

Adaptive Control of a Variable-Speed Variable-Pitch Wind Turbine Using Radial-Basis Function Neural Network

Hamidreza Jafarnejadsani, Jeff Pieper, and Julian Ehlers

Abstract—In order to be economically competitive, various control systems are used in large scale wind turbines. These systems enable the wind turbine to work efficiently and produce the maximum power output at varying wind speed. In this paper, an adaptive control based on radial-basis-function neural network (NN) is proposed for different operation modes of variable-speed variable-pitch wind turbines including torque control at speeds lower than rated wind speeds, pitch control at higher wind speeds and smooth transition between these two modes. The adaptive NN control approximates the nonlinear dynamics of the wind turbine based on input/output measurements and ensures smooth tracking of the optimal tip-speed-ratio at different wind speeds. The robust NN weight updating rules are obtained using Lyapunov stability analysis. The proposed control algorithm is first tested with a simplified mathematical model of a wind turbine, and then the validity of results is verified by simulation studies on a 5 MW wind turbine simulator.

Index Terms—Adaptive control, generator torque control, pitch control, radial-basis function (RBF) neural network (NN), transition mode of operation, variable-speed variable-pitchwind turbine, varying wind speed.

I. INTRODUCTION

TODAY, wind turbine technology is one of the fastest growing power generation technologies. Wind turbines operate in time-varying wind speed. Therefore, in high wind speeds to prevent over speeding, the control should limit the rotation rate of the rotor. In large wind turbines, variable pitch blades are used. Active control of blade pitch angle can limit the speed of rotation by increasing the angle of attack, reducing the lift on the blades [1].

Although fixed speed wind turbines with stall controlled blades once prevailed in large wind turbine applications for many years, recently, with the fast growth in the wind turbine industry, variable speed wind turbines with variable pitch blade have become the new norm because of their efficiency in capturing more wind power and their ability to achieve the higher power quality. Moreover, variable speed wind turbines with active control on the turbine speed and power output can reduce load and stresses on various parts of the turbine

Manuscript received June 27, 2012; revised November 4, 2012; accepted December 22, 2012. Manuscript received in final form December 29, 2012. Date of publication January 23, 2013; date of current version October 15, 2013. Recommended by Associate Editor P. Korba.

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Digital Object Identifier 10.1109/TCST.2012.2237518

structure, including the blades and tower. As a result, higher power efficiency, longer life time, and improved power quality make these wind turbines economically competitive, despite their higher initial costs [2].

The contribution of this paper is in proposing a new control accounting for the varying operating conditions of a wind turbine. This paper follows the ideas presented in [3]. Many works have proposed controllers to work around an operating point using control of the generator torque to keep the turbine at a condition of maximum power point tracking, e.g., [4]. Some previously published works proposed pitch control methods to limit the rotor speed at high wind speeds, e.g., [5]. There are relatively few works that suggest control strategies based on varying operating condition for wind turbines and their dynamics. In this paper, the controller includes torque control at speeds lower than rated rotor speed, pitch control at rated power area, and a smooth transition mode between two conditions.

Neural networks (NNs) are powerful methods for approximation of arbitrary input-output mappings. Many works [6], [7] have suggested this method for nonlinear control systems. Radial basis function networks are one example of a successful method for this purpose. The structure of radial-basis function (RBF) networks consists of a single hidden layer of nonlinear nodes, centered so that each of them is specialized on a particular zone of the input space. The desired response is obtained by adjusting weights connecting the hidden layer with a linear output node, with a training procedure [8].

The main advantages of NNs are: 1) the neural weights are tuned online without any pre-training phase, and 2) the stability and performance of the closed-loop systems can be guaranteed. Because of this, adaptive NN control has become very suitable to control uncertain nonlinear dynamical systems like wind turbines. The theory of adaptive NN control of nonlinear systems is discussed in [9] and [10]. The online adaptation for approximation of nonlinear dynamics ensures a robustness against disturbances and uncertainties in the system. Adaptation will be demonstrated by observing the results of a simulation study and noting that when the control is not adaptive, i.e., when the control gains are not updated, robustness over an operating range is reduced. Wind turbine control structure consists of:

- 1) electrical subsystem (inner loop) with fast time response including the generator and pitch actuator;
- 2) mechanical subsystem (outer loop) with much slower time response including aerodynamics and drive-train.

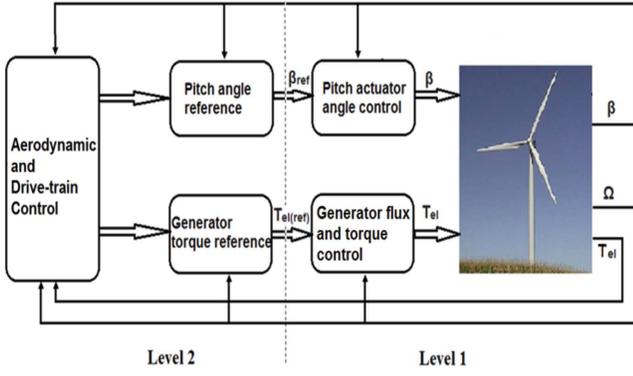


Fig. 1. Wind turbine control levels [11].

This defines a cascaded structure [11] as shown in Fig. 1. Our concern in this paper is the outer loop that provides the reference inputs of the inner loop. The pitch control is a non-affine nonlinear system. Adaptive control rule for non-affine nonlinear systems is suggested in various works [12] and we will provide an example of application of these methods.

This paper is organized as follows. The mathematical aerodynamic and drive-train model of variable-speed variable-pitch (VSVP) wind turbines is presented in Section II. In Section III, the control strategy including control structure and objectives are presented. Then, the RBF NN is introduced. In Section IV, the controller is presented and the robust weight updating rules derived using Lyapunov stability analysis. This section includes three parts:

- 1) torque control for rotor speeds lower than rated rotor speed;
- 2) pitch control for rated power region to limit rotor speed;
- 3) a control strategy for smooth transition between the two modes of operation of the wind turbine.

