC2 under a turbulent wind case.

Figure 1 depicts the operating trajectories of the normal and down-regulation strategies under various wind conditions. At low wind speeds, three trajectories are identical with high tip-speed ratios and optimal pitch angles. In contrast, at high wind speeds, the trajectories are different based on the control strategies. As a result, the system observabilities are likely to be different upon the types of down-regulation strategies and it is of interest to this study.

In addition, in Figure 2, the simplified nonlinear turbine model (2) is compared with the aeroelastic turbine simulation tool (HAWC2 [13]), which contains more than 1000 states and can handle flexible blades and structures. Both simulations are conducted under the same turbulent wind field. As shown in Figure 2, there is a small modelling error for all operations, which could be mainly due to the $C_p$ surface obtained from steady-state simulation.

3. Observability: definition and analysis

In this section, the basic definitions of observability and its analytical tools for linear and nonlinear systems are presented. Subsequently, it is followed by the key results of this work, which is the assessment of the observability measures for turbines under different down-regulating strategies.

3.1. Fundamentals of observability

In linear system theory, a system is observable if the complete internal state of the system can be reconstructed from the system output and input. Considering a linear discrete-time
time-invariant system:

\[ x_{k+1} = Ax_k + Bu_k, \]  
\[ y_k = Cx_k + Du_k, \]  

the observability analysis is typically conducted based on examining the rank deficiency of the observability matrix \( O \in \mathbb{R}^{ny \times nx} \), defined as follows:

\[ y_k = [C, CA, CA^2, \ldots, CA^{nx}]^T x_k. \]  

where \( y_k := [y_k, \ldots, y_{k+n_x-1}]^T \in \mathbb{R}^{ny \times nx} \). However, this method only reveals whether the system state is observable but no information about how easy the state can be estimated. Alternatively, the observability Gramian \( W_{o, \text{linear}} \in \mathbb{R}^{nx \times nx} \) is used, defined as follows:

\[ y_k^T y_k = x_k^T O^T O x_k = x_k^T W_{o, \text{linear}} x_k, \]  
\[ W_{o, \text{linear}} = \sum_{m=k_0}^{k_1} (A^T)^m C^T C A^m. \]  

Similar to (8), the system is observable if the observability Gramian in (9) has full rank. More importantly, the state-to-output behaviour is captured in the Gramian (9) and it reveals much important information, for example, the relative difficulty of the state estimation and in which direction. Thus, singular value decomposition of the Gramian is investigated to evaluate the system observability.

One measure of observability is the estimation condition number \( \mu = \sigma_{\text{max}} / \sigma_{\text{min}} \), which is a ratio of the largest singular value \( \sigma_{\text{max}} \) to the smallest \( \sigma_{\text{min}} \). If the condition number is large, the estimation problem is ill-conditioned. In other words, the effect on the output of a small change in the state in most observable direction (singular vector) overwhelms the effect on the output caused by a change in another direction. In general, a small estimation condition number implies it is relatively easier to estimate the state from the measurements and control input.

3.2. Empirical observability gramian

However, the wind turbine model in (2) is a nonlinear system. Observability analysis of a nonlinear system is challenging and computationally expensive. Derivation of the observability Gramian for such a system is less straightforward. One possibility is to linearise the nonlinear system around an operating point and derive the linear observability Gramian as shown in (9). However, linearisation may not adequately capture the behaviour of the nonlinear system over an operating region. Another possibility is to derive the nonlinear observability matrix by using Lie derivative but this can be complicated even for a simple system.

One practical alternative is to use the empirical observability Gramian [16], which is an analytical tool to access the (local) observability of nonlinear systems. The benefits of empirical Gramian is that it can be computed based solely upon simulating the observed dynamical system. In other words, the Gramian can be constructed by measuring the degree of excitation on the output caused by each state.

