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Optimal Adaptive Robust Pitch Control with Load Mitigation for Uncertain Variable Speed Wind Turbines

S. Majidi[1] and R. Shahnazi[1*]

[1]Department of Electrical Engineering, Faculty of Engineering, University of Guilan, Rasht, Iran

ABSTRACT: In this paper, an optimal adaptive robust pitch controller is proposed for variable speed wind turbines (VSWTs). The proposed pitch controller has stability analysis, while it simultaneously keeps the generated power of the wind turbine at the rated power and mitigates the mechanical loads on the gearbox. The proposed pitch controller in this paper has two terms. The first term is a radial basis function neural network (RBFNN), to approximate unknown nonlinear functions of the wind turbine. Another term is a chattering-free continuous robust structure, which can cope with the approximation error. The weights of RBFNN and the gain of the robust structure are derived via the Lyapunov synthesis approach. It is proved that the closed-loop signals are semi-globally uniformed and ultimately bounded. The optimal parameters of the proposed controller are derived by solving a proposed multi-objective optimization problem using non-dominated sorting genetic algorithm-II (NSGA-II) and multi-objective particle swarm optimization (MOPSO) algorithm. The effectiveness of the proposed controller is compared to the baseline PI controller designed by NREL. First, both the proposed and the baseline PI controllers are applied to the general model (2-mass model) of the wind turbine, and then they are validated via a highly reliable simulator called FAST. The results demonstrate the effectiveness and applicability of the proposed pitch controller.

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1- INTRODUCTION

Wind energy has major and crucial advantages; it is environment-friendly, has a large capacity, and is considered one of the most significant renewable energy resources in the world [1]. There are two types of wind turbines used to transform wind energy into electrical energy: Fixed Speed Wind turbines (FSWTs) and Variable Speed Wind turbines (VSWTs). In FSWTs, the rotor speed is constant and can be connected to the grid directly. However, VSWTs follow the changes in wind speed and work in different rotor speeds. The main advantage of VSWTs is that they mostly produce the highest power [2]. The control of VSWTs is more challenging with the gearbox since not only the performance of wind turbines such as power quality should be considered, but also the fatigue damages should be studied due to mechanical loads caused by the gearbox. Control of VSWTs is usually accomplished by considering different regions. In this paper, the focus is on the above-rated speed, i.e., full load region. The major challenges are improving the performance of the wind turbine, increasing the power quality, and mitigating mechanical loads while ensuring system stability. One of the most effective approaches to ensure these objectives is to utilize adaptive control methods. In adaptive control methods, the controller's parameters are tuned effectively concerning the changes in the environment. Meanwhile, this tuning is accomplished in a way that the closed-loop stability is also guaranteed.

In recent years, several studies have been devoted to the adaptive pitch control of VSWTs with the gearbox in the full load region [1, 3-51]. The $\ell 1$ adaptive method is used, such as in [3, 4]. The controllers in [5-10] are based on sliding mode control, furthermore [11, 12] are used an adaptive integral sliding mode controller. Model reference adaptive method is offered in [13, 14]. In [15, 16], the authors designed an adaptive collective pitch controller for a wind turbine operating in the full load region. Some papers use a self-tuning regulator (STR) as the adaptive control [17-20]. In [21-24], the back-stepping control method is used. The authors in [25] propose a multiple model adaptive control method. An adaptive decoupling controller is designed in [26] to capture power from the wind, and to provide pitch adjustment to power regulation. In [5, 21, 27-40], the authors design controllers to reduce load mitigation, suppress blade fluttering caused by unsteady aerodynamic loads, and stabilize the wind turbine under different control conditions. The authors in [41] propose a control method based on vector control theory. In [1, 42-44], the authors suggest neural network methods to deal with uncertainties and nonlinearities. The fuzzy control method is suggested in [45-48]. In [49], the authors propose

*Corresponding author's email: shahnazi@guilan.ac.ir

an adaptive controller based on RBFNN for partial, full load regions, and smooth transition between these two operating regions of the wind turbine. In [50], a non-affine dynamic concerning the pitch angle is considered for the wind turbine. An adaptive RBFNN is proposed to approximate non-parametric uncertainties. The closed-loop system is robust against unknown disturbances, and the stability is proved by the Lyapunov method. In [51], the authors use a simple affine control problem and employ the feedback linearization technique. An online learning approximator (OLA) is utilized to estimate the unknown nonlinearities. A high-gain observer is implemented to obtain an estimation of rotor acceleration.