Simulation results are given in Section V and the controller performance is compared with a conventional gain-scheduled PID control as is common in wind turbine systems. Finally Section VI concludes this paper.

II. WIND TURBINE MODELING

In this section, we present a reduced order nonlinear model of wind turbine that is used to introduce the adaptive NN control for wind turbines. In Section V, we use FAST wind turbine simulation software to test the designed controller. The two main dynamical equations expressing the aerodynamic and mechanical modeling of a wind turbine are rotor speed dynamics and elastic tower fore–aft motion [13], which are given in the following equations.

A. Rotor Speed Dynamics

$$(J_R + J_G)\dot{\Omega} + C_t\Omega + T_g - T_a(\Omega, \beta, V_w, \dot{d}) = 0. \quad (1)$$

B. Elastic Tower Fore–Aft Motion

$$M_T\ddot{d} + C_T\dot{d} + K_Td - F_a(\Omega, \beta, V_w, \dot{d}) = 0 \quad (2)$$

where V_w is the wind speed, Ω is the rotor speed, d is the tower displacement, and β is the blade pitch angle. The term $C_t\Omega$ is the resistance torque in the gearbox proportional to rotor speed. J_R and J_G are the rotor and generator moments of inertia, respectively. M_T , C_T , and K_T are the equivalent mass, damping coefficient, and stiffness of the wind turbine tower, respectively, in second order dynamical model (2) of tower-top fore–aft displacement (d). T_a is the aerodynamic torque induced in the blades and F_a is the drag force on the turbine due to the wind flow. T_g is the electrical torque induced in the generator. System parameters are shown in Fig. 2. T_a and F_a are given by

$$T_a = \frac{1}{2}\rho\pi R^3 \frac{C_p(\lambda, \beta_e)}{\lambda} (V_w - \dot{d})^2 \quad (3)$$

$$F_a = \frac{1}{2}\rho\pi R^2 C_f (V_w - \dot{d})^2 \quad (4)$$

where λ is the so-called tip-speed ratio given by

$$\lambda = \frac{\Omega R}{V_w - \dot{d}} \quad (5)$$

where ρ is the air density and R is the length of blades. C_p is the power coefficient and C_f is the drag coefficient. In this paper, we assume C_f is constant for simplicity and C_p is a function of tip-speed ratio and pitch angle. The following relation is a mathematical model for C_p given by [14]:

$$C_p(\lambda, \beta) = c_1 \left(\frac{c_2}{\lambda_i} - c_3\beta - c_4 \right) e^{-\frac{c_5}{\lambda_i}} + c_6\lambda \quad (6)$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \quad (7)$$

$$c_1 = 0.5176, \quad c_2 = 116, \quad c_3 = 0.4$$

$$c_4 = 5, \quad c_5 = 21, \quad c_6 = 0.0068.$$

Note that the dynamics of the pitch servo-motors and the generator are much faster than those of rotor speed and tower displacement. Therefore, pitch activity and electrical torque equations can be ignored relative to rotor speed and tower displacement equations. In this paper, our concern is control of rotor speed and power optimization. Tower displacement is not a control objective but the tower displacement is considered as a source of disturbance to the control system, because of its effect on the relative wind speed faced by the wind turbine blades.

III. CONTROL STRATEGY AND OBJECTIVES

The time response of the electrical system of wind turbines is faster than for the mechanical system. This introduces two control levels in wind turbines (Fig. 1) that will be considered separately:

- 1) the inner control loop concerns the electric generator via the power converters;
- 2) the outer loop concerns the mechanical system that provides the reference inputs of the inner loop.

The final goals of wind turbine control are capturing the maximum wind power, alleviating mechanical loads, and power quality. Our concern in this paper is maximizing energy capture. The ideal power curve for a typical wind turbine is shown in Fig. 3.

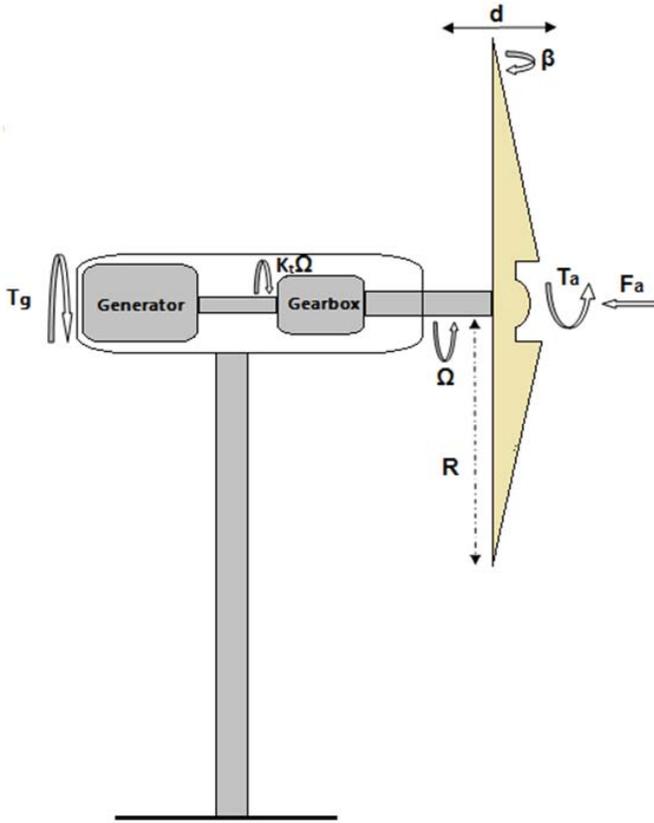


Fig. 2. Wind turbine system parameters.

