ABSTRACT This study presents a full operational envelope controller for a full nonlinear 5 MW Supergen exemplar wind turbine based on multivariable model predictive control (MPC). Below the rated wind speed, the primary objective of the controller is to maximize the energy capture. Above the rated wind speed, the controller maintains the rated power. The controller switches between control modes according to the prevailing wind speed to maintain control over the full envelope of operating regions. A linearized model is derived from a model of an exemplar 5 MW Supergen wind turbine in state-space form. The linearized model is then used to realize a feedback MPC (FB-MPC) and feedforward MPC (FF-MPC) to consider the lack and incorporation, respectively, of wind speed information. The switching strategy is tracked on the torque–speed plane. Simulations are performed at multiple wind speeds to evaluate the robustness and switching performances of the designed controllers by applying them to a full nonlinear 5 MW Matlab/SIMULINK model of the same exemplar Supergen wind turbine. Improved tracking is achieved over the full envelope with FF-MPC rather than FB-MPC. Simulation results are presented in the time and frequency domain in addition to the torque–speed plane demonstrating that the control performance is improved without an increase in the control activity (i.e., pitch action) of the turbine; that is, the controller’s gain crossover frequency remains within the acceptable range, around 1 rad/s. Note that most work presented in the literature focus on specific wind speeds only; that is, either only below rated wind speed or above rated wind speed. In contrast, the controllers reported here cover the full envelope of operation regions, making this work more practical and novel.

INDEX TERMS Wind turbine, modeling, predictive control, feedforward control.
Several studies focused on the control of wind turbines in the last few decades [8], [9], [10]. Most of the work focuses on the stability of linear controllers in specific modes, and the switching between the linear controllers in different modes as part of the full envelope control design, which is more challenging, is ignored. A typical approach is to use two or more distinct controllers to regulate the generator speed and power independently, which forms two or more independent control loops. Conventional PI controllers have been used within such control loops [11], [12], [13], but they are designed for a single operating point. Hence, the control performance can degrade when the system is not at this operating point. A gain scheduling technique is used in [11] to adjust the PI controller’s parameters to obtain good performance within the operating regions. However, in most of the literature, the multivariable nature of the full envelope control problem has been ignored.

Sliding mode control (SMC), instead of more conventional PID, is proposed in [14] to capture the maximum wind energy by reducing the complexity of high-order systems. However, it suffers from chattering problems due to the discontinued term used in the SMC control law. A backstepping algorithm has been proposed in [15] using the Lyapunov function to stabilize the system despite wind variances, and it guarantees a good convergence. The major drawback is the explosion of terms, a defect formed by a recurrence of differentiation of the inputs [16]. To overcome these issues, some modifications are made by adding a few observers, such as neuron networks and fuzzy logic. The developments are also justified by increasing the controller’s order and combining two or more separate controllers. However, implementation and calculation time are associated with these methods’ difficulties [17]. Hence, MPC has become the most attractive alternative due to its simplicity, fast dynamic response, multivariable nature, and consideration of nonlinear constraints. Bossouf et al. in [18] discuss an adaptive backstepping control based on the Lyapunov stability technique applied to a doubly fed induction generator (DFIG). Yang et al. in [19] implemented SMC on DFIG. However, the obtained results are ineffective regarding robustness and the chattering phenomenon. A robust sliding-backstepping technique, which improves the control system’s performance in terms of parameter variations of the turbine, is presented in [20].

In [21], an MPC is designed using linearized models of a wind turbine at two regions, i.e., the full and the partial-load regions. In [22], an MPC has been used to regulate the pitch angles to control load frequency oscillations in the electrical system. In [23], the predictive control method has been used for a different purpose, i.e., the control of the nacelle angle. A low-complexity MPC-based controller is established in [24] for design computations to the offline method. MPC has been used for operational and economic purposes in wind turbine control using economic approaches [25], [26] and aero-elastic blades [27]. In some literature, MPC-based multiple-input multiple-output predictive control [28], [29] and practical nonlinear MPC for variable-speed wind turbines are presented [30]. In [31], a comparison of predictive control with advanced control methods, such as linear quadratic [6] and H∞ control [32], is presented.

Note that most work presented in the literature focus on specific wind speeds only; that is, either only below rated wind speed or above rated wind speed. In contrast, the controller reported here cover the full envelope of operation regions, making this work more practical and novel.

Below the rated wind speed of a turbine, the system is single-input single-output (SISO). Above the rated wind speed, the wind turbine is pitch-regulated, and the system is still SISO. SISO controllers can be combined to realize a multivariable controller. A proper multivariable control system is required to control the full envelope of operating regions (i.e., both below and above the rated wind speeds).

In this study, firstly, a feedback MPC (FB-MPC) is designed as an alternative to the PI controller using linearized models derived from a DNV-GL Bladed model of a 5 MW Supergen wind turbine [33]. MPC has attracted attention for wind turbine control because the objective function is easily modified to incorporate the wind speed. Then, a feedforward MPC (FF-MPC) is designed to improve the performance where the upstream wind speed is fed into the controller [34], [35]. The wind speed can be measured by a Light Detection and Ranging (LiDAR) [36]. Note that the price of LiDARs has been reducing in recent years, making them more economically viable.

In this study, a multivariable controller based on MPC is designed that can be operated over the full envelope of wind speeds. The novelty is, rather, designing a multivariable full envelope controller using the existing switching algorithm, and a control strategy based on operational curves in the torque–speed plane. The contributions include designing linearized controllers in each mode using FB-MPC and FF-MPC and subsequently switching between these...
linearized controllers to yield a full envelope multivariable MPC. The main advantage of the proposed strategy is that it effectively uses the full capabilities of the controlled system to obtain the desired performance in the full envelope of operating regions while keeping the system variables within their limits. Note that most work discussed in the literature [11], [12], [13], [14], [15], [19], [20], [21], [22], [23], [24], [25], [26], [27], [30], [31], [32], and [33] reports a linearized controller at specific wind speeds only and ignores the switching between the linearized controllers. In contrast, the work reported here covers the full envelope of operation regions, which is one of the main contributions of this work.

