A Novel Frequency Regulation Control Method for Deloaded Wind Turbines

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Abstract

The recent proliferation of converter-based power generating systems used within renewable energy sources has increased the need to consider how renewable energy sources, including wind turbines, may participate in ancillary services to ensure the security of the power grid. In this paper, we discuss a modern control methodology known as exact output regulation (EOR) and investigate its application to the problem of wind turbine provision of grid frequency support services. The EOR method assumes that both wind preview information from LIDAR measurements and the power demand curve from the grid are available in the design of the turbine control law. Our simulation study will compare the performance of EOR with a baseline controller, for the tracking of a time-varying power demand curve. Our work focuses on region 3 wind signals, however it has the capability to extend to other wind speed region. The simulations will employ the FAST simulator for a 5MW wind turbine, with wind signals generated by TurbSim. The simulations show that the LIDAR-enhanced EOR method has the potential to substantially improve power demand tracking performance, relative to a baseline controller.

1 Introduction

Wind turbines are important technologies in the generation of electricity with the goal of reducing carbon emissions. However, the rapid growth of renewable energy generation is displacing synchronous power sources, leading to grid stability issues arising from the mismatch between power supply and demand. Such imbalances cause regulation problems, as the frequency deviates from the normal operating value. Frequency regulation has been deteriorating in recent years due to the proliferation of renewable energy systems (RES) and many other factors [4].

Grid events occur when there is loss of generation or increase in demand causing a mismatch between supply and demand, with insufficient supply leading to a fall in system frequency, and increased frequencies arising from excess of power supply. These responses can be categorized in different groups such as inertial, primary, secondary and tertiary responses [14].

The inertial response, typically lasting less than 10 seconds, of a synchronous generator refers to its capacity to respond to sudden increase in load or loss of generation elsewhere. The generator responds by releasing stored kinetic energy in the turbine [3]. After the immediate inertial response, three control phases are employed to reestablish the normal operating frequency. For between 10
and 60 seconds after the grid event, primary frequency control (droop control) is used to improve the frequency nadir [17, 16, 13]. After 60 seconds, the secondary response aims to increase the frequency to its normal operating level. This is done through automatic generation control (AGC) in which the transmission system operator (TSO) coordinates the power set points of multiple generators. The tertiary response to reestablish operating frequency involves the TSO calling on tertiary reserves to provide additional power generation or reduce consumption.

Renewable energy providers usually operate in a “take-all” fashion in which all their power generation is supplied to the grid, unless circumstances demand curtailment. To date there has been little participation of wind turbine operators in the provision of frequency control ancillary services (FCAS). However, the problem has been the subject of ongoing academic research, and papers proposing control methods for turbines to participate in AGC include [1, 2, 7]. A survey of recent efforts to investigate the potential for the participation of renewables in the provision of FCAS was given by [5] and concluded that further research was required for renewables to provide effective and robust frequency regulation.

In this work we address the problem of controlling the turbine operation so that the turbine power output tracks a power demand signal, specified by the market operator. The signal is assumed to take step values within a known power range. Our performance measure will be the rms error of the power generation, being the difference between the power command signal and the actual power generated.

To address this problem, we investigate the performance of a control methodology known as exact output regulation (EOR) for a wind turbine operating in Region 3 wind speeds. The EOR method has been widely studied in the control systems literature for several decades [15] however an investigation of its suitability for the control of wind turbines was only recently conducted in [11]-[12]. LIDAR wind preview information was used to model the wind signal as a low-order linear dynamical system. This linear system may then be incorporated into the EOR control methodology as an exosystem whose outputs provide the input disturbance and the output reference signal. The method was shown to be able to substantially reduce turbine fatigue loads, without compromising the power production, in comparison with conventional baseline control methods.

The EOR method assumes a plant model in the form of a system of differential equations is available for controller design, and this formulation naturally accommodates multiple-input-multiple-output (MIMO) control problems. The methodology can accommodate both the tracking of specified reference signals, and also the rejection of known disturbance signals. Hence it is well-suited to the region 3 operation of a 5 MW turbine, where torque and blade pitch angle control inputs are simultaneously used. The tracking of a known power command signal is an output regulation problem, and minimising the load fatigue impact of the wind variations on the tower and blades is a disturbance rejection problem. While the focus of the present paper is for wind speeds in Region 3, the EOR method has the potential for application to Region 2 wind speeds also.