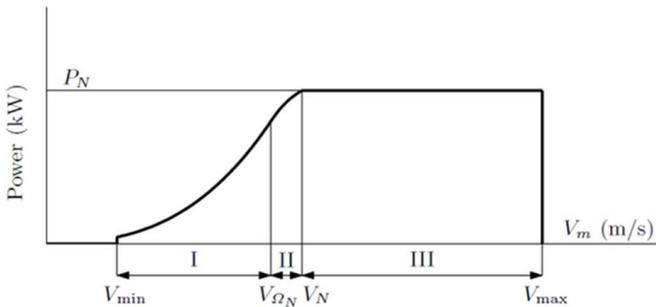


Fig. 3. Ideal power versus wind speed curve.

As is shown in Fig. 3 in the range of operation of wind turbines, three regions can be identified. For the wind speeds below the rated speed, the turbine captures the maximum available power in the wind flow. This region is specified by Region I. In this region, the pitch angle is fixed and the optimal rotor speed is tracked via generator torque control.

In Region III, the turbine should work at the constant rated power. In this region, there is more wind power available than the captured rated power. Therefore, the turbine works at lower efficiency less than C_{Pmax} . In this region, the generator torque is constant at its rated value and pitch control limits the rotor speed. For less fluctuation in output power, the generator torque can vary so that the multiply of rotor speed and generator torque remains constant i.e., the power is kept fixed. Both constant torque and constant power strategies can be used in Region III.

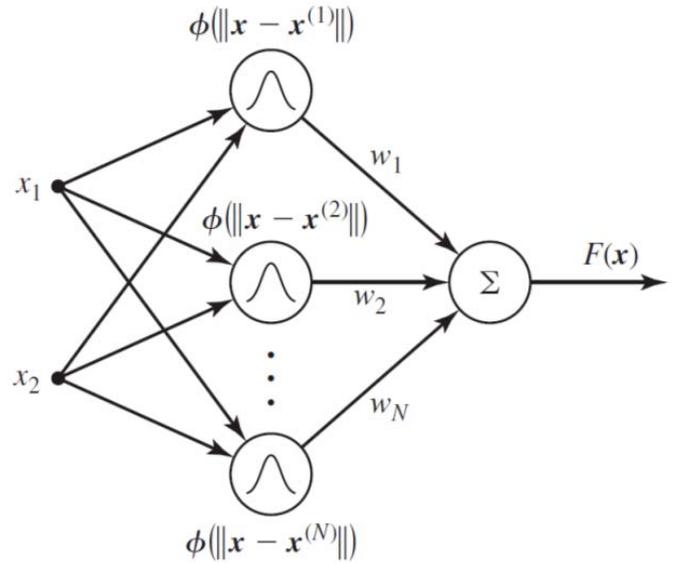


Fig. 4. Two-point radial-basis function.

Region II is a transition region between Regions I and III, and authority over rotor speed is transferred between the generator torque and the blade pitch. In some cases, this region may be ignored by connecting the maximum power region to the constant power region [1].

In this paper, we use a RBF NN for adaptive control of the wind turbine system. The number of inputs in the wind turbine control system is less than 4. Therefore, it is reasonable computationally and more accurate to use the RBF network approximation. The functions $\phi(\|x - x^{(i)}\|)$, $i = 1, 2, \dots, N$ are called the RBFs, where $\|\cdot\|$ denotes a p-norm, usually the Euclidean 2-norm [10]. A common choice for ϕ is

$$\phi(\|x - x^{(i)}\|) = \exp\left(-\frac{\|x - x^{(i)}\|^2}{2\sigma_i^2}\right) \quad (8)$$

where $x^{(i)}$ is the center of the basis function and σ_i is sometimes called its radius. The function given by (8) is called Gaussian RBF. A linear combination of basis functions can be used for approximation of a nonlinear function. As Fig. 4 shows, RBF networks have three layers: an input layer, a hidden layer with a nonlinear RBF activation function, and a linear output layer. The output : $\mathcal{R}^n \rightarrow \mathcal{R}$, of the network is thus

$$F(x) = \sum_{i=1}^N w_i \phi(\|x - x^{(i)}\|) \quad (9)$$

where N is the number of neurons in the hidden layer and the real parameters w_i , $i = 1, 2, \dots, N$ are the weights of the linear output neurons.

RBF networks are universal approximators, i.e., a RBF network with enough hidden neurons can approximate any continuous function with arbitrary precision. In this paper, the input domain is divided by uniformly-spaced grid (i.e., the same number of grid cell in each direction) and the system nonlinearity is evaluated in each node. To train the RBF NN,

we used the Lyapunov stability analysis to derive the updating rules for RBF network weights.

To implement the algorithm physically the sampling rate of the instruments that measure the rotor speed, pitch angle, and the wind speed should be high (0.001–0.1 s) to ensure a fast adaptation of the NN. In addition, the computational effort for RBF NN approximation and adaptation training (depending on the number of neurons and input layer grid size) demand sufficient memory (RAM) on the computer. The CPU used for computation should be fast enough to ensure the controller response meets the real-time dynamics of wind turbine.

IV. ADAPTIVE CONTRL DESIGN USING RBF-NN AND STABILITY ANALYSIS

In this section, adaptive control for three modes of operation of the wind turbine described in Section III is designed using Lyapunov stability analysis.