Both full envelope controllers, i.e., FB-MPC and FF-MPC, are applied to a full nonlinear 5 MW Supergen turbine to evaluate their control performance over the full envelope of wind speeds and switching transients. FB-MPC and FF-MPC have previously been applied to linearized models that they are based on, and therefore there is no model–plant mismatch. In particular, the FF-MPC designed based on the linearized model has never been applied to the corresponding full nonlinear model of the Supergen 5 MW turbine before. The model–plant mismatch, i.e., between the controller design model and the full nonlinear model, present in this case, allows the robustness of the controller design to be tested to some degree.

Simulations are performed to investigate the dynamics and control of a torque-regulated and pitch-regulated variable-speed Supergen wind turbine. The control performances of FB-MPC and FF-MPC at various wind speeds are compared to evaluate their effectiveness in each control mode. Improved tracking and smooth switching on the torque–speed plane are achieved by maintaining the controller bandwidth or gain crossover frequency within the acceptable range, around 1 rad/s. Wind turbine control can be categorized into two, first related to the mechanical and aerodynamic engineering side and second related to the power electronics side. The work presented here is only concerned with the former, and the latter is beyond the scope of the paper.

The paper’s outline is organized as follows: Section II briefly describes modeling of the 5 MW Supergen wind turbine. The switching strategies of operating regions are explained in Section III. The synthesis of controllers are discussed in Section IV. Section V presents detailed simulation results, discussions, comparisons, and computational analysis, respectively. Finally, conclusions are drawn, and the future scope is discussed in Section VI.

II. WIND TURBINE MODEL

An efficient wind turbine model is required for designing and testing of a wind turbine controller. The drive-train dynamics of a wind turbine consists of several dynamic modes, such as tower, blades, hub, low and high-speed shaft, gearbox, gear-tain, and generator rotor. They can be represented by a simple model which approximates closely the drive-train dynamics for most wind turbines [37], [33]. The equations and parameters used in the 5 MW Supergen turbine model are briefly discussed in this section. A model of the 5 MW Supergen turbine in DNV-GL Bladed is then used to derive a linearized model. The linearized model is used to design the controllers, and the full nonlinear Supergen model is exploited for simulating the wind turbine. Also, the mismatch between the two models allows the robustness of the controller design to be tested to some degree. An effective wind speed model for simulating the wind turbine is also presented in this section.

A. PITCH COMPONENT

The pitch can be expressed by a second-order transfer function [33], [38], and [39]:

\[ P(s) = \frac{a_1}{s^2 + a_2s + a_1} \]  

where \( a_1 \) and \( a_2 \) determine the pitch actuator characteristics; the input is the pitch demand; and the output is the actual pitch angle.

B. AERODYNAMIC COMPONENT

The simplest form of the aerodynamics is expressed as follows [33], [38], and [39]. The in-plane rotor torque \( (A_{\theta_R}) \) is given by

\[ A_{\theta_R} = \frac{1}{2} \rho \pi V^2 R^3 C_p(\lambda, \beta). \]  

where \( \lambda \) is the tip-speed ratio, \( \beta \) is the blade pitch angle (rad), \( \rho \) is the air density (kg/m³), \( R \) is the rotor radius (m), and \( V \) is the wind speed (m/s). \( C_p \) is the aerodynamic power coefficient.

The out-of-plane torque of the rotor \( (A_{\phi_R}) \) is described by

\[ A_{\phi_R} = \frac{1}{2} \rho \pi V^2 R^2 C_T(\lambda, \beta). \]  

where \( C_T \) is the out-of-plane bending moment coefficient.

The thrust force \( (F_t) \) is represented by

\[ F_t = \frac{1}{2} \rho \pi V^2 R^2 C_T(\lambda, \beta). \]  

where \( C_T \) is the thrust coefficient.

C. ROTOR COMPONENT

The Lagrangian for the rotor dynamics is given by [37] and [33].

\[
L_R = 0.5 \left( J_{\dot{\theta}_p}^2 + J_{\dot{\phi}_p}^2 + J_T \dot{\phi}_p^2 + J_C \phi_T \dot{\phi}_T \right) \\
- 0.5 L_e \left[ (\theta_p - \theta_v) \cos \beta - (\phi_T - \omega_{v_0}) \sin \beta \right]^2 \\
- 0.5 L_f \left[ (\theta_p - \theta_v) \sin \beta + (\phi_T - \omega_{v_0}) \cos \beta \right]^2 \\
- 0.5 J \left( \omega_e^2 - \omega_{v_0}^2 \right) \left( \Omega^2 / \Omega_{v_0}^2 \right) \left( \theta_p - \theta_v \right)^2 \\
- 0.5 J \left( \omega_{\phi_T}^2 - \omega_{\phi_T}^2 \right) \left( \Omega^2 / \Omega_{\phi_T}^2 \right) \left( \phi_T - \omega_{v_0} \right)^2 - 0.5 L_T \phi_T^2 \\
+ D_T \phi_T + M_0 (\theta_p - \theta_v) + M_0 (\phi_T - \omega_{v_0}) + F_T \phi_T \\
(5)
\]
where $J$, $J_C$, and $J_T$ are the rotor, tower/rotor cross-coupling, and tower fore-aft inertia [kg m²], respectively. $\Omega$ and $\Omega_p$ are the in-plane and rated in-plane rotor speeds [rad/s], respectively. $\omega_e$ and $\omega_{es}$ rotating blade edge and stationary blade edge natural frequency [rad/s], respectively. $\omega_f$ and $\omega_{fs}$ rotating blade flap and stationary blade flap natural frequency [rad/s], respectively. $L_T$ is the tower fore-aft stiffness [Nm/rad], $L_e$ and $L_T$ are the edge-wise and flap-wise stiffness of single blade [Nm/rad], respectively. $M_\theta$ and $M_\beta$ are the out-of-plane and in-plane rotor aerodynamic torque on blade [Nm], respectively. $h$ is the tower height [m]. $\phi_p$ and $\phi_T$ are the out-of-plane displacements of centre of mass of blade and fore-aft angular displacement of hub [rad], respectively. $\theta_p$ and $\theta_T$ are the angular displacements of rotor and hub [rad], respectively. $\theta_p$ and $\theta_T$ are the fore-aft tower and side-to-side speeds, respectively. $D_T$ is a function of $\phi_T$ and $L_a$ is the shape factor of tower.