In this paper, an optimal direct adaptive robust controller is proposed for controlling the pitch angle of a general VSWT with the gearbox, which works in the full load region. The pitch angle is approximated based on the universal approximation theorem by RBFNN. The reason for using RBFNN is that its desirable performance is demonstrated in practical applications in comparison to the other common approximators [52, 53]. The weights of the RBFNN are tuned with suitable adaptive laws. Furthermore, a continuous robust adaptive structure is considered to cope with the neural network approximation error, which is chattering-free due to its continuity. The closed-loop stability is proved via the Lyapunov synthesis approach. To derive the optimal parameters of the proposed controller, two objective functions are considered. First, is the integral absolute error (IAE), used to minimize the tracking error of generator speed desirably. The second considers the integral absolute rate of the control signal (IARCS) to minimize pitch control fluctuations and thus mitigate mechanical loads. These two objective functions are contradictory and thus we have a multi-objective optimization problem. In this regard, the multi-objective particle swarm optimization (MOPSO) algorithm [54] and non-dominated sorting genetic algorithm-II (NSGA-II) [55], which are the most effective algorithms for this purpose, are applied. The proposed method is applied to the NREL model for $5\,MW$ VSWT with the gearbox [56]. To confirm the effectiveness of the proposed controller, we compared it with a baseline PI controller designed by NREL with some suitable simulations. Meanwhile, to show that the proposed optimal adaptive controller is practical, it is validated using one of the most reliable simulators called FAST. The contributions of the proposed method are summarized as follows:

1. The closed-loop stability of the wind turbines is extremely important, and it is generally a safety issue in the engineering of the system. However, in [13, 17, 20, 39, 45, 47] despite many advantages, the closed-loop stability has not been studied. In this paper, the closed-loop stability is analyzed by the Lyapunov synthesis approach and it is proved rigorously that all the closed-loop signals are semi-globally uniformed and ultimately bounded.

2. Due to different uncertainties, the robustness of the controller is an important factor. Due to the sophisticated nature of the structure and the presence of variable inputs, the use of a robust controller is a significant issue in wind turbines. When using a robust term, the harmful phenomenon called chattering should be avoided. In [1, 4, 15-18, 20, 25-29, 31-33, 38-40, 42, 45-47, 49] the authors proposed precious methods, but did not use a robust term in the controller. In [5, 6, 9, 14, 21, 22, 41, 50], despite using a robust term, the controller is not chattering-free, and in [7, 9, 21, 24, 37, 51], the robust term of the controller is not adaptive. In this paper, a continuous adaptive robust term is considered, which is chattering-free due to continuity and does not need the bound of uncertainties due to adaptiveness.

3. Most controllers have many free parameters. The selection of these parameters greatly affects the performance and lifetime of the wind turbines. Despite the numerous advantages of the methods in [4, 6, 9, 14, 17-19, 21, 23, 25, 28, 29, 33, 35-37, 49, 51], the control parameters are derived by trial and error. This procedure is not only a time-consuming process but also it does not necessarily give the optimal parameters. In this paper, a nonlinear multi-objective optimization problem is defined to derive the optimal parameters of the proposed controller to achieve both satisfactory performance and mitigating mechanical loads.

4. One of the most important steps in control design is to validate the performance and robustness of the proposed controller. In this regard, one of the most effective tools for wind turbine validation is the FAST simulator developed by NREL. Despite the importance of this issue, the validation section exists only in a few articles such as [14, 15, 39]. In this paper, the performance of the proposed controller is validated by the FAST simulator, which verifies the effectiveness and applicability of the proposed controller.