The performance of EOR will be compared against the conventional wind turbine controller used in power demand tracking presented in [7], in which an open-loop torque control law is combined with gain-scheduling PI control for the pitch angle. The turbine response will be simulated with the NREL FAST 7 simulator [10] for a 5 MW wind turbine, with wind signals generated by TurbSim [8]. We will compare the ability of the two methods to accurately track a specified power demand curve. The root-mean-squared error of the power outputs obtained from two methods will be used to measure the accuracy of their power regulation. Additionally, we compare the actuator usage for the two methods.

The paper is organised as follows. In Section 2, we describe the fundamentals of turbine power generation and develop the turbine model to be used in this paper. In Section 3 we provide a summary
of the EOR control methodology. In Section 4 we describe how the EOR may be applied to a wind turbine for the problem of tracking a power demand signal. We also describe the baseline controller that will be used as a benchmark for performance comparisons. Section 5 describe our turbine simulation environment and provides the performance comparison of the two control methods.

2 Wind turbine Power Generation and Modelling
In this section we describe the power tracking problem we will investigate, and also develop our wind turbine model that will be used for the EOR controller design.

2.1 Power generation and power command signal
The quantity of power generated by a wind turbine depends on the rotor speed $\Omega_r$ and blade pitch angle $\theta$. The tip speed ratio (TSR) is the ratio of the speed of the tip of the blade to the wind speed, and is denoted by $\lambda$. The power co-efficient $C_p$ represents the fraction of the available wind power extracted by the wind turbine, and is determined by $\lambda$ and $\theta$.

Figure 1 shows the $C_p$ surface for a 5MW wind turbine [11].

![Figure 1. Power coefficient surface $C_p(\lambda, \theta)$ [11]](image)

We assume the power command signal to be generated by the turbine is of the form [2]:

$$P_{cmd}[n] = P_S + P_{AGC}[n],$$  \hspace{1cm} (1)

where $n$ is the time index. The power schedule $P_S$ takes a constant value, and the time-varying AGC power signal $P_{AGC}$ takes step values within the range $[-R^D, R^U]$. The rms error in the power generation tracking performance is

$$RMSE = \sqrt{\frac{\sum_n (P_{gen}[n] - P_{cmd}[n])^2}{N}},$$  \hspace{1cm} (2)

where $N$ is the number of time samples.

2.2 Low order nonlinear Wind turbine model
The fifth order nonlinear model of a wind turbine, describing the drive-train considered as two mass system could be modelled as in (3)-(6) [12]:

...
\[ J_r \dot{\Omega}_r = -C_d(\Omega_r - \Omega_g) - K_d\phi + M_a(\Omega_r, v_x, \theta). \]  

\[ \dot{\phi} = \Omega_r - \Omega_g. \]  

\[ J_g \dot{\Omega}_g = C_d(\Omega_r - \Omega_g) + K_d\phi - M_g \]  

\[ \dot{\theta} = -2\zeta\omega\theta + \omega^2(\theta_c - \theta), \]  

where \( \Omega_r, \Omega_g, \phi \) and \( \theta \) are the rotor speed, generator speed, drive train torsion and blade pitch angle, respectively. The control inputs are the generator torque \( M_g \) and blade pitch control input \( \theta_c \). \( J_r \) and \( J_g \) are the moment of inertia for the rotor and generator. \( C_d \) and \( K_d \) are the drive train damping and stiffness coefficient. \( \zeta \) and \( \omega \) are the blade pitch actuator damping parameter and undamped natural frequency. \( M_a \) is aerodynamic torque of the rotor, given by

\[ M_a(\Omega_r, v_x, \theta) = \frac{1}{2} \rho \pi R^3 C_p(\lambda, \theta) \lambda v_x^2. \]  

where \( v_x \) is the horizontal component of the wind speed, \( \rho \) is the air density and \( R \) is the blade radius. Also \( \Omega_g \) has been normalized for the gearbox ratio \( i \) so that it is in the same range as \( \Omega_r \). Values for all of these parameters for a 5 MW turbine are given in [9] and [12].

### 2.3 Linearized Turbine Model

To obtain a linearized turbine model we introduce \( x = [\Omega_r \quad \phi \quad \Omega_g \quad \theta \quad \dot{\theta}]^T \) as the state variable vector and \( u = [\theta_c \quad M_g]^T \) as the control input. The input wind disturbance \( d = v_x \) generates the aerodynamic torque \( M_a \) that creates undesirable oscillations on the blades and tower. For a given mean horizontal wind speed \( v_x^* \) in Region 3, we seek an equilibrium point \((x^*, u^*, d^*)\) that satisfies

\[ \dot{x}^* = f(x^*, u^*, d^*) = 0, \]

where the nonlinear mapping \( f : \mathbb{R}^5 \rightarrow \mathbb{R}^5 \) represents the turbine dynamics (3)-(6).