A. Torque Control

In the first mode of operation of a wind turbine, i.e., for wind speeds less than rated speed, the pitch angle is fixed and the electrical torque is used to control the rotor speed to make it track the optimal tip-speed ratio. We can write the rotor speed equation in standard affine form as follows:

$$\dot{\Omega} = f(\Omega, V_w) + gT_g \quad (10)$$

where T_g is the input and

$$f(\Omega, V_w) = \frac{\frac{1}{2}\rho\pi R^3 \frac{C_p(\lambda)}{\lambda} (V_w)^2 - K_t \Omega}{(J_R + J_G)}, \quad g = \frac{-1}{(J_R + J_G)} \quad (11)$$

where g is constant. Using the RBF NN, we train a nonlinear approximator so that

$$\frac{f(\Omega, V_w)}{g} = \vartheta(\Omega, V_w) w + d(\Omega, V_w) \quad (12)$$

where $|d(\Omega, V_w)| \leq d_{\max}$ is the NN approximation error. Now we define the tracking error, e , such that

$$e = \Omega - \Omega_{\text{opt}}(V_w) \quad (13)$$

where Ω_{opt} is the optimal rotor speed, and is given by the following relation:

$$\Omega_{\text{opt}}(V_w) = \frac{\lambda_{\text{opt}} V_w}{R}. \quad (14)$$

The optimal tip-speed-ratio, λ_{opt} , can be calculated from a polynomial fit of the C_p curve. C_p curves depend on the blade design and are given by the wind turbine manufacturer [4]. In this paper, for computer modeling, the C_p curve is given in (6) and (7). λ_{opt} is obtained by finding λ corresponding to the maximum of the curve.

In order to design a NN-control that stabilizes the system, we define Lyapunov function V as follows:

$$V = \frac{1}{(-2g)}e^2 + \frac{1}{2\beta_1}\tilde{w}^T \tilde{w} \quad (15)$$

where g is a negative constant and $\beta_1 > 0$. w is the ideal weight and \hat{w} is the estimated weight. $\tilde{w} = w - \hat{w}$ is the

weight error. V is a positive definite function and $\dot{V} \leq 0$ is a sufficient condition for the stability of the system

$$\dot{V} = (\Omega - \Omega_{\text{opt}}) \left(-\frac{f(\Omega, V_w)}{g} - u + \frac{\lambda_{\text{opt}} \dot{V}_w}{Rg} \right) - \frac{1}{\beta_1} \tilde{w}^T \dot{\hat{w}}. \quad (16)$$

β_1 is the positive adaptation gain. We use the neural network to obtain approximations $[f(\Omega, V_w)]/g = \vartheta(\Omega, V_w) w + d(\Omega, V_w)$ and $[\dot{f}(\Omega, V_w)]/\dot{g} = \vartheta(\Omega, V_w) \hat{w}$. Now we can design the appropriate controller to stabilize the system. We assume the controller to take the form

$$\hat{u} = T_g = -\vartheta(\Omega, V_w) \hat{w} + k(\Omega - \Omega_{\text{opt}}(V_w)) \quad (17)$$

where $k > 0$ is the error feedback gain.

Stability Proof:

$$\begin{aligned} \dot{V} = & (\Omega - \Omega_{\text{opt}}) \left(-d(\Omega, V_w) - k(\Omega - \Omega_{\text{opt}}) + \frac{\lambda_{\text{opt}} \dot{V}_w}{Rg} \right) \\ & + \tilde{w}^T \left(-\vartheta^T(\Omega, V_w) (\Omega - \Omega_{\text{opt}}) - \frac{1}{\beta_1} \dot{\hat{w}} \right). \end{aligned} \quad (18)$$

We can use the e-modification method for a robust weight updating rule as follows:

$$\dot{\hat{w}} = -\beta_1 \left(\vartheta^T(\Omega, V_w) (\Omega - \Omega_{\text{opt}}) + \nu |\Omega - \Omega_{\text{opt}}| \hat{w} \right) \quad (19)$$

where ν is a positive constant. We rewrite the time derivative of V as

$$\begin{aligned} \dot{V} = & (\Omega - \Omega_{\text{opt}}) \left(-d(\Omega, V_w) + \frac{\lambda_{\text{opt}} \dot{V}_w}{Rg} \right) - k(\Omega - \Omega_{\text{opt}})^2 \\ & + \nu |\Omega - \Omega_{\text{opt}}| \tilde{w}^T \hat{w}. \end{aligned} \quad (20)$$

We assume the rate of optimal rotor speed change is bounded

$$|\dot{\Omega}_{\text{opt}}| = \left| \frac{\lambda_{\text{opt}} \dot{V}_w}{Rg} \right| \leq d_w \quad (21)$$

$$\dot{V} \leq |\Omega - \Omega_{\text{opt}}| \left((d_{\max} + d_w) - k |\Omega - \Omega_{\text{opt}}| - \nu \tilde{w}^T \tilde{w} + \nu \tilde{w}^T w \right). \quad (22)$$

If $\delta_x = |\Omega - \Omega_{\text{opt}}| \geq (d_{\max} + d_w)/k + (\nu w^2)/4k$ or $\delta_w = \|\tilde{w}\| \geq (w/2) + \sqrt{(d_{\max} + d_w)/\nu + w^2/4}$ then, we have $\dot{V} \leq 0$.

Therefore, we can conclude the system is uniformly ultimately bounded (UUB).

B. Pitch Control

In Region III of wind turbine operation, at wind speeds higher than rated wind speed, the electrical torque remains constant. At high wind speeds, we try to limit the aerodynamic force induced in blades by varying the angle of attack of blades through manipulating the pitch angle. The turbine in this mode works around the rated generator speed and nominal power capacity. Power output higher than nominal capacity of the generator may cause serious damage. The governing equation of rotor speed in this mode is given by

$$\dot{\Omega} = \frac{\frac{1}{2}\rho\pi R^3 \frac{C_p(\lambda, \beta)}{\lambda} (V_w)^2}{(J_R + J_G)} - \frac{1}{(J_R + J_G)} (T_{\text{nom}} + K_t \Omega) \quad (23)$$

where $T_{\text{nom}} = P_{\text{nom}}/\Omega$ is the nominal generator torque in the Region III assuming constant power strategy. Constant torque strategy can be considered for Region III as well, where $T_{\text{nom}} = P_{\text{nom}}/\Omega_r$ is constant. P_{nom} is the nominal power capacity of the wind turbine, Ω is the rotor speed, and Ω_r is the rated rotor speed. We can rewrite (23) in the form

$$\dot{\Omega} = f(V_w, \Omega, \beta). \quad (24)$$

The system is an implicit function of pitch angle (input). Therefore, it cannot be formulated as an affine system. As such, we introduce a method to develop the adaptive control for the non-affine system. Consider the following transformation:

$$v = \dot{\Omega}, \quad v = f(V_w, \Omega, \beta^*) \quad (25)$$

where v is commonly referred to as the pseudo-control signal. The pseudo-control is chosen in this derivation as a linear operator.