This paper is organized as follows; in Section 2, the mathematical model of the wind turbine and universal approximation theorem are described. The proposed optimal robust adaptive controller has been stated in Section 3. Section 4 applies the proposed controller on NREL $5\,MW$ VSWT with the gearbox and compares it with the PI baseline controller designed by NREL, later validates the performance of the proposed controller by the FAST simulator. Finally, Section 5 concludes the paper with some discussions.

2- WIND TURBINE MODEL AND UNIVERSAL APPROXIMATION THEOREM

In this paper, the offshore $5\,MW$ baseline wind turbine model has been used. This wind turbine is a conventional three-blade upwind variable, speed variable pitch angle turbine [56]. The general structure of a wind turbine is presented in Fig. 1, which includes 4 sub-models; Aerodynamics, drive train, generator and pitch actuator. The next subsections gives a brief explanation of them.

2.1. Aerodynamics

The aerodynamic power captured by the rotor from the wind can be calculated as follows: [57]

$$P_a = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\overline{\beta})v_w^3, \tag{1}$$

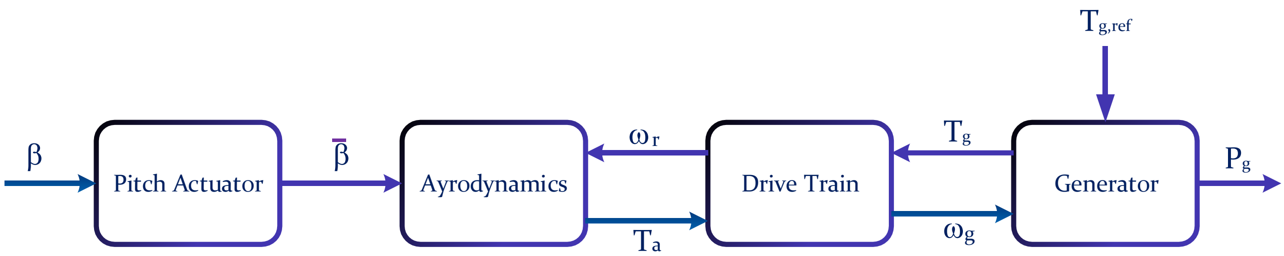

Fig. 1. Sub-models of wind turbine system

where P_a is the aerodynamic power (W), C_p is the power coefficient and depends on λ and $\bar{\beta}$, R is the radius of the rotor (m), $\lambda = \omega_r R / v_w$ is the tip speed ratio with v_w is the wind speed ($m.s^{-1}$) and ω_r is the rotor angular speed ($rad.s^{-1}$), $\bar{\beta}$ is the blade pitch angle ($^\circ$), ρ is the air density ($kg.m^{-3}$). Aerodynamic power and the aerodynamic torque are related as follows

$$P_a = \omega_r T_a, \tag{2}$$

$$T_a = \frac{1}{2}\rho\pi R^3 C_q(\lambda, \bar{\beta}) v_w^2, \tag{3}$$

in which $C_q(\lambda, \bar{\beta}) = \dfrac{C_p(\lambda, \bar{\beta})}{\lambda}$ is the torque coefficient.

2.2. Drive Train

The drive train consists of the low-speed shaft, gearing, torsion spring, and high-speed shaft. This part of the system converts the rotational speed of the rotor to a higher speed and transmits it to the generator. One of the conventional models for drive train is the 2-mass model. In this model, each shaft is considered a moment of inertia. The dynamics of the rotor side is as follows: [58]

$$J_r \dot{\omega}_r = T_a - T_{ls} - B_r \omega_r, \tag{4}$$

$$T_{ls} = K_{ls}(\theta_r - \theta_{ls}) + B_{ls}(\omega_r - \omega_{ls}), \tag{5}$$