Since we assume Region 3 operation, we use \( \Omega_r^* = \Omega_{r,\text{rated}} \) and obtain equilibrium TSR \( \lambda^* \) from

\[ \lambda^* = -\frac{\Omega_r^* R}{v_x^*}. \]

Then \( \theta^* \) is obtained from the power coefficient surface presented in Figure 1, such that

\[ C_p^*(\lambda^*, \theta^*) = \frac{P_g}{P_{\text{wind}}}, \]

where \( P_{\text{wind}} = \frac{1}{2} \rho A_R v_x^2 \) and \( A_R \) is the blade swept area. We evaluate \( M_a^*(\Omega_r^*, v_x^*, \theta^*) \) from (7), and the remaining equilibrium values are given by

\[ \phi^* = -\frac{M_a^*}{K_d}, \quad \Omega_g^* = \Omega_r^*, \quad \theta_c^* = \theta^*, \quad M_g^* = M_{a,\text{rated}}^*, \quad d^* = v_x^*. \]

After obtaining Jacobian system matrices at the equilibrium point, the linearized state space model in homogenised coordinates is

\[ \dot{x}(t) = Ax(t) + Bu(t) + H\bar{d}(t), \]

where \( x \) is the state vector, \( A \) is the state matrix, \( B \) is the input matrix, \( H \) is the disturbance matrix, and \( \bar{d} \) is the disturbance vector.
where $\tilde{x} = x - x^*$, $\tilde{u} = u - u^*$ and $\tilde{d} = d - d^*$ represent coordinates homogenised to the equilibrium point. The state matrices are

$$A = \begin{bmatrix}
\frac{(\gamma - C_d)}{J_e} & -\frac{K_d}{J_e} & \frac{C_d}{J_e} & \frac{\beta}{J_e} & 0 \\
1 & 0 & -1 & 0 & 0 \\
\frac{C_d}{J_e} & \frac{K_d}{J_e} & -\frac{C_d}{J_e} & 0 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & -\omega^2 & -2\zeta\omega
\end{bmatrix}, \quad B = \begin{bmatrix}
0 & 0 \\
0 & 0 \\
0 & \frac{1}{J_e} & 0 \\
0 & 0 & 0 \\
0 & \omega^2 & 0
\end{bmatrix}, \quad H = \begin{bmatrix}
\alpha \\
0
\end{bmatrix}, \quad \gamma \quad (13)$$

where $\gamma$, $\beta$ and $\alpha$ are given by evaluating the partial derivatives

$$\gamma = \frac{\partial M_a}{\partial \Omega_r}(x^*, u^*, d^*), \quad \alpha = \frac{\partial M_a}{\partial v_x}(x^*, u^*, d^*), \quad \beta = \frac{\partial M_a}{\partial \theta}(x^*, u^*, d^*). \quad (14)$$

### 3 The EOR control methodology

EOR methodology for a linear time-invariant multivariable system is shown in the block diagram of Fig 2. The plant is assumed to be described by state equations involving plant state $x$, control input $u$, and plant output $z$. A known linear time-invariant exosystem $\Sigma_{exo}$ with state $w$ generates the autonomous time-varying reference signal $r$ and input disturbance signal $d$. The error signal $e = z - r$ represents the difference between the plant output and the reference.

![Block diagram of EOR control methodology for wind turbines](image)

**Figure 2.** Block diagram of EOR control methodology for wind turbines [12]

The plant dynamics are given by

$$\Sigma_{plant} : \begin{cases}
\dot{x}(t) = Ax(t) + Bu(t) + Hd(t), & x(0) = x_0 \\
z(t) = Cx(t) + Du,
\end{cases} \quad (15)$$

and the exosystem is described by

$$\Sigma_{exo} : \begin{cases}
\dot{w}(t) = Sw(t), & w(0) = w_0 \\
d(t) = L_dw(t) \\
r(t) = L_rw(t)
\end{cases}. \quad (16)$$