To compute the Gramian, firstly, a set of state with its initial value \( (x_k^{m,i}) \) is systematically perturbed as follows:

\[ x_k^{m,i} = x_k^0 + \epsilon_{m,i} e_j, \]  

where \( \epsilon_{m,i} \) is a perturbation factor. Then, the empirical Gramian is calculated using:

\[ W_{o, \text{empirical}}(m,i) = \frac{1}{N} \sum_{n=1}^{N} y_n^T y_n, \]  

where \( N \) is the number of observations and \( y_n \) is the output at time \( n \).
Figure 3: The simulation outputs of the nonlinear turbine systems with various operational strategy and in down-regulation, the turbine is operating at 50% of the rated power. The outputs are caused by perturbations at each state in the positive \( (x^i) \) and negative \( (x^-i) \) directions. The left and right columns show the simulations with perturbations in the first and second state.

where \( x^0 \in \mathbb{R}^{n_x} \) denotes the nominal (unperturbed) state, \( e_i \in \mathbb{R}^{n_x} \) is the standard unit vector and \( \epsilon_{m,i} \in \mathbb{R} \) is the perturbation. The index \( i \in \mathbb{Z}^* \) is indicating which state is perturbed and the index \( m \in \mathbb{Z}^* \) is for selecting the size and direction (positive or negative) of the perturbation.

Subsequently, once the outputs \( y^{m,i}_k \in \mathbb{R}^{n_y} \) are collected, we normalise and sum up the difference between the perturbed output \( y^{m,i}_k \) and nominal output \( y^0_k \in \mathbb{R}^{n_y} \) as follows:

\[
\delta y_k := \frac{1}{M} \sum_{m=1}^{M} \frac{1}{\epsilon_{m,i}} (y^{m,i}_k - y^0_k),
\]

Finally, the Gramian at time step \( k \) is defined as follows:

\[
W_k = \begin{bmatrix}
(\delta y^1_k)^T \delta y^1_k & (\delta y^1_k)^T \delta y^2_k & \cdots & (\delta y^1_k)^T \delta y^{n_x}_k \\
(\delta y^2_k)^T \delta y^1_k & (\delta y^2_k)^T \delta y^2_k & \cdots & (\delta y^2_k)^T \delta y^{n_x}_k \\
\vdots & \vdots & \ddots & \vdots \\
(\delta y^{n_x}_k)^T \delta y^1_k & (\delta y^{n_x}_k)^T \delta y^2_k & \cdots & (\delta y^{n_x}_k)^T \delta y^{n_x}_k
\end{bmatrix},
\]

and the empirical observability Gramian over a finite time interval \( k \in [k_0, k_t] \) is computed as follows:

\[
W = \sum_{k=k_0}^{k_t} W_k \delta t_k,
\]
where $\delta t_k \in \mathbb{R}$ denotes the sampling time. Notice that the key benefit of using empirical Gramian in (13) over the observability Gramian obtained by linearisation is that the empirical Gramian in (13) maps state-to-output behaviours of a nonlinear system more accurately. In addition, for linear systems, the empirical Gramian coincides with the linear observability Gramian (9).

Now, the estimation condition number $\mu$ for the turbine nonlinear system (2) operating in each control strategy can be computed using the largest and smallest singular values of the empirical Gramian (13).

### 3.3. Observability analysis upon turbine down-regulating operations

This section presents the key results of this work, examining the observability Gramians for the nonlinear turbine system under normal and down-regulating operations.

Following the procedure in Section 3.2, simulations of the nonlinear model (2) were conducted with different perturbed states. For example, Figure 3 shows the output of the nonlinear turbine model (2) caused by perturbed state at operating wind speed 8 m/s with different control strategies. The perturbation size is chosen to be 0.01 for the rotor speed state and 0.1 for the wind speed state.