Assumption: there exist positive constants f^L , f^H , and H such that

$$\begin{aligned} -f^H &\leq \frac{\partial f(V_w, \Omega, \beta)}{\partial \beta} \leq -f^L < 0 \\ &\leq H \left| \frac{d}{dt} \left[\frac{\partial f(V_w, \Omega, \beta)}{\partial \beta} \right] \right|. \end{aligned} \quad (26)$$

Since the pseudo-control v is, in general, not a function of the control β but rather a state-dependant operator, the assumption leads to

$$\frac{\partial [v - f(V_w, \Omega, \beta^*)]}{\partial \beta} \neq 0. \quad (27)$$

Using the fact that the expression in (25) is non-singular implies that in a neighborhood of every $\forall(V_w, \Omega, \beta)$, there exists an implicit function $\alpha(V_w, \Omega, v)$ such that

$$v - f(V_w, \Omega, \alpha(V_w, \Omega, v)) = 0. \quad (28)$$

Therefore

$$\beta^* = \alpha(V_w, \Omega, v). \quad (29)$$

By the mean value theorem in [15], there exists $\lambda \in (0, 1)$ such that

$$f(V_w, \Omega, \beta) = f(V_w, \Omega, \beta^*) + (\beta - \beta^*) f_\beta \quad (30)$$

where $f_\beta = [(\partial f(V_w, \Omega, \beta))/\partial \beta]_{\beta=\beta_\lambda}$, $\beta_\lambda = \lambda\beta + (1-\lambda)\beta^*$.

Now we define the tracking error $e = \Omega - \Omega_r$, where Ω_r is the rated speed of the rotor. It is the maximum allowed rotor speed and the wind turbine operates around this constant speed, ($\dot{\Omega}_r = 0$ for rated power Region III). Therefore, the error dynamic can be written as

$$\begin{aligned} \dot{e} &= \dot{\Omega} - \dot{\Omega}_r \\ &= f(V_w, \Omega, \beta) - \dot{\Omega}_r \\ &= f(V_w, \Omega, \beta^*) + (\beta - \beta^*) f_\beta - \dot{\Omega}_r. \end{aligned} \quad (31)$$

Based on the transformation introduced in (25), we know that for $\beta^* = \alpha(V_w, \Omega, v)$ we have $v = f(V_w, \Omega, \beta^*)$. Using this fact, in terms of the error dynamics

$$\dot{e} = v + (\beta - \beta^*) f_\beta - \dot{\Omega}_r. \quad (32)$$

The pseudo-control is designed as

$$v = \dot{\Omega}_r - ke = -ke \quad (33)$$

where $k > 0$ is the error feedback gain. The ideal controller function (29) may be represented by an RBF NN approximation, such that

$$\beta^* = \vartheta(V_w, \Omega, v) w^* + \varepsilon(V_w, \Omega) \quad (34)$$

where w^* is the vector of ideal weights and $\varepsilon(V_w, \Omega)$ is called the NN approximation error satisfying $|\varepsilon(V_w, \Omega)| \leq \varepsilon_N$. Now we define an adaptive control to estimate w^* with \hat{w} . This estimate is used to formulate the control law as

$$\beta = \varphi(V_w, \Omega, v) \hat{w}. \quad (35)$$

Stability Proof: A weight error is now defined as $\tilde{w} = \hat{w} - w^*$ for the system to rewrite the error dynamics by substituting (33)–(35) in (31)

$$\dot{e} = -ke + \vartheta(V_w, \Omega) \tilde{w} f_\beta - \varepsilon(V_w, \Omega) f_\beta. \quad (36)$$

Now we can find the network updating rule by Lyapunov stability analysis. Consider the following Lyapunov function:

$$V = \frac{1}{2} \frac{e^2}{(-f_\beta)} + \frac{1}{2\gamma} \tilde{w}^T \tilde{w}, \quad f_\beta < 0. \quad (37)$$

γ is the positive adaptation gain. We use the definition of the error dynamics (36) to write the time derivative of V as

$$\begin{aligned} \dot{V} &= \frac{k}{f_\beta} e^2 + \tilde{w}^T \left(-e \vartheta^T(V_w, \Omega, v) + \frac{1}{\gamma} \dot{\tilde{w}} \right) \\ &\quad + e \varepsilon + \frac{e^2}{2f_\beta^2} \dot{f}_\beta. \end{aligned} \quad (38)$$

We define robust weight-updating rule using e-modification rule as

$$\dot{\tilde{w}} = \gamma (e \vartheta^T(V_w, \Omega, v) - \mu |e| \hat{w}) \quad (39)$$

where μ is a positive constant. From assumption, we have $-f^H \leq f_\beta \leq -f^L < 0 \rightarrow (1/-f_u) \leq (1/f_L), (1/f_u) \leq (1/-f_H)$. Furthermore, knowing that $|\varepsilon| \leq \varepsilon_N$ we can obtain the following upper bound for the time derivative of V

$$\begin{aligned} \dot{V} &\leq \left(-\frac{k}{f^H} + \frac{H}{2(f^L)^2} \right) e^2 \\ &\quad + |e| \varepsilon_N + \mu |e| \tilde{w}^T w - \mu |e| \tilde{w}^T \tilde{w}. \end{aligned} \quad (40)$$

We define: $K = -(-(k/f^H) + (H/2)(f^L)^2)$ and assuming $k > (Hf^H/2)(f^L)^2$. So that, $K > 0$.

$$\dot{V} \leq -K e^2 + |e| \varepsilon_N + \mu |e| \tilde{w}^T w - \mu |e| \tilde{w}^T \tilde{w} \quad (41)$$

$$\dot{V} \leq |e| \left(-K |e| + \varepsilon_N - \mu \left(\tilde{w} - \frac{w}{2} \right)^2 + \frac{\mu w^2}{4} \right). \quad (42)$$

If $\delta_x = |e| \geq (\varepsilon_N/K) + (\mu w^2/4K)$ or $\delta_w = \|\tilde{w}\| \geq w/2 + \sqrt{(\varepsilon_N \mu) + (w^2/4)}$ then, we have $\dot{V} \leq 0$.