Here $S$ represents the exosystem dynamics and $w$ is the state of the exosystem. Output matrices $L_d$ and $L_r$ construct the disturbance and reference signals from the exosystem states. By defining

$$E_w = HL_d \quad (17)$$

$$D_w = -L_r \quad (18)$$
we combine the plant and exosystem dynamics to obtain the augmented system $\Sigma_{\text{aug}}$:

$$\Sigma_{\text{aug}} : \begin{cases} 
    \dot{x}(t) &= Ax(t) + Bu(t) + E_{w}w(t), \\
    \dot{w}(t) &= Sw(t), \\
    e(t) &= Cx(t) + Du + D_{w}w(t). 
\end{cases} \tag{19}$$

A feedback controller $u$ for the system $\Sigma_{\text{aug}}$ is said to achieve exact output regulation [15] if the closed-loop system is internally stable and, for all initial states $x_0$ and $w_0$ of the plant and exosystem, the error signal satisfies $\lim_{t \to \infty} e(t) = 0$. Ensuring the error signal vanishes means that the input disturbance is asymptotically rejected, and the controlled output $z$ asymptotically tracks the desired reference signal $r$.

For the case where all states $x$ are measurable, a state feedback controller law

$$u = Fx + Gw \tag{20}$$

may be used to reject the disturbances and track the reference signal according to the following theorem: [15] Assume system $\Sigma_{\text{aug}}$ in (15) satisfies the following assumptions

(A.1) The pair $(A, B)$ is stabilizable and matrix $S$ is anti-Hurwitz-stable.

(A.2) There exist matrices $\Gamma$ and $\Pi$ satisfying

$$P\Pi = A\Pi + B\Gamma + E_{w} \tag{21}$$

$$0 = C\Pi + D_{w} \tag{22}.$$ 

Let $F$ be any matrix such that $A + BF$ is Hurwitz stable, and let $G = \Gamma - F\Pi$. Then the state feedback control law $u = Fx + Gw$ achieves exact output regulation for $\Sigma_{e}$.

The Sylvester matrix equations (21)-(22) are known as the regulator equations and generic solvability conditions are given in [15]. The matrix $S$ is anti-Hurwitz stable if none of its eigenvalues are stable. In fact, this assumption is not essential and was adopted in [15] only to avoid a trivial problem formulation in which output regulation is achieved by default because the exosystem states vanish.

(21),(22) can be applied to the discrete time version of (19)

4 Turbine Control Methodologies

Here we briefly introduce the two control methodologies considered in this study. Firstly we adapt the EOR controller for a wind turbine, and then describe the baseline active power generation controller given in [7] that will be used for our performance comparison.

4.1 EOR control for turbine AGC capability

Here we describe the adaption of the EOR control methodology to improve wind turbine AGC capability. The performance objectives are to achieve a power output that tracks a specified power demand curve, while also minimising the undesirable oscillations on the blades and tower caused by the wind disturbance.

First we extend adapt and extend the turbine model of Section 2.2 into the form (15). We assume a Region 3 mean horizontal wind speed $v_{x}^{*}$, with corresponding equilibrium point $(x^{*}, u^{*}, d^{*})$. We employ the same homogenised state, control and disturbance variables $\bar{x}$, $\bar{u}$ and $\bar{d}$ given in (12), and use state matrices $A$, $B$ and $H$ obtained in (13). For implementation we will use a digital controller, and hence work with a discretized plant model.
To track a power command curve, we will take as our reference signal $r$ to be the blade pitch angle and rotor torque. Thus in (15), we have

$$z = \begin{bmatrix} \theta \\ M_g \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad D = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}. \quad (23)$$

Our exosystem dynamics $S$ will be comprised of three separate dynamics, labelled as $S_1$, $S_2$ and $S_3$, with state vectors $w_1$, $w_2$, and $w_3$ respectively. The first subsystem will model the horizontal wind signal $v_x$. The second subsystem will model the blade pitch angle $\theta$ and the third subsystem models the generator torque $M_g$ required to track the power command signal. We then combine these matrices and state vectors into block diagonal form

$$S = \begin{bmatrix} S_1 & 0 & 0 \\ 0 & S_2 & 0 \\ 0 & 0 & S_3 \end{bmatrix}, \quad w = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \quad (24)$$

The disturbance and reference signals are the first components of each of these vectors so

$$L_d = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad L_r = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \quad (25)$$

yield (16). Finally defining

$$E_w = [H L_d \ 0], \quad D_w = [0 \ -L_r]$$

we obtain (19). These exosystem dynamics will be modeled in the form of a third-order difference equations, for $i = 1 \ldots 3$, as follows:

$$w_i[n+1] = a_{i,1}w_i[n] + a_{i,2}w_i[n-1] + a_{i,3}w_i[n-2], \quad (25)$$

at sample time $n$. For the wind signal model $S_1$ we use state vector $w_1$ given by

$$w_1[n] = v_x[n] - v_x^*,$$

to represent the deviation of LIDAR measured horizontal wind speed $v_x[n]$ from $v_x^*$, the mean horizontal wind speed.