where J_r is the rotor moment of inertia ($kg.m^2$), T_{ls} is low speed shaft torque ($N.m$), B_r and B_{ls} are rotor external damping and low speed shaft damping coefficients respectively ($N.m.rad^{-1}.s$), K_{ls} is spring constant of the low-speed shaft ($N.m.rad^{-1}$), θ_r and θ_{ls} are rotor side angular deviation and gearbox side angular deviation respectively (rad), ω_r and ω_{ls} are respectively the angular velocities ($rad.s^{-1}$). The dynamic of generator side is described by:

$$J_g \dot{\omega}_g = T_{hs} - K_g \omega_g - T_g, \tag{6}$$

where J_g is the generator moment of inertia ($kg.m^2$), T_{hs} and T_g are high speed shaft and generator torque respectively ($N.m$), K_g is the generator external damping ($N.m.rad^{-1}.s$), and ω_g is angular velocity of the generator ($rad.s^{-1}$). The gearbox is considered lossless with the ratio n_g as

$$n_g = \frac{T_{ls}}{T_{hs}} = \frac{\omega_g}{\omega_{ls}} = \frac{\theta_g}{\theta_{ls}}. \tag{7}$$

2.3. Generator

The generator subsystem can be approximated by a first order system: [57]

$$\dot{T}_g = \frac{1}{\tau_g}(T_{ref} - T_g), \tag{8}$$

$$P_g = n_g \omega_g T_g, \tag{9}$$

in which P_g is the power generated by generator (W) and τ_g is the time constant ($\sec$).

2.4. Pitch Actuator

Pitch angle is the angle of the blades in relation to the wind direction. The pitch actuator rotates the blades in the longitudinal axis to control the angle of the blades. The pitch actuator can be modeled as a first order dynamic as follows [57]

$$\dot{\bar{\beta}} = \frac{1}{\tau_\beta}(\beta - \bar{\beta}). \tag{10}$$

where β is the reference pitch angle ($^\circ$) and τ_β is the pitch actuator's time constant ($\sec$).

2.5. Universal Approximation Theorem

An RBF neural network is a universal approximator, and it can approximate any continuous function defined on a compact set to any degree of accuracy [52, 59].

Theorem 1. Consider $f(x): \Omega \to \mathbb{R}$ to be a continuous function defined on a compact set Ω. For any $\varepsilon > 0$ there exists an RBF neural network $w^{*T}\varphi(x)$ with w^* to be vector of optimal weights such that

$$\sup_{x\in\Omega}\left|f(x) - w^{*T}\varphi(x)\right| < \varepsilon. \tag{11}$$

It should be noted that by choosing M number of neurons for the RBF neural network we have $w^* = [w_1^*,\dots,w_M^*]^T$ and $\varphi(x) = [\varphi_1(x),\dots,\varphi_M(x)]^T$, where $\varphi_i(x)$ is

$$\varphi_i(x) = \exp\left(-\frac{\left\|x-\mu_i\right\|^2}{\sigma_i^2}\right), \tag{12}$$

with σ_i and μ_i are the width and the center of the Gaussian function $\varphi_i(x)$.

3- Proposed Method

3.1. Proposed Adaptive Robust Control Design

In this paper, the full load region is considered, i.e., it is assumed that the wind speed is above the rated speed. It should be noted that the control of wind turbines in this region is a challenging task, since the pitch controller should be designed to keep the output power and electrical torque on their nominal values while mitigating the mechanical loads. Using(4), we can generally consider the rotor speed equation in the following form: [60]

$$\dot{\omega}_r = f(\omega_r, v_w, \beta). \tag{13}$$

Thus, we have a non-affine system that is an implicit function of β. Consider the following change of variables:

$$\upsilon = \dot{\omega}_r, \quad \upsilon = f(\omega_r, v_w, \beta^*), \tag{14}$$

where υ is defined as a pseudo-control signal and β^* is ideal pitch control signal introduced later. The following assumption is considered: [60]

Assumption 1.

$$-f^H \le \frac{\partial f(\omega_r, v_w, \beta)}{\partial\beta} \le -f^L < 0, \qquad \left|\frac{d}{dt}\frac{\partial f(\omega_r, v_w, \beta)}{\partial\beta}\right| \le H, \tag{15}$$

where f^H, f^L and H are unknown positive constants.