The rotor dynamics can be modeled as follows [37], [33]:

$$\ddot{\theta}_p = -\omega_{es}^2[(\theta_p - \theta_T) \cos \beta - (\phi_p - L_\phi \phi_T) \sin \beta] \cos \beta$$

$$- \left(\omega_e^2 - \omega_{es}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_p - \theta_T) + M_\theta / J$$

$$- \left(\omega_f^2 - \omega_{fs}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_p - \theta_T)$$

$$+ (\phi_p - L_\phi \phi_T) \cos \beta \sin \beta$$

$$\frac{JJ_T - J_c^2}{JJ_T + L_a J_c} \ddot{\theta}_T = -\omega_{es}^2[(\theta_p - \theta_T) \cos \beta - (\phi_p - L_\phi \phi_T) \sin \beta \sin \beta]$$

$$- \left(\omega_e^2 - \omega_{es}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_p - \theta_T)$$

$$+ (\phi_p - L_\phi \phi_T) \cos \beta \cos \beta$$

$$+ \left(\omega_f^2 - \omega_{fs}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_T - L_\theta \theta_T)$$

$$+ M_\theta / J + J / J_T + L_a J_c$$

$$\times (L_T \phi_T + B_T \phi_T - hF_T)$$

$$\frac{JJ_T - J_c^2}{JJ_T + L_a J_c} \ddot{\phi}_T = -\omega_{es}^2[(\theta_p - \theta_T) \cos \beta - (\phi_p - L_\phi \phi_T) \sin \beta \sin \beta]$$

$$- \left(\omega_e^2 - \omega_{es}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_p - \theta_T)$$

$$+ (\phi_p - L_\phi \phi_T) \cos \beta \cos \beta$$

$$+ \left(\omega_f^2 - \omega_{fs}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_T - L_\theta \theta_T)$$

$$+ M_\theta / J + J / J_T + L_a J_c$$

$$\times (L_T \phi_T + B_T \phi_T - hF_T)$$

The dynamics of hub torque ($T_H$) can be described by the following equation [37], [33]:

$$T_H = J \omega_{es}^2[(\theta_p - \theta_T) \cos \beta - (\phi_p - L_\phi \phi_T) \sin \beta] \cos \beta$$

$$+ J \omega_{es}^2[(\theta_p - \theta_T) \sin \beta + (\phi_p - L_\phi \phi_T) \cos \beta] \sin \beta$$

$$- J \left(\omega_e^2 - \omega_{es}^2\right) \left(\Omega^2 / \Omega_p^2\right) \times (\theta_p - \theta_T)$$

**D. LINEAR MODEL**

In this study, linearized models are derived using the DNV-GL Bladed wind turbine model to design optimal predictive controllers. Note that the nonlinear model in Matlab/SIMULINK and the DNV-GL Bladed wind turbine model represents the same 5 MW Supergen exemplar turbine. Hence, the linearized model of the Bladed model is a good approximation to the full nonlinear model presented in Section II [33], [40].

The linearized models derived in state-space form using DNV-GL Bladed wind turbine model are as follows [5].

$$\Delta \dot{x}(t) = A \Delta x(t) + B \Delta u(t)$$

$$\Delta y(t) = C \Delta x(t) + D \Delta u(t)$$

where $A$, $B$, $C$, and $D$ represents state space matrices.

$$\Delta x(t) \in K^a, \Delta u(t) \in K^b$$

where $a$, $b$, and $c$ are defined as: $a$ is related to number of states; 240 here, $b$ is related to number of inputs such as pitch angle, wind speed, and generator torque demand, and $c$ is related to output) are defined as following:

$$\Delta x(t) = x(t) - x_{op}(t)$$

$$\Delta u(t) = u(t) - u_{op}(t)$$

$$\Delta y(t) = y(t) - y_{op}(t)$$

where $x(t)$, $u(t)$, and $y(t)$ represent the states, input, and output, respectively. $x_{op}(t)$, $u_{op}(t)$, and $y_{op}(t)$ are the operating points around which the models are linearized.

The state-space models can be derived by discretizing the continuous model in (10) [5].

$$X_{k+1} = A X_k + B_a U_k$$

$$Y_{k+1} = C X_{k+1}$$

where $B_a$ is the input matrix, denotes pitch angle, wind speed, and generator torque demand, respectively. $C$ is the output matrix, denotes generator speed. $U_k = [\Delta \text{pitch angle or generator torque demand}]$.

The inputs to the linear model can be the generator torque or pitch angle depending on the wind speed, and the output is the generator speed. The required prediction equations are given in (13) for FB-MPC [5]. Here, direct feedthrough is not considered, so matrix $D$ is zero.
\[ u \rightarrow [u_k, u_{k+1}, ..., u_{k+n_y}, u_{k+n_y}, ..., u_{k+n_h}]^T \]  \hspace{1cm} (14)

where \( n_y \) and \( n_h \) represent the prediction and control horizon, respectively.

**E. MODELING OF WIND SPEED**

The wind varies randomly with time and continuously interacts with the turbine. In this work, the point wind obtained from DNV-GL Bladed is filtered by using the model introduced in [41] and [42] to yield the effective wind speed. This effective wind speed is then used as an input for the MATLAB/Simulink turbine model. Fig. 2 shows the effective and point wind speeds at 8 m/s. The point wind speed is plotted against the effective wind speed for comparison.

The wind speeds shown in the Fig. 2 are for a mean wind speed of 8 m/s, and similar results could be expected from the wind speeds at different mean wind speeds.

**III. CONTROL OBJECTIVES AND SWITCHING**

This section discusses the objectives and strategy of the wind turbine controller that covers the full wind speed range. Fig. 3 shows the objectives of a full envelope controller designed to operate in different control modes on the torque–speed plane.

In modes II and III, the generator torque is the input, and the pitch demand is zero. In mode IV, the generator torque is fixed, and the pitch demand is the input.

**A. OBJECTIVES IN EACH CONTROL MODE**

In mode II, the \( C_{p_{\text{max}}} \) curve is tracked by varying the generator torque \( T_e \) to maximize the energy capture. This is achieved by minimizing the following index:

\[ y_1 = T_e - k\omega_0^2, \]  \hspace{1cm} (15)

where \( \omega_0 \) is the generator speed and \( k \) is a parabolic constant.

In mode III, the vertical line at 120 rad/s is tracked by minimizing \( y_2 \):

\[ y_2 = \omega_0 - \omega_0_{\text{rated}}, \]  \hspace{1cm} (16)

where \( \omega_0_{\text{rated}} \) is 120 rad/s.