Therefore, we can conclude the system is UUB.

TABLE I

NREL-OFFSHORE-BASELINE-5 MW WIND TURBINE CHARACTERISTICS

Rating	5 MW
Rotor Orientation, Configuration	Upwind, 3 Blades
Control	Variable Speed, Variable Pitch
Rotor, Hub Diameter	126 m, 3 m
Hub Height	90 m
Cut-In, Rated, Cut-Out Wind Speed	3 m/s, 11 m/s, 25 m/s
Cut-In, Rated Rotor Speed	6.9 rpm, 12.1 rpm
Rotor Mass	110000 kg
Optimal Tip-Speed-Ratio	7.55
Rated Generator Torque	43100 Nm
Maximum Generator Torque	47400 Nm
Rated Generator Speed	1174 RPM

C. Transition Mode

For a smooth transition between Regions I and III, the following control strategy is proposed. Nominal rotor speed (or rated power) and maximum torque are important generator specifications that are given by manufacturers. In wind turbines, the rotor speed reaches the rated value at wind speeds slightly below the rated wind speed and at that point the rotor speed is maintained fixed using torque control. In this period, generator torque may hit its maximum. In the transition mode (Region II), at rated wind speed, the pitch control is activated and as the pitch angle increases, the generator torque slowly decays to the rated torque. Because of continuity in controls (generator torque and pitch angle), this control strategy induces a smooth transition. Moreover, because of constant rotor speed during the transition Region II, mechanical loads are kept below severe levels in the wind turbine components. Fig. 5 illustrates the control strategy during the transition.

V. SIMULATION STUDY

The proposed control strategy was validated using the fatigue, aerodynamics, structures and turbulence (FAST) aero-elastic simulator. FAST code was developed by NREL¹ [16]. The parameters of the National Renewable Energy Laboratory (NREL) Off shore-Baseline-5 MW wind turbine, which can be found in [17] are used for simulation. NREL-Offshore-Baseline-5 MW is a variable-speed variable-pitch wind turbine with a nominal power rating of 5 MW and hub height of 90 m and has three blades with rotor diameter of 126 m. The main parameters of the wind turbine are summarized in Table I.

The proposed adaptive control is implemented on the model using a SIMULINK interface provided in FAST. The results are shown in Fig. 6. The necessary wind turbine model specifications for controller design are the rated rotor speed, maximum generator torque, optimal tip-speed-ratio, and length of the blades. The adaptive controller is able to approximate the nonlinearity in the wind turbine model. Wind speed is the input of control system and can be measured or estimated.

¹NREL, Golden, CO.

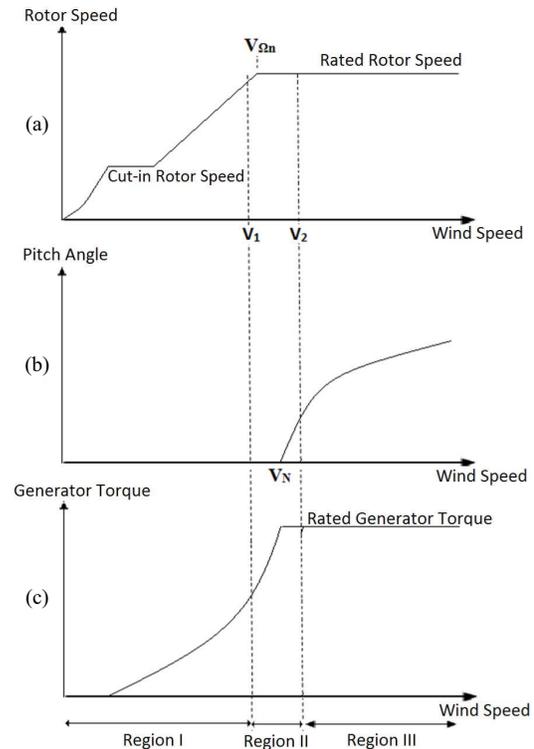


Fig. 5. (a) Control inputs, (b) pitch angle, and (c) generator torque at different wind conditions. The control strategy results in acceptable rotor dynamics as shown in (a).

The average ambient wind speed as a reference input to the controller enables the controller to track the optimal tip-speed ratio and ideal power curve. There are approaches to estimate the rotor-effective wind speed without directly measuring the wind speed [18], [19]. A sensor-less wind speed measurement is proposed in [20] using NNs to generate the reference rotor speed from an output power evaluation. In this simulation, wind speed is a ramp input first. Also, a disturbance caused by fore-aft motion of tower and a measurement noise is added to the input wind speed.

Fig. 6(a) shows the wind speed profile. Wind speed increases over time and is affected by a disturbance because of tower fore-aft motion and measurement noise. As the wind speed increases, the speed of the rotor versus wind speed is shown in Fig. 6(b). The initial rotor speed is 6RPM in this simulation. The electrical power output of the turbine versus wind speed is shown in the Fig. 6(c) and it roughly matches the ideal power curve. At wind speeds below the rated power area, the wind turbine controller maintains the power coefficient at its maximum and at higher wind speeds, the power coefficient decreases to limit the rotor speed. As shown in Fig. 6(d), for high wind speeds at rated power area, the generator torque is saturated and constant. The speed of rotor has been limited by pitch control. Fig. 6(e) shows the pitch angle (control input) as wind speed increases. As shown, at the wind speeds less than the rated rotor speed, the pitch angle is fixed and the speed of rotor is controlled by generator torque.