Since υ generally is not a function of β, so from Assumption 1, it means that

$$\frac{\partial[\upsilon - f(\omega_r, v_w, \beta)]}{\partial\beta}\Big|_{\beta=\beta^*} \ne 0. \tag{16}$$

The expression in (14) is non-singular. It means that in a vicinity of $\forall(\omega_r, v_w, \beta)$, there exists an implicit function $\alpha(\omega_r, v_w, \upsilon)$:

$$\upsilon - f(\omega_r, v_w, \alpha(\omega_r, v_w, \upsilon)) = 0. \tag{17}$$

Therefore,

$$\beta^* = \alpha(\omega_r, v_w, \upsilon). \tag{18}$$

Now by using the mean value theorem we have: [61]

$$f(\omega_r, v_w, \beta) = f(\omega_r, v_w, \beta^*) + (\beta - \beta^*)f_\beta, \tag{19}$$

where $f_\beta = [\partial f(\omega_r, v_w, \beta)/\partial\beta]_{\beta=\beta_\lambda}$, $\beta_\lambda = \lambda\beta + (1-\lambda)\beta^*$ with $\lambda \in (0,1)$.

The rotor speed error is defined as follows:

$$e = \omega_r - \omega_{nom}, \tag{20}$$

where ω_{nom} is the nominal rotor speed. Note that the value of $\dot{\omega}_{nom}$ in full load region is zero. Using (14), (19) and (20) error dynamics becomes as follows

$$\dot{e} = f(\omega_r, v_w, \beta) = f(\omega_r, v_w, \beta^*) + (\beta - \beta^*)f_\beta. \tag{21}$$

According to (14), for $\beta^* = \alpha(\omega_r, v_w, \upsilon)$ we have $\upsilon = f(\omega_r, v_w, \beta^*)$. Therefore the dynamic of error can be written as follows

$$\dot{e} = \upsilon + (\beta - \beta^*)f_\beta. \tag{22}$$

The pseudo-control signal is considered as follows

$$\upsilon = -ke. \tag{23}$$

Using Theorem 1, there exists an RBF neural network to approximate the ideal pitch control signal, i.e.,

$$\beta^* = w^{*T}\varphi(\omega_r, v_w, \upsilon) + \varepsilon(\omega_r, v_w), \tag{24}$$

in witch w^* is the ideal weight and $\varepsilon(\omega_r, v_w)$ is the error of neural network approximation and there exists a positive constant ε_N such that $\left|\varepsilon(\omega_r, v_w)\right| \le \varepsilon_N$.

Since β^* is unknown, the following pitch control law is proposed to approximate it:

$$\beta = \hat{w}^T \varphi(\omega_r, v_w, \upsilon) + \hat{\eta}\tanh(\frac{e}{\varsigma}), \tag{25}$$

where $\hat{w}$ is the estimate of w^* and is determined using a suitable adaptive law defined later. Also, $\hat{\eta}\tanh(e/\varsigma)$ is a robust adaptive term used to cope with approximation error of neural network and unknown uncertainties. It is remarkable that the robust term does not require the bounds of uncertainties, and has a continuous structure, thus is chattering-free. The following Lemma is considered: [62]

Lemma 1. For any $\vartheta \in \mathbb{R}$ and $\varsigma > 0$ we have

$$0 \le |\vartheta| - \vartheta \tanh\left(\frac{\vartheta}{\varsigma}\right) \le 0.2785\varsigma = \xi. \tag{26}$$

Assumption 2. The ideal parameter vectors w^* and η^* lie in some compact regions:

$$\begin{aligned} U_w &= \{w \in \mathbb{R}^{M_w} \mid \|w\| \le m_w\}, \\ U_\eta &= \{\eta \in \mathbb{R} \mid |\eta| \le m_\eta\}, \end{aligned} \tag{27}$$

where m_w and m_η are unknown positive constants.