For the pitch angel model $S_2$, since we assume the mean wind speed $v_x^*$ in region 3, we use $\Omega_r = \Omega_{r,rated}$ so we obtain the desired TSR at sample time $n$ from the following relation:

$$\lambda[n] = \frac{\Omega_{r,rated} R}{v_x[n]}. \quad (26)$$

Following the computation of TSR, $C_p$ is calculated using:

$$C_p[n] = \frac{P_{cmd}[n]}{P_{wind}[n]}. \quad (27)$$

Then $\theta[n]$ is obtained from the power coefficient surface presented in Figure 1, and the exosystem dynamics are modelled with the state vector

$$w_2[n] = \theta[n] - \theta^*,$$

representing the deviation of $\theta[n]$ from $\theta^*$. 

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For the torque model $S_3$ we use state vector $w_3$ given by

$$w_3[n] = M_g[n] - M_g^*$$

where

$$M_g[n] = \frac{P_{cmd}[n]}{P_{rated}}$$

and $M_g^*$ is defined in (11). Thus $S_1$ to $S_3$ can be modelled in the form of:

$$w_i[n + 1] = \begin{bmatrix} a_{i,1}^* & a_{i,2}^* & a_{i,3}^* \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} w_i[n],$$

for $i = 1, 2, 3$, with optimal coefficients $a_{i,1}^*$, $a_{i,2}^*$ and $a_{i,3}^*$ obtained using a recursive least squares parameter estimation.

### 4.2 Baseline Controller augmented for power demand tracking

In [7] the authors introduced and compared a number of torque-based and pitch angle based control methodologies for the power demand tracking problem. They concluded that their torque-based APC control method provided the best performance in region 3, and hence we have chosen to use this control method as the point of comparison in our study. We first offer a brief description of this method. While [7] considered the NREL CART-3 turbine, we have adapted their control parameters for the 5 MW turbine model given in [9].

**Figure 3.** Augmented baseline controller

In Figure 3, the components of the control scheme presented in black represent the conventional turbine baseline controller described in [9]. This employs the torque controller $M_g$ given by

$$M_g = \begin{cases} \frac{k(0.74 \Omega_{g,\text{rated}})^2}{0.17 \Omega_{g,\text{rated}}} (\Omega_g - 0.57 \Omega_{g,\text{rated}}) & \Omega_g < 0.57 \Omega_{g,\text{rated}} \\ \frac{k\Omega_g^2}{M_{g,\text{rated}} - k(0.99 \Omega_{g,\text{rated}})^2} (\Omega_g - \Omega_{g,\text{rated}}) + M_{g,\text{rated}} & 0.57 \Omega_{g,\text{rated}} < \Omega_g < 0.74 \Omega_{g,\text{rated}} \\ \frac{P_{\text{rated}}}{\Omega_g} & 0.74 \Omega_{g,\text{rated}} < \Omega_g < 0.99 \Omega_{g,\text{rated}} \\ \frac{P_{\text{rated}}}{\Omega_g} & \Omega_g > \Omega_{g,\text{rated}} \end{cases}$$

(29)
For Region 3 wind speeds, the pitch controller is a gain-scheduled PI controller designed to track a speed reference of the form

\[
\theta = K_p G_k (\Omega_g - \Omega_{g,\text{setpoint}}) + K_I \int_0^t (\Omega_g - \Omega_{g,\text{setpoint}}) dt \tag{30}
\]

\[
G_k = \frac{1}{1 + \frac{\theta_k}{\theta}}, \tag{31}
\]

where the coefficients \(K_p\), \(K_I\) and \(\theta_k\) are defined in [9].

The components of Figure 3 presented in blue represent the augmentation of the baseline controller by the authors of [7] for the purpose of power command tracking. The torque control input \(M_{g,\text{final}}\) scales the torque \(M_g\) in (29) by the gain \(K_{APC}\)

\[
M_{g,\text{final}} = K_{APC} \cdot M_g \tag{32}
\]

where

\[
K_{APC} = \frac{P_{cmd}}{P_{rated}}, \tag{33}
\]

and \(P_{rated}\) is the rated mechanical output power. The superior performance of torque-based power regulation control, relative to the pitch angle control based methods also considered in [7], was attributed by the authors to torque actuation being much faster than pitch actuation.