Similarly, a set of empirical observability Gramians was computed for each wind speed case $v_{op} = \{4, \ldots, 12\} \in \mathbb{Z}$. For down-regulating cases, the power set-point is at 50%. The estimation condition numbers are shown in Figure 4. Firstly, the overall trend is that with higher wind speed, the condition numbers become worse (larger) for all control strategies. Secondly, the torque-based down-regulation strategy possessed the worst degree of observability. This indicates the reconstruction of effective wind speed is relatively difficult based on the information of the rotor speed and control inputs. Notice that only the below-rated wind region is covered because the focus of this work is to use the effective wind speed for calculating the power reserve in the wind.

### 4. Extended Kalman filter design

This section presents an estimator design based on a celebrated Kalman filtering approach [17] for the purposes of validating the proposition made in the earlier section.

A Kalman filter is a computationally efficient and recursive algorithm that provides the optimal state estimates $\hat{x}_k \in \mathbb{R}^{n_x}$ of a linear system by minimising the mean square state error, also known as the state error co-variance matrix $P_k := E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]$. Since the turbine model in this work is a nonlinear model (2), an extended Kalman filter (EKF) is employed to estimate the states, namely, the rotor speed and wind speed. The EKF is similar to standard Kalman filter except that it computes the estimates based on the nonlinear equations and determines the state co-variance matrix $P_k$ by linearising the system around the current state estimate.

Typically, an EKF design consists of two steps: prediction and measurement update. The superscripts $x^+_k, x^-_k$ are denoted as the variable $x$ at sample time $k$ after the measurement update and before the measurement update, respectively. The discrete time EKF based on the model in (2) is defined as follows:

\begin{align}
\text{Prediction} : \\
\hat{x}_k^- = f(\hat{x}_{k-1}^+, u_k), & \quad P_k^- = F_k P_{k-1}^+ F_k^T + Q_k, \quad F_k := \frac{\partial f(\hat{x}_{k-1}^+)}{\partial x}, \\
\text{Measurement update} : \\
\hat{y} = h(\hat{x}_k^-, u_k), & \quad \hat{x}_k^+ = \hat{x}_k^- + L_k (y_k - \hat{y}^-), \quad P_k^+ = (I - L_k H_k) P_k^- , \quad H_k := \frac{\partial h(x_k^-)}{\partial x},
\end{align}

(14a) (14b)
where $L_k \in \mathbb{R}^{n_x \times n_y}$ is the filter grain and it is computed as follows:

$$L_k = P^{-1}_k H_k^T (H_k P^{-1}_k H_k^T + R_k)^{-1}, \quad (14c)$$

where $Q_k \in \mathbb{R}^{n_x \times n_x}$, $R_k \in \mathbb{R}^{n_u \times n_u}$ are the co-variance matrices of the process and measurement noises, respectively, that can be computed as $Q_k = E[w_n, w_n^T]$, $R_k = E[v_n, v_n^T]$. The process co-variance $Q_k$ is chosen by approximating the variance of the modelling error and the typical wind speed. In this study, the measurement noise is not considered. Therefore, the measurement co-variance $R_k$ is chosen to be smaller than the process co-variance $Q_k$ by a few orders of magnitude.

5. Simulation results

Simulation results are presented in this section to validate the studies of estimation condition number in Section 3 and also investigate the estimation performance for different operating strategies.

The reference turbine model is the DTU10MW [18] and the aeroelastic simulation code is HAWC2 [13]. The EKF based on the turbine model (2) was implemented together with the open-source DTU Basic Controller\(^1\). The focus of this study is on calculating the power reserve based on the wind estimate, that is particularly important in the below-rated wind region. Thus, two turbulent wind cases with mean wind speeds of 8 m/s (in the middle of the below-rated region) and 11 m/s (around the rated wind speed transition) were considered. Both turbulent intensities were based on IEC standard Class B [19].