Although, the adaptation rate of the NN is very fast, in the transition region there may be a problem in switching between the two controllers during wind gusts. The proposed

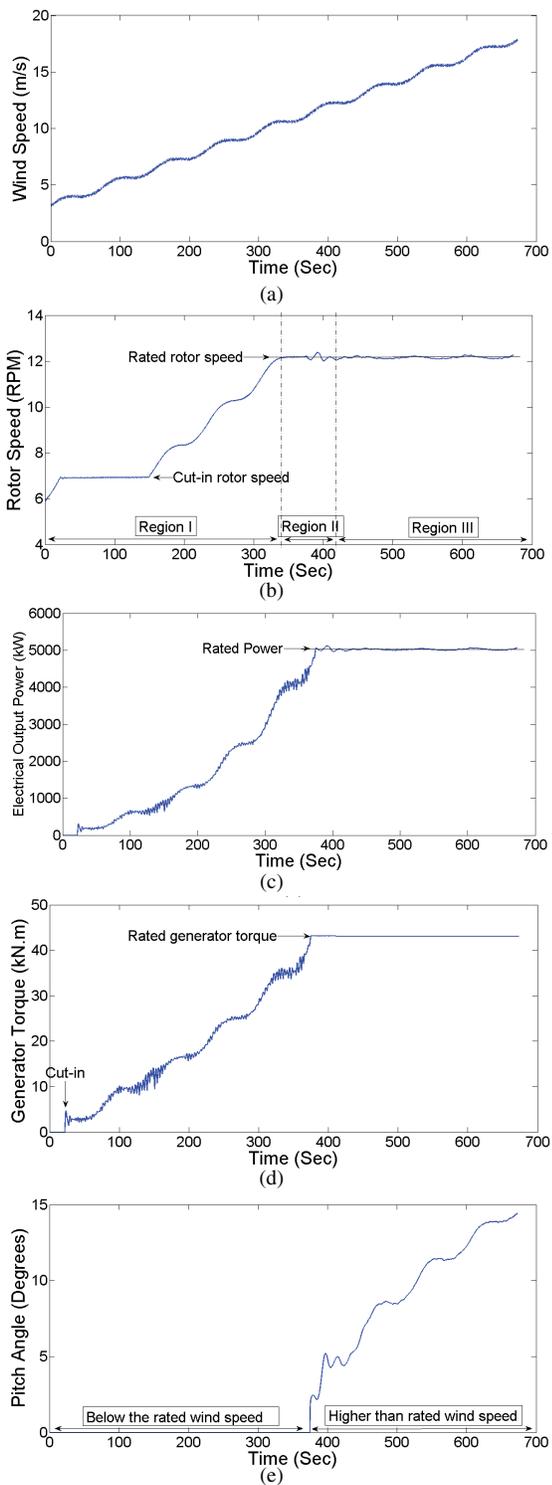


Fig. 6. Simulation results of adaptive control of NREL-offshore-baseline-5 MW wind turbine using RBF-NN in full range of operation. (a) Wind speed profile. (b) Rotor speed. (c) Electrical output power. (d) Generator torque. (e) Pitch angle shown in a time interval of 11 mins.

controller switching method causes large overshoot and transient loads in this region. This problem can be avoided by pre-training the NN around the range of network variables in the transition region. Number of neurons in the hidden layer of NNs is specified based on the domain that variables are

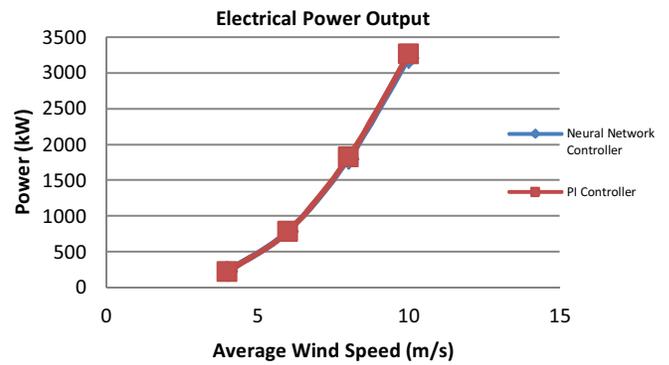


Fig. 7. Average power at different wind speeds below the rated wind speed (Region I) for NN control and gain-scheduled PI control.

defined and the size of the grid. This number is chosen by a tradeoff between calculation effort and the accuracy needed for reasonable approximation of nonlinearity by the NN. The range of change of each variable should be chosen reasonably to avoid extra calculations in real-time control. Outside of this domain, a supervisory controller can be considered to ensure the stability of the control system as discussed in [8].

Fig. 6 shows that the adaptive control induces good performance over a wide range of wind speeds. The NN weights are not pre-tuned and by an online adaptation, the nonlinear dynamics are approximated at different operating points. The online training of the NN ensures robustness against disturbances in turbulent wind flow. To test the robustness to disturbances, a series of simulations were run under simulated full-field turbulent wind conditions over a range of mean wind speeds. Fig. 8 compares pitch and power performance of the adaptive control to that of a well-tuned PI controller [17]. Wind inputs to these simulations are TurbSim-generated [21] 24×24 grids of IEC Class A Kaimal-spectrum turbulence [22], sampled every 50 ms, with a logarithmic vertical wind profile corresponding to a roughness length of 0.03 m. Six turbulence realizations per mean wind speed are simulated. Each simulation is 600s in length; results are computed based on the final 500s of each simulation in order to eliminate the effect of initial conditions.