Theorem 2. Consider a general variable speed, variable pitch wind turbine model described in Section 2 with the pitch control law in (25) , pseudo-control signal in (23) and the following adaptive rules:

$$\dot{\hat{w}}_i = \begin{cases} \gamma_{1i} e\varphi_i(\omega_r, v_W, \upsilon) & \begin{array}{l} if \quad |\hat{w}_i| < m_{wi} \quad or \\ (|\hat{w}_i| = m_{wi} \quad and \quad e\hat{w}_i\varphi_i \\ (\omega_r, v_W, \upsilon) \le 0) \end{array} \\ \Pr\left[\gamma_{1i} e\varphi_i(\omega_r, v_W, \upsilon)\right] & \begin{array}{l} if \quad |\hat{w}_i| = m_{wi} \quad and \\ e\hat{w}_i\varphi_i(\omega_r, v_W, \upsilon) > 0 \end{array} \end{cases} \tag{28}$$

$$\dot{\hat{\eta}} = \begin{cases} \gamma_2 |e| & \begin{array}{l} if \quad |\hat{\eta}| < m_\eta \quad or \\ (|\hat{\eta}| = m_\eta \quad and \quad \hat{\eta} \le 0) \end{array} \\ \Pr\left[\gamma_2 |e|\right] & if \quad |\hat{\eta}| = m_\eta \quad and \quad \hat{\eta} > 0 \end{cases} \tag{29}$$

where $\gamma_{1i}, i = 1,\ldots,M$, γ_2 and ς are positive constants. If Assumptions 1 and 2 are satisfied then all the closed-loop signals are uniformly ultimately bounded. The projection operator $\Pr[\cdot]$ is defined as [63]

$$\dot{\Lambda} = \Pr\left[\Upsilon\Theta\varpi\right] = \Upsilon\Theta\varpi - \Upsilon\frac{\Lambda\Lambda^T}{\Lambda^T\Upsilon\Lambda}\Upsilon\Theta\varpi. \tag{30}$$

Proof. Substituting, (23)-(25) in (22) leads to

$$\begin{aligned} \dot{e} &= -ke + \hat{w}^T\varphi f_\beta + \hat{\eta}\tanh(\frac{e}{\varsigma})f_\beta - \\ & w^{*T}\varphi f_\beta - \varepsilon f_\beta = -ke + \tilde{w}^T\varphi f_\beta + \hat{\eta}\tanh(\frac{e}{\varsigma})f_\beta - \varepsilon f_\beta \end{aligned} \tag{31}$$

where $\tilde{w} = \hat{w} - w^*$ is the estimation error of the weight. For simplicity, $\varphi(\omega_r, v_w, \upsilon) \triangleq \varphi$ and $\varepsilon(\omega_r, v_w) \triangleq \varepsilon$ are considered. The Lyapunov function candidate is considered as follows

$$V = \frac{1}{2}\frac{e^2}{-f_\beta} + \frac{1}{2}\tilde{w}^T\Gamma^{-1}\tilde{w} + \frac{1}{2\gamma_2}\tilde{\eta}^2. \tag{32}$$

where $\tilde{\eta} = \eta^* - \hat{\eta}$ and $\eta^* = \varepsilon_N$ is the ideal value of $\hat{\eta}$ and $\Gamma = diag(\gamma_{1i})$ witch $i = 1,2,\ldots,M$. The time derivative of V with adding and subtracting $|e|\hat{\eta}$ and using Lemma 1, becomes

$$\begin{aligned} \dot{V} \le & \frac{ke^2}{f_\beta} + \frac{\dot{f}_\beta e^2}{2f_\beta^2} + \sum_{i=1}^{M}\tilde{w}_i[-\varphi_i e + \frac{1}{\gamma_{1i}}\dot{\hat{w}}_i] + \\ & |\hat{\eta}|\xi + \tilde{\eta}\left[|e| - \frac{1}{\gamma_2}\dot{\hat{\eta}}\right]. \end{aligned} \tag{33}$$