In mode IV, active pitching is used to maintain the rated power \( P_{\text{rated}} \), which is tracked by minimizing \( y_3 \):

\[ y_3 = P_g - P_{\text{rated}}, \]  \hspace{1cm} (17)

where \( P_{\text{rated}} \) is 5 MW.
A. Routray, S.-H. Hur: Full Operational Envelope Control of a Wind Turbine Using Model Predictive Control

B. SWITCHING BETWEEN OPERATING REGIONS
A full envelope controller needs to operate both below and above the rated wind speed of the wind turbine. The design of controllers for variable-speed wind turbines can be divided into two parts: determining the operating strategies for the controllers and their synthesis. The controller is realized by combining suitable strategies below the rated wind speed with those above the rated wind speed. The switching between the strategies must be realized in a smooth manner, which avoids the introduction of large transients. One of the switching procedures introduced in [43] is employed. Fig. 3 shows the primary operating regions: maximum power tracking (mode II), constant speed (mode III), and rated power (mode IV). The controller is designed to switch between control modes to realize the necessary torque and pitch actions for each operating region.

C. SWITCHING PROCEDURE
Below and above the rated wind speed, the wind turbine is a SISO system. A typical approach to combining strategies is to switch between SISO controllers, such as tracking the $C_{p_{\text{max}}}$ curve at very low wind speeds, tracking a constant rotor speed at intermediate wind speeds below the rated wind speed, and tracking a constant power above the rated wind speed. In this study, the individual SISO controllers are combined to design a multivariable controller for switching control of the wind turbine. $y_1$ is the error when tracking the $C_{p_{\text{max}}}$ curve by the generator torque, $y_2$ is the error when tracking the constant rotor speed, and $y_3$ is the error when tracking the constant power curve. The controller that corresponds to $y_i$ ($i = 1, 2, 3$) is switched on, as illustrated in Fig. 4. An integrator is placed after the switch to smoothen discontinuities during switching.

Differences in spectra are partially removed by the multivariable MPC; however, the remaining differences are removed by low-pass filters $g_i(s)$ (for $i = 1, 2, 3$). These filters help reduce the high-frequency components of $y_i$ to avoid chattering because of fast switching. The scaling constants $k_i(s)$ (for $i = 1, 2, 3$) are used to tune the relative distance to the strategy curve. The overall control architecture of the wind turbine is shown in Fig. 5 and the inputs from the controller to turbine are the generator torque set point $T_g^*$ and the desired pitch angle $\beta^*$.

D. LINEARIZED MODEL USING DNV-GL BLADED
In this study, linearized models are derived using the DNV-GL Bladed wind turbine model to design optimal predictive controllers, which initially contain too many states. Tuning and realization could be complex for a turbine model with many such states. An implicit balancing technique is adopted to compute the reduced-order approximation [44]. Figs. 6(a) and 6(b) show the original DNV-GL Bladed and

![FIGURE 4. Overall switching architecture.](image-url)

![FIGURE 5. Overall control architecture of the Supergen wind turbine.](image-url)
reduced-order models at wind speeds of 8 and 16 m/s, respectively. These figures illustrate that the original and reduced-order models demonstrate similar characteristics in the significant frequency range of $10^{-2}$ to $10^2$ rad/s.

First, the linearized model is used to design FB-MPC, as described in Section II-D. To improve the control performance, wind speed information is incorporated to result in FF-MPC.

**IV. SYNTHESIS OF CONTROLLERS**

MPC has been used in several industrial applications owing to its capability to handle multivariable control problems with nonlinear constraints on the system variables [5]. In this study, multivariable FB-MPC and FF-MPC are applied to operate in the full envelope of wind speeds considering necessary constraints.

FB-MPC is designed by using (13), as discussed in Section II-D. FF-MPC is designed by using the following modified state-space equation,

$$x_{k+1} = A x_k + B_1 u_k + B_2 w_k$$
$$y_k = C x_k + D_1 u_k + D_2 w_k,$$  

where $y_k$ is the generator speed deviation, $u_k = [\Delta \text{generator torque or pitch demand depending on the control mode, and}]$. $w_k = [\Delta \text{wind speed}]$. $B_1$ and $D_1$ are input state-space matrices related to the control input, and $B_2$ and $D_2$ are state-space matrices associated with the wind speed information; hence, these terms are only used for FF-MPC.

Note that the matrix $D_2$ is zero for FB-MPC but non-zero for FF-MPC because the latter accepts direct feedthrough to incorporate the wind speed. The predicted output is then given by

$$\begin{bmatrix} y_{k+1} \\ y_{k+2} \\ y_{k+3} \\ \vdots \\ y_{k+n_y} \end{bmatrix} = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n_y-1} \end{bmatrix} x_k \begin{bmatrix} D_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} u_k + \begin{bmatrix} C B_1 \\ D_1 \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} B_1 \\ \vdots \\ \vdots \\ B_1 \end{bmatrix} u_{k-1} + \begin{bmatrix} C A^{n_y-2} B_1 \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} A^{n_y-2} B_1 \\ \vdots \\ A^{n_y-1} B_1 \end{bmatrix} u_{k-2} + \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix} \begin{bmatrix} D_1 \\ \vdots \\ D_2 \end{bmatrix}$$

where $n_y$ and $n_h$ represent the prediction and control horizons, respectively.

The predicted output can be rewritten as

$$y_k = S_x x_k + Q_u u_k + T_w w_k.$$  

where the predictive state space matrices $S_x$, $Q_u$, and $T_w$ are defined in (19).
FF-MPC can be expressed as follows:

$$J = \sum_{j=1}^{n_T} e_{k+j}^T e_{k+j} + \sum_{j=0}^{n_k} \Delta u_{k+j}^T R \Delta u_{k+j},$$  \hspace{1cm} (23)$$

where $e_k = r_k - y_k$ is the tracking error, $r_k$ is the reference, $R$ is the weighting factor for control input, and $\Delta u_k$ is the control increment.

Using (19)-(23), the cost function $J$ can be derived as follows:

$$J = |Lr_k - S \omega_k - Q_u u_{k+j} - T_w w_k - L \times \text{offset}|_2 + R_s \| u_{k+j} \|_2,$$  \hspace{1cm} (24)$$

where $L$ is a vector of ones whose size is $n_y$, $R_s$ is the control weighting factor matrix, and $u_{k+j}$ is the future input. Here, the offset is defined as the difference between the process and model output.