Gain scheduling strategies are widely used in wind turbines. Gain-scheduled controller is a well-known strategy that makes it possible to use linear control theory for these nonlinear systems. In fact, gain-scheduled controllers are a type of linear time-invariant controllers together with an algorithm that changes the controller applied to the plant as the operation point changes. These controllers are often designed in the framework of linear parameter varying systems. In this paper, a gain-scheduled PI control as developed by NREL [17] is compared with the proposed adaptive NN control. The PI controller gains are tuned for optimal performance of the 5 MW wind turbine.

Fig. 7 compares the average power generation for PI and NN controllers at several turbulent wind realizations with mean speeds below the rated wind speed (Region I). Fig. 7 indicates that the power generation for the two controllers is almost the same. We simulated the wind turbine in Region III,

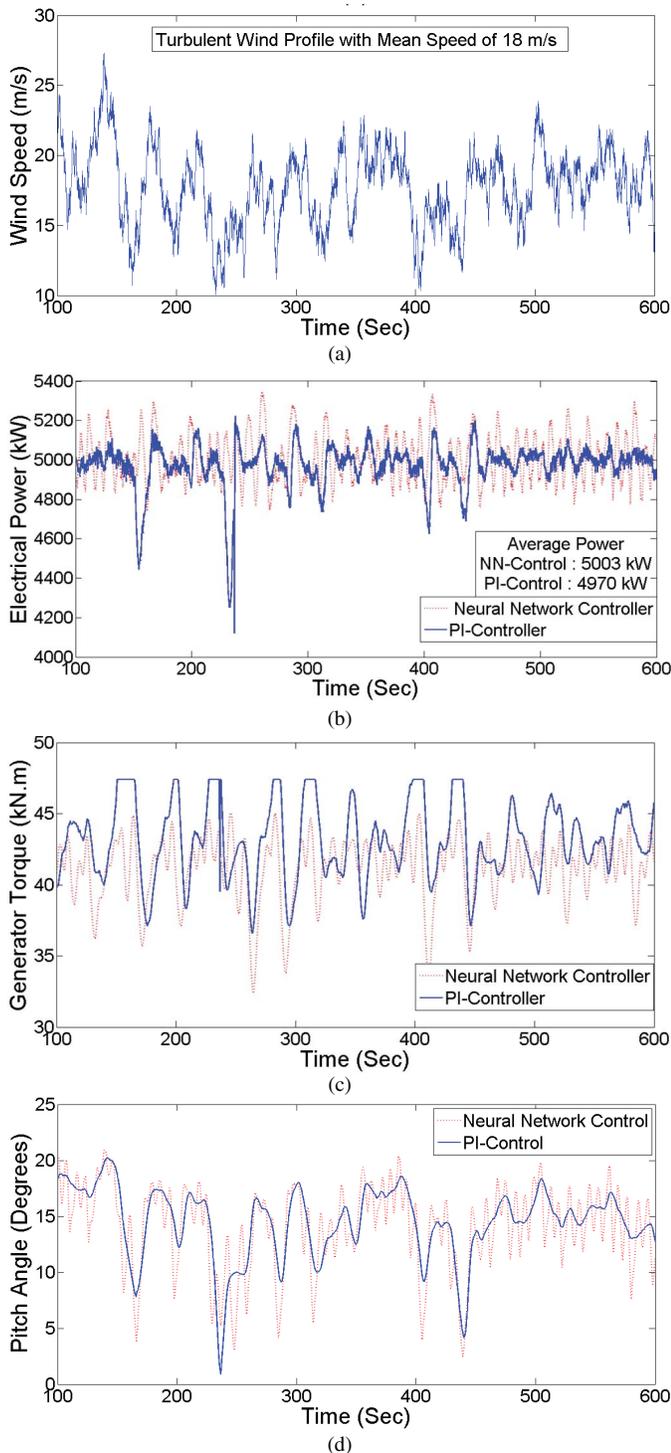


Fig. 8. NN and PI control of NREL-offshore-baseline-5 MW wind turbine in the rated power area (Region III) are compared. (a) Wind speed profile. (b) Electrical output power. (c) Generator torque. (d) Pitch angle are shown in a time interval of 10 mins.

applying the turbulent wind input with mean speed of 18 m/s shown in Fig. 8(a), to compare PI and NN controllers. Fig. 8(b) illustrates the generated power over time. As shown in Fig. 8(b), the NN controller has improved the power generation by 33 kW while reducing the amplitude of power fluctuations. Fig. 8(c) indicates that the generator torque

reaches the maximum torque several times under PI control, but the torque saturation does not happen under NN control. Frequent operation at maximum generator torque induces high stresses in the mechanical components and may cause over heating in the electric circuits. As shown in Fig. 8(d), the NN control has more pitch activity than the PI control. These oscillations in pitch angle induce wear and fatigue loads in mechanical components and cause extra fluctuations in power and generator torque. However, various works have addressed the problems in RBF NNs. Reference [12] has proposed a noise rejection technique for robust NN control of non-affine systems. If the high pitch activity is addressed, the NN controller will be a promising alternative to the PI controller in wind turbines due to faster its response to wind variations.

VI. CONCLUSION

In this paper, a controller for VSVP wind turbine was proposed. The proposed adaptive controller approximates the complex nonlinear dynamics of a wind turbine using RBF NNs and induces good power performance. The control strategy was designed for a wide range of wind conditions. The main goal is capturing maximum wind power.

The proposed adaptive NN control is robust to uncertainty in the wind turbine model and the simulation study showed that the controller allows rejection of disturbance caused by turbulent wind flow while the whole control system is stable that proves the theory developed in this paper. This paper suggested a successful control strategy at different regions of operation of wind turbine, including maximum power region and rated power region as compared to optimized gain-scheduled PI controller. The NN control increased the power and reduced the maximum torque in Region III. Pitch activity closer to the PI can be achieved using noise reduction techniques for NNs.

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