5.1. Rotor effective wind speed estimation

Figure 5 shows the effective wind speed estimations under both turbulent wind cases. The baseline is the spatially-averaged wind speed, collected from 9 points across the rotor-plane. Three estimates were shown. The first one was the wind speed estimation in normal operation, whilst the other two were the estimations in down-regulation. The down-regulating turbines were operating at 50% of the rated power. In $v_{\text{op}} = 8$ m/s, the estimate from torque-based down-regulating turbines was less accurate than the estimates of the other two strategies, which confirms the observability study. In addition, comparing two figures, the discrepancy between the estimates of all strategies became larger in the high wind speed case. That indicates it is relatively harder to achieve good estimation near or above rated wind region.

1 \(https://gitlab.windenergy.dtu.dk/OpenLAC/BasicDTUController\)
5.2. Power reserve estimation

Next, the wind estimate was employed to compute the power reserve in the wind. A simple mapping between the power and wind estimate $\hat{v}$ is employed, defined as follows:

\begin{align}
\hat{P}(t) &= 0.5\rho \pi R^2 \hat{v}(t)^3 n_{\text{eff}} C_{p,\text{max}}, & \text{if } P_{\text{est}}(t) \leq P_{\text{rated}}, \tag{15a} \\
\hat{P}(t) &= P_{\text{rated}}, & \text{if } P_{\text{est}} > P_{\text{rated}}, \tag{15b}
\end{align}

where $C_{p,\text{max}} \in \mathbb{R}$ denotes the maximum power co-efficient whilst $\rho, n_{\text{eff}} \in \mathbb{R}$ denote the air density and generator efficiency. The baseline is the instantaneous power in normal operation. If the discrepancy between the actual power and its estimate is small, that implies the down-regulating turbines are able to provide the reserved amount of power accurately when needed.

Figure 6 shows the time series of the power estimates calculated based on (15). For turbines in normal operations, there were good matches between the true power reserve and its estimate in both turbulent wind field. In contrast, the power estimate in the torque-based down-regulation was the worst among other strategies. The mismatch became severer in higher wind speed.

5.3. Error histogram

Figure 7 illustrates the histograms of estimation errors in wind speed and power in both wind cases. Table 1 summarises the means and standard deviations of the errors in the wind speed and power estimates. As expected, the estimation errors in the torque-based down-regulation have a greater degree of dispersion for both wind speed and power estimates. In addition, large peaks at the 0% power estimation error were contributed by the estimate power greater than the rated power. Amongst all strategies, it is clear that the power estimation error for torque-based down-regulation case could be up to $\pm 10\%$. The simulation results are coherent with the observability analysis in Section 3. Additional measurements or better modelling might be needed to improve the observability of the torque-based down-regulation strategy.

One interesting observation is that the wind estimate in normal operation was slightly biased. However, such bias did not reflect in the error of the power estimate under normal operation. This leaves a question whether the spatially-averaged wind speed is a good baseline. The better candidate might be the spatially-weighted wind speed or the wind speed obtained by inverting the power law.
Figure 6: Time series of the normal power and estimated available power under different control strategies. The left and right plots indicate the results in turbulent wind cases with a mean wind speed of 8 m/s and 11 m/s, respectively.

Figure 7: Histograms of the errors in both turbulent wind cases under different control strategies. The left and right plots show the estimation errors in the wind speed and power, respectively.

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<th>Error in power estimation</th>
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Table 1: Summary of estimation errors in wind speed and power in various control operations.
6. Conclusions and future work
In this work, the observability analysis of turbines operating upon various normal and down-regulating operations was presented, examining the relative difficulty of estimating the effective wind speed from the turbine measurements. Based on these insights, the extended Kalman filters were proposed to reconstruct the wind speed based on measurements of the rotor speed. Analytical and simulation results were presented that showed for turbines operating in the torque-based down-regulation strategy, the measure of observability and estimation errors were the worst amongst other strategies. Future work will look to the possibility of improving the power reserve estimation by adding additional sensors and improving the model.

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References