Then, (24) can be derived as a function of the control input:

$$(u, k) = \frac{u_{k+j}^T (Q_u^T Q_u + R_s) \times u_{k+j} + 2u_{k+j}^T M}{N} \times \left[ ((Q_u^T S \omega_k \times x_k) - (Q_u^T L + R_s M)) \times (r_k - \text{offset})) + ((Q_u^T T_w) \times w_k) \right],$$  \hspace{1cm} (25)$$

where $M = (u_{k+j} \times (r_k - \text{offset}))$ is the steady-state input gain.

The overall cost function $J$ for multivariable FB-MPC and FF-MPC can be expressed as follows:

$$\min J = \sum_{j=1}^{n_T} e_{11, k+j}^T e_{11, k+j} + e_{12, k+j}^T e_{12, k+j}$$

subject to (26)

$$\omega_0, \text{min} \leq \omega_r (k+j) \leq \omega_0, \text{max}$$

$$\Delta \beta, \text{min} \leq \Delta \beta (k+j) \leq \Delta \beta, \text{max}$$

$$\beta, \text{min} \leq \beta (k+j) \leq \beta, \text{max}$$

$$\Delta T_e, \text{min} \leq \Delta T_e (k+j) \leq \Delta T_e, \text{max}$$

$$T_e, \text{min} \leq T_e (k+j) \leq T_e, \text{max}$$  \hspace{1cm} (27)$$

where $e_{11} = \omega_0 - \omega_0, \text{rated}$, $e_{12} = T_e - k \cdot \omega_0^2$, and $e_{21} = P_G - P_0, \text{rated}$. $\omega_0$ is the generator speed, $\omega_0, \text{rated}$ is the rated generator speed. $P_G$ is the output power. $q_1$, $q_2$, and $q_3$ are the output matrices for related control objectives. $\omega_0, \text{min}$ and $\omega_0, \text{max}$ are the boundaries of generator speed for related control objectives. $T_e, \text{min}$ and $T_e, \text{max}$ are the boundaries of generator torque for associated control objectives. $\Delta T_e, \text{min}$ and $\Delta T_e, \text{max}$ are the limit of generator torque increment. $\Delta \beta, \text{min}$ and $\Delta \beta, \text{max}$ are the limit of pitch increment. $\beta, \text{min}$ and $\beta, \text{max}$ are the boundaries of input pitch. $r_1$ and $r_2$ are weight matrices for related control inputs.

V. SIMULATIONS

In this section, the performance of multivariable FB-MPC and FF-MPC based full envelope controllers are examined by application to the full nonlinear 5 MW Supergen wind turbine model in MATLAB/Simulink. FB-MPC has been applied to the linearized models based on which the controllers were designed before (such that there is no model-plant mismatch). In contrast, in this work, FB-MPC and
A. Routray, S.-H. Hur: Full Operational Envelope Control of a Wind Turbine Using Model Predictive Control

FIGURE 8. Tracking on torque–speed plane at 8 m/s wind speed: (a) FB-MPC (without wind) and (b) FF-MPC (with wind).

FF-MPC are applied to the full nonlinear model reported in Section II. The model-plant mismatch, i.e., between the control design model and the full nonlinear model, present in this case, allows the robustness of the controller design to be tested to some extent. Simulation results are obtained in the time and frequency domains, and the tracking of the strategy curve on the torque–speed plane by both controllers is observed.

In mode II, the prediction horizon \( n_y \) is taken as 20, the control horizon \( n_h \) is set to 15, and the weight is set to \( 3 \times 10^{-12} \). In mode III, \( n_y \) and \( n_h \) are the same as in mode II, and the weight is set to \( 2 \times 10^{-5} \). In mode IV, \( n_y \) and \( n_h \) are set to 20 and 10, respectively, and the weight is set to \( 2 \times 10^{-10} \). The sampling time is taken as 0.5 s.

A. MEAN WIND SPEED OF 8 M/S

This section demonstrates the response of controllers at 8 m/s mean wind speed. Fig. 7 shows the responses of FF-MPC (with LiDAR) and FB-MPC (without LiDAR) at wind speed of 8 m/s. Fig. 7(a) shows the measured outputs (i.e., generator speed), and Fig. 7(b) shows the corresponding inputs (i.e., generated torque).

Based on the results shown in Fig. 7, it is difficult to assess the controllers in terms of tracking the \( C_{\text{pmax}} \) curve, which is the control objective in mode II. However, the tracking of the \( C_{\text{pmax}} \) curve can be better represented on the torque–speed plane, as shown in Fig. 3. Thus, Figs. 8(a) and 8(b) show the tracking performances of FB-MPC and FF-MPC on the torque–speed plane, respectively. FF-MPC demonstrated improved tracking compared to FB-MPC. Thus, an improved \( C_{\text{pmax}} \) tracking on the torque–speed plane (higher power efficiency) is achieved with wind speed information (i.e., FF-MPC) than without (i.e., FB-MPC).

FIGURE 9. Frequency response at a wind speed of 8 m/s.

Fig. 9 shows the control performance of FF-MPC in frequency domain. The controller should produce an acceptable gain crossover frequency (GCF) of 0.6–2 rad/s [45]. A GCF of <0.6 rad/s can create a very slow control action, whereas a GCF of >2 rad/s can cause an excessively aggressive action. Fig. 9 shows that the GCF is acceptable for the controller. Hence, the improved performance of FF-MPC is achieved without a corresponding increase in control activity. For the controller, the peaks at \( \approx 10 \) rad/s are kept at <0 dB. This is significant because, with conventional PI controllers, a drivetrain damper is required to keep these peaks <0 dB [46].

B. MEAN WIND SPEED OF 10 M/S

This section demonstrates the response of controllers at 10 m/s mean wind speed. Fig. 10(a) depicts the measured
output (i.e., generator speed) with FB-MPC and FF-MPC, and Fig. 10(b) shows the corresponding inputs (i.e., generated torque). At this wind speed, the controllers switched between modes II and III (refer to Fig. 3). Figs. 11(a) and 11(b) show the tracking of the strategy curve on the torque–speed plane when the controllers are switching between mode II and mode III. It can be observed that the FF-MPC has a smoother transition and improved tracking compared with FB-MPC.