5 Simulation Software and Results

The simulation software is comprised of the following components:

(i) Turbine Simulation: To simulate the response of a 5MW NREL wind turbine FAST 7 software [10] is utilised. FAST does not include a model for pitch actuator, and therefore, a second-order servo-system according to (6) with \(\zeta = 0.7\) and \(\omega = 2\pi \text{ rad/s}\) has been added to the Simulink environment.

(ii) Wind signals: We employed NREL software TurbSim for the generation of a class-A turbulent wind signal of duration 1000 seconds and with Region 3 mean wind speed of 15 \(\text{m/s}\).

(iii) LIDAR Model: We used the continuous wave CW-LIDAR model described in [6] to simulate the horizontal wind speed \(v_x\). The effect of the averaging is equivalent to passing the wind signal through a non-phase distorting low-pass filter. The horizontal wind speed (from TurbSim) and the LIDAR-filtered wind signals are shown in Fig 4. The wind signals are applied to FAST under the assumption of Taylor’s Frozen Wind Hypothesis, which models the wind field as a turbulence box moving towards the wind turbine at its average wind speed. Further details of the FAST, TurbSIM and LIDAR implementation are given in [12].

(iv) Power Demand Curve: We chose a power command signal of the form (1) with \(P_s = 4.5 \text{ MW}\) and \(P_{AGC}\) bounded by \([-500 \text{ kW}, 800 \text{ kW}\] \). The AGC signal was of duration 1000 seconds, with step values changing every 100 seconds.

(v) Controller Implementation: Both the Augmented Baseline and EOR controllers were digitally implemented with the sampling rate of 0.25 seconds.

(vi) Power computation: The outputs from FAST are used to compute the instantaneous power generation. In this paper the efficiency of generator is considered to be 100\%, and hence the mechanical power equals the electrical power generated.
(vii) Power tracking performance: The relative power regulation performance of the two controllers is compared by computing their root-mean-square errors from the power demand curve, as in (2). The first 50 seconds of turbine performance are excluded from the comparison as these are needed to initialise the EOR controller. This set up time is used to obtain an estimate of the mean wind speed and hence obtain the linearisation point for the LTI turbine model in (12).

Fig 4 shows the LSS torque, rotor speed and generated power for EOR and Baseline controllers. The EOR controller consistently achieves significantly reduced deviations from the power demand signal over the simulation time interval. This performance is revealed by the substantially reduced variations in both the rotor torque and speed.

Figure 4. Illustrative responses for mean wind speed of 15 m/s using Baseline control and EOR

Finally, Table 1 summarises the relative performance of the two controllers by comparing their root mean square error (RMSE) of their power tracking performance, as defined in (2). Significantly,
EOR achieved a reduction of 15% in the RMSE of the power regulation. It also had reduced use of pitch and torque actuation, and smaller standard deviation in the change of generator torque and blade pitch angle.

### Table 1. Performance indices for frequency regulation

| Comparison factor                        | Augmented Baseline | EOR  |
|------------------------------------------|--------------------|------|
| Power tracking RMSE (kW)                 | 108.8              | 93.27|
| Average pitch angle (°)                  | 9.375              | 9.319|
| Standard deviation pitch angle (°)       | 3.913              | 3.755|
| Mean rotor torque (KNm)                  | 3763               | 3793 |
| Standard deviation rotor torque (KNm)    | 391.1              | 382.3|
| Mean generator torque (KNm)              | 38.79              | 39.02|
| Standard deviation generator torque (KNm)| 3.730              | 3.540|

### 6 Conclusions

We have investigated the application of the classical EOR control methodology for the power regulation of a large wind turbine operating in region 3. The results showed that EOR can potentially deliver substantially improved tracking of a power demand curve, which may greatly facilitate the capacity for wind turbines to contribute to secondary frequency control services. Actuator usage reduction is another important outcome of this controller with expected load fatigue reduction capabilities observed in [12]. Future work will investigate the performance of EOR under a wide range of wind signals and power references in all regions of operations. It is expected that EOR will again demonstrate superior power regulation performance than a Baseline controller, due to its ability to incorporate wind preview information into the controller design.

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