C. MEAN WIND SPEED OF 12 M/S

Fig. 12 shows the controller response at 12 m/s mean wind speed. Fig. 12(a) shows the measured output (i.e., generator speed), and Fig. 12(b) shows the corresponding control inputs, (i.e., pitch angles) with FF-MPC and FB-MPC. It is clear that the improvement in control performance is attained due to phase lead in control input (pitch angle) rather than an increase in the pitch action, as depicted in Fig. 12(b). Figs. 13(a) and 13(b) exhibit the tracking of the strategy curve and switching between mode III and mode IV by the controllers. Note that the FF-MPC tracks somewhat more closely on the torque–speed plane than FB-MPC. The transient peaks are not observed in the time response of FF-MPC.

D. MEAN WIND SPEED OF 16 M/S

This section demonstrates the response of the controllers at above-rated wind speed. The outputs of the wind turbine
(i.e., generator speed) are portrayed in Fig. 14(a). The speed should be \(\approx 120\) rad/s for the 5 MW Supergen wind turbine, such that the rated power is maintained, as illustrated in Fig. 14(b). The controller maintains the generator speed very well when wind information is unavailable, keeping fluctuations below, i.e., 12%. However, FF-MPC (with wind speed information) significantly outperforms FB-MPC.

Fig. 15 shows the corresponding control inputs (i.e., pitch angles) with and without wind speed information. FF-MPC demonstrated an improved control performance owing to a phase lead in the control input (pitch demand) rather than increased pitch activity, i.e., the wind speed information allows FF-MPC to respond to changes in the upcoming wind speed earlier than FB-MPC, resulting in a significant improvement in power fluctuations. Figs. 16(a) and 16(b) show the tracking of the strategy curve on the torque–speed plane by FB-MPC and FF-MPC. It can be observed that the FF-MPC yields improved tracking with better power regulation compared to FB-MPC.

Fig. 17 shows the open-loop frequency response of FF-MPC above the rated wind speed (16 m/s). The controller should produce an acceptable GCF of 0.6–2 rad/s [45]. The GCF is within the acceptable limit which indicates that the improved performance by FF-MPC is achieved without becoming more aggressive at all, which is significant. The peaks at \(\approx 10\) rad/s are maintained \(< 0\) dB. This noteworthy as, with PI controller, a drive-train damper is needed to retain these peaks at \(< 0\) dB [46].
In order to validate the robustness of controller, the control performance of FF-MPC is validated through frequency domain analysis plots (bode plot). To attain robustness, the controller GCF of the controller should remain within 0.6–2 rad/s [45]. To analyze the robustness, simulations are carried on 5 MW Supergen wind turbine at a mean wind of 16 m/s. Robustness is confirmed by running the controller at several design parameters. The parameters such as prediction horizon, control horizon, and control weighting values are varied to examine frequency response of the controller. Fig. 18 shows that the GCFs (related to the bandwidth of the controller) are within the acceptable limit, which signifies the controller’s robustness and improved FF-MPC performance without becoming more aggressive, which is noteworthy.

Case: I (GCF-1.02 rad/s), $n_y$ and $n_h$ are set to 20 and 10, respectively, and the weight is set to $2 	imes 10^{-10}$
Case: II (GCF-1.13 rad/s), $n_y$ and $n_h$ are set to 15 and 10, respectively, and the weight is set to $2 	imes 10^{-12}$
Case: III (GCF-1.2 rad/s), $n_y$ and $n_h$ are set to 25 and 15, respectively, and the weight is set to $3 	imes 10^{-10}$

### E. FULL ENVELOPE

This section portrays full envelope tracking and switching transitions on the torque-speed plane over the full envelope of wind speeds. For both FB-MPC and FF-MPC, full envelope tracking is shown in Figs. 19(a) and 19(b), respectively.

These figures clearly show that the FF-MPC closely tracks the strategy curve on the torque–speed plane and achieved a smoother switching transition than FB-MPC.

### F. DISCUSSION

In summary, the time and frequency responses depicted in Figs. 7–19 demonstrate that FF-MPC outperforms FB-MPC. Precise tracking on the torque/speed plane are achieved when the FF-MPC is implemented. It is also important to highlight that those improvements are obtained not due to increased control action, i.e., pitch activity. The model-plant mismatch, i.e., between the control design model and the full nonlinear model, allows the controller design’s robustness to be somewhat verified. In this work, the wind information is obtained from LiDAR using DNV-GL Bladed. However, wind measurements from LiDAR are not perfect in real life, which may harm control performance. Moreover, applying a controller to a real-life turbine may deteriorate the control performance due to process-model mismatch.
The controllers could be sensitive to the sampling time ($T_s$); thus, it needs to be considered. As discussed earlier, the controllers should be tuned to produce a GCF in the range of 0.6 to 2 rad/s [45]. GCFs over this range may lead to large control action, hence actuator saturation, especially at high wind speeds. Thus, the controller will be too aggressive. GCFs below this range could lead to too slow control action. The peaks above 0 dB, somewhat indicates that the controllers would be susceptible to noise and uncertainty. Hence, the controllers should be adjusted to ensure that peaks at high frequencies are kept below 0 dB or as small as possible.

The control performance is also affected by the prediction and control horizon. A frequency response shown in Fig. 20(a) with the prediction and control horizon set to 20 and 15, respectively, at different sampling times at 12 m/s mean wind speed. The peaks at around 11 rad/s are kept below 0 dB. By increasing the sampling time, the peaks tend to reduce further, still maintaining the GCF within the acceptable range of 0.6 to 2 rad/s.

The control performance is also affected by the control weighting factor. A bode plot is illustrated in Fig. 20(b), with the prediction and control horizon set to 20 and 10, respectively. They use different weighting factors. The controller becomes unstable when the control weighting is set to $2 \times \times 10^{-13}$. Thus, the weighting factor needs to be selected appropriately. Also, there is a tradeoff among design parameter selections, such as sampling time, prediction, and control horizons, which all affect the time and frequency responses of the wind turbine.

High-order linearized control design models have a tendency to cause the controllers to become over-aggressive at higher frequencies and lack robustness. Thus, it is suggested that the control design model be kept as simple as possible.
The proper tuning of design parameters is required when designing MPC to achieve improved robustness.

**H. COMPARISON**

As discussed earlier, the wind turbine control can be categorized into the mechanical aerodynamic engineering side and other one related to the power electronics. This study mainly focuses on control of wind turbine (mechanical/aerodynamic engineering) rather than a wind energy conversion system and the latter is beyond the scope of the paper. Hence, possible performance comparisons are included in Table 1.

Other comparisons are also made for 5 MW wind turbine at 16 m/s mean wind speed. Root mean square error (RMSE), standard deviation (STD), and mean of generator speed (rad/s) are taken into account for comparison purpose as given in Table 2. The proposed work performs most satisfactorily in terms of RMSE, STD, mean of generator speed (rad/s), and robustness.

**I. COMPUTATIONAL COMPLEXITY ANALYSIS**

To analyze the total running time of the 5 MW full nonlinear SuperGen wind turbine, simulations are carried out for 500 s using various different values for the sampling time,
TABLE 2. Control performance comparison.

| Publication | RMSE of power | Mean of generator speed (rad/s) | STD of pitch |
|-------------|---------------|---------------------------------|--------------|
| [31]        | $1.9310 \times 10^4$ | 124.49                          | 1.1246       |
| [31]        | $1.8972 \times 10^4$ | 123.91                          | 0.9073       |
| [36]        | -              | 121.98                          | 0.0587       |
| [31]        | $3.0723 \times 10^4$ | 129.91                          | 1.4651       |
| [30]        | $2.07 \times 10^1$   | 122.90                          | 0.0434       |
| [28]        | $2.2207 \times 10^4$ | 126.25                          | 2.4707       |
| [29]        | $3.7 \times 10^4$    | 120.01                          | 1.1673       |
| [46]        | $3.1275 \times 10^4$ | 129.73                          | 2.5353       |
| Proposed    | $1.7709 \times 10^4$ | 120.15                          | 0.0386       |

FIGURE 21. Running time of controller at different sampling instances.

prediction, and control horizon at 16 m/s mean wind speed. The running time at different values of sampling, prediction, and control horizons are plotted in Fig. 21. For Case I: prediction and control horizon are taken as 15 s and 10 s; Case II: 20 s and 10 s, and Case III: 70 s and 30 s, respectively.

From the results above, the longest running time occurs when the sampling time is 0.01 s, i.e., Case III. Moreover, the fluctuation exceeds 12%, (around 20.2%) making the controller impractical. In all cases, acceptable results can be obtained by increasing the sampling time (up to 0.6 s). In Case I: At the cost of 19.6% increase in the computational time, there is an improvement of approx. 4.7% in RMSE of generator speed. Without a substantial increase in computational time, there is an improvement in generator speed accuracy, therefore sampling time of 0.5 s is considered in the current study.

The computing speed for solving the quadratic programming problem expressed by cost function is one of the main drawbacks of MPC. However, benefiting from the fast development of computer technology, the fast-processing speed is competent to handle this challenge [47]. This study mainly focuses on full envelope control including the switching strategy on the torque/speed plane based on MPC, and complex robust MPC is not considered in this work.

VI. CONCLUSION AND FUTURE WORK

This study presents a multivariable controller based on MPC that can be operated over the full envelope of wind speeds. The controllers in each mode are designed using the linearized models derived from the DNV-GL Bladed model of a 5 MW Supergen turbine. Subsequently, switching between these linearized controllers are made to yield a full envelope multivariable MPC on the torque–speed plane. The controllers reported here cover the full envelope of operation regions, making this work more practical and novel. To improve the control performance, the wind information obtained from LiDAR is incorporated into the controller, resulting FF-MPC.

Simulations are carried out at multiple wind speeds to evaluate the robustness and switching performances of the designed controllers by applying them to a full nonlinear 5 MW Matlab/SIMULINK model of the same exemplar Supergen wind turbine. The results demonstrated that improved tracking and smoother switching are achieved with FF-MPC. Moreover, the control objectives are achieved without a corresponding increase in control activity (i.e., pitch action of wind turbine); that is, the controller’s GCF remains within the acceptable range, around 1 rad/s. The stability of the controller is also examined through frequency domain analysis to confirm robustness of controller. It is also illustrated that FF-MPC does not require a drive-train damper, unlike the PI-based controller, which is a significant achievement.

Future work will also consider the application of the controller to a full nonlinear high-fidelity aeroelastic model in DNV-GL Bladed to investigate tracking performance, which represents the same exemplar turbine. This model produces not only more realistic wind speeds, but also extra dynamics allowing further results to be achieved, including all important variables and loads and lifetime equivalent fatigue load estimates.

APPENDIX

WIND TURBINE

$P_{\text{rated}} = 5 \text{ MW}$, $\omega_0 = 120 \text{ rad/s}$, $R = 63 \text{ m}$, Hub height, $h = 90 \text{ m}$, One blade mass = 17,741 kg; Rotor inertia, $J = 3.88167 \times 10^7 \text{ kg} \cdot \text{m}^2$; Rotor and nacelle mass = 350,004 kg.

WIND

Cut-in and cut-out wind speeds: 4 and 25 m/s.

PITCH ACTUATOR

Minimum pitch angle, $\text{PIT}_{\text{MIN}} = 0^\circ$; Maximum pitch angle, $\text{PIT}_{\text{MAX}} = 90^\circ$.

TOWER PARAMETERS

Tower fore-aft inertia = 2,403,926,100 kg-m²; Tower fore-aft damping = 0.007; Tower fore-aft damping
moment = 58,199,531.67 Nm; Tower fore-aft stiffness = 7,188,889.24 Nm/rad; Tower side-side natural frequency = 1.7293 rad/s; Tower side-side inertia = 2,835,032,400 kg·m²; Tower side-side damping = 0.007; Tower side-side damping moment = 6,863,649,804 Nm.

**DRIVE-TRAIN PARAMETERS**
Hub inertia 115,926 = kg·m²; Low-speed shaft damping = 1.5 × 10⁶; High-speed shaft damping = 5; Low-speed shaft stiffness = 4.45 × 10⁸ Nm/rad; Low-speed shaft material damping = 4.2 × 10⁶; High-speed shaft material damping = 1000; High-speed shaft stiffness = 1 × 10¹⁰ Nm/rad; Gearbox ratio = 97; High-speed shaft inertia = 5 kg·m²; Generator inertia = 534.116 kg·m²; Nominal generator torque = 43,093 Nm.

**REFERENCES**
[1] Gwee/Global Wind Report 2021, Global Wind Energy Council, Brussels, Belgium, 2021.
[2] (2014). Manufacturers and Turbines Database: GE Energy. [Online]. Available: https://www.thewindpower.net/turbine_technical_en_57_ge-energy_1.5sle.php
[3] M. G. Santos, “Aerodynamic and wind field models for wind turbine control,” Ph.D. dissertation, Dept. Electron. Elect. Eng., Univ. Strathclyde, Glasgow, U.K., 2016.
[4] J. Bao, H. Yue, W. E. Leithead, and J.-Q. Wang, “Feedforward control for wind turbine load reduction with pseudo-LIDAR measurement,” Int. J. Autom. Comput., vol. 15, no. 2, pp. 142–155, Apr. 2018.
[5] S. Hur and W. E. Leithead, “Model predictive and linear quadratic Gaussian control of a wind turbine,” Optim. Control Appl. Methods, vol. 38, no. 1, pp. 88–111, Jan. 2017.
[6] A. Rantzer and M. Johansson, “Piecewise linear quadratic optimal control,” IEEE Trans. Autom. Control, vol. 45, no. 4, pp. 629–637, Apr. 2000.
[7] B. S. Chen and W. Zhang, “Stochastic H₂/H₄ control with state dependent noise,” IEEE Trans. Autom. Control, vol. 49, no. 1, pp. 45–57, Jan. 2004.
[8] G. Chesi, P. Colaneri, J. C. Geromel, R. Middleton, and R. Shorten, “Computation of upper bounds of the minimum dwell time of linear switched systems via homogeneous polynomial Lyapunov functions,” in Proc. Amer. Control Conf., Jun. 2010, pp. 2487–2492.
[9] I. Daubechies and J. C. Lagarias, “Sets of matrices all infinite products of which converge,” Linear Algebra Appl., vol. 161, pp. 227–263, Jan. 1992.
[10] D. Leith, R. N. Shorten, W. E. Leithead, O. Mason, and P. Curran, “Issues in the design of switched linear control systems: A benchmarking study,” Int. J. Adapt. Control Signal Process., vol. 17, no. 2, pp. 103–118, Mar. 2003.
[11] A. D. Hansen, P. Sorensen, F. Iov, and F. Blaabjerg, “Control of variable speed wind turbines with doubly-fed induction generators,” Wind Eng., vol. 28, no. 4, pp. 411–443, Jun. 2004.
[12] D. L. Salle, D. Reardon, W. E. Leithead, and M. J. Grimble, “Review of wind turbine control,” Int. J. Control, vol. 52, pp. 1295–1310, 1990.
[13] F. Wu, X. P. Zhang, K. Godfrey, and P. Ju, “Small signal stability analysis and optimal control of a wind turbine with doubly fed induction generator,” IET Gener. Transmiss. Distrib., vol. 1, no. 5, pp. 751–760, Sep. 2007.
[14] F. Mohd Zaihidee, S. Mekhilef, and M. Mubin, “Robust speed control of DFIG wind turbine using fuzzy logic,” Gaz U. Univ. Sci., vol. 31, no. 2, pp. 532–542, 2018.
[15] B. Bossoufi, M. Karim, A. Lagrioui, M. Taoussi, and A. Derouich, “Observer backstepping control of DFIG-generators for wind turbines variable-speed: FPGA-based implementation,” Renew. Energy, vol. 81, pp. 903–917, Sep. 2015.
[16] Z.-J. Yang, T. Nagai, S. Kanae, and K. Wada, “Dynamic surface control approach to adaptive robust control of nonlinear systems in semi-strict feedback form,” Int. J. Syst. Sci., vol. 38, no. 9, pp. 709–724, Sep. 2007.
[17] N. E. L. Ouanjli, M. Taoussi, A. Derouich, A. Chebabbia, A. E. L. Ghizilal, and B. Bossoufi, “High performance direct torque control of doubly fed induction motor using fuzzy logic,” Gaz U. Univ. Sci., vol. 31, pp. 532–542, 2018.
[43] W. E. Leithead and B. Connor, “Control of variable speed wind turbines: Design task,” *Int. J. Control*, vol. 73, no. 13, pp. 1189–1212, 2000, doi: 10.1080/002071700417849.

[44] M. H. Beale, M. T. Hagan, and H. B. Demuth, *Deep Learning Toolbox Getting Started Guide*, 14th ed. Natick, MA, USA: The MathWorks, 2020.

[45] D. J. Leith and W. E. Leithead, “Appropriate realization of gain-scheduled controllers with application to wind turbine regulation,” *Int. J. Control*, vol. 65, no. 2, pp. 223–248, 1996.

[46] A. P. Chatzopoulos, “Full envelope wind turbine controller design for power regulation and tower load reduction,” Ph.D. Thesis, Dept. Electron. Elect. Eng., Univ. Strathclyde, Glasgow, U.K., 2011.

[47] O. Gulbudak and E. Santi, “FPGA-based model predictive controller for direct matrix converters,” *IEEE Trans. Ind. Electron.*, vol. 63, no. 7, pp. 4560–4570, Jul. 2016.

**ABHINANDAN ROUTRAY** received the B.Tech. degree in electrical and electronics engineering from the Biju Patnaik University of Technology, Rourkela, India, in 2012, and the Ph.D. degree in electrical engineering from the Indian Institute of Technology IIIT (BHU) at Varanasi, India, in 2020. He is currently a Postdoctoral Researcher with the School of Electronic and Electrical Engineering, Kyungpook National University, South Korea. His research interests include wind turbine control, wind farms, predictive control, multilevel inverters, power quality improvement, and design of power electronics converters for microgrids.

**SUNG-HO HUR** received the B.Eng. degree in electronics and electrical engineering from the University of Glasgow, U.K., in 2004, and the M.Sc. (Hons.) and Ph.D. degrees in electronic and electrical engineering from the University of Strathclyde, Glasgow, U.K., in 2005 and 2010, respectively. He is currently an Associate Professor with the School of Electronics Engineering, Kyungpook National University, South Korea. Previously, he has been employed at the Wind Energy and Control Group, University of Strathclyde. His research interest includes control, with a particular interest in wind turbines and farm.