Using Assumption 1, we have $ke^2/f_\beta + \dot{f}_\beta e^2/2f_\beta^2 \le \left[-ke^2/f_H + He^2/2f_L^2\right]$, denoting $\Psi = \left[k/f_H - H/2f_L^2\right]$. since k is set by designer, there is a k that $\Psi \ge 0$, so we have

$$\begin{aligned} \dot{V} \le & -\Psi e^2 + \sum_{i=1}^{M}\tilde{w}_i[-\varphi_i e + \frac{1}{\gamma_{1i}}\dot{\hat{w}}_i] + \\ & \tilde{\eta}\left[|e| - \frac{1}{\gamma_2}\dot{\hat{\eta}}\right] + |\hat{\eta}|\xi. \end{aligned} \tag{34}$$

If $|\hat{w}_i| < m_w$ or ($|\hat{w}_i| = m_w$ and $e\hat{w}_i\varphi_i(\omega_r, v_W, \upsilon) \le 0$), from the first line of adaptation law (28) we have $\dot{\hat{w}}_i = \gamma_{1i}e\varphi_i(\omega_r, v_W, \upsilon)$, thus $\tilde{w}_i[-\varphi_i e + \frac{1}{\gamma_{1i}}\dot{\hat{w}}_i] = 0$. Now, if $|\hat{w}_i| = m_w$ and $e\hat{w}_i\varphi_i(\omega_r, v_W, \upsilon) > 0$, from the second line of adaptation law we have

$$\begin{aligned} \dot{\hat{w}}_i &= \Pr\left[\gamma_{1i}e\varphi_i(\omega_r, v_W, \upsilon)\right] = \gamma_{1i}e\varphi_i(\omega_r, v_W, \upsilon) - \\ & \gamma_{1i}\frac{\hat{w}_i\hat{w}_i^T}{\hat{w}_i^T\gamma_{1i}\hat{w}_i}\gamma_{1i}e\varphi_i(\omega_r, v_W, \upsilon). \end{aligned} \tag{35}$$

Thus

$$\begin{aligned}&\tilde{w}_i[-\varphi_i e + \frac{1}{\gamma_{1i}}\dot{\hat{w}}_i] = \\ &\tilde{w}_i[-\frac{\hat{w}_i \hat{w}_i^T}{\hat{w}_i^T \gamma_{1i} \hat{w}_i}\gamma_{1i} e \varphi_i(\omega_r, v_W, \upsilon)] = \\ &-\frac{\tilde{w}_i \hat{w}_i}{\left|\hat{w}_i\right|}\hat{w}_i^T e \varphi_i(\omega_r, v_W, \upsilon).\end{aligned} \tag{36}$$

However, $\tilde{w}_i \hat{w}_i \geq 0$ since $\left|w_i^*\right| \leq m_w$ and $\left|\hat{w}_i\right| = m_w$ so that $-\frac{\tilde{w}_i \hat{w}_i}{\left|\hat{w}_i\right|}\hat{w}_i^T e \varphi_i(\omega_r, v_W, \upsilon) \leq 0$. Similarly using adaptive law (29), it can be easily deduced $\tilde{\eta}\left[\left|e\right| - \frac{1}{\gamma_2}\dot{\hat{\eta}}\right] \leq 0$.

Thus, we have

$$\dot{V} \leq -\Psi e^2 + \left|\hat{\eta}\right| \xi. \tag{37}$$

Using Assumption 2 and (29), there exists a positive constant d such that $\left|\hat{\eta}\right| \xi \leq d$. Thus (37), becomes

$$\dot{V} \leq -\Psi e^2 + d, \tag{38}$$

which guarantees $\dot{V}$ is negative-definite whenever e belongs to the following set

$$\Omega_e = \left\{ e \mid |e| > \sqrt{\frac{d}{\Psi}} \right\}. \tag{39}$$

Therefore, based on [64], it can be deduced that all the closed-loop signals are uniformly ultimately bounded (UUB)

Remark 1. It is noteworthy that, based on universal approximation theorem, the above stability proof is valid whenever the states are within a compact set which can be arbitrarily large. Therefore, the proved stability is semi-global.

3.2. Proposed Optimization Framework

As can be seen from (25), the proposed adaptive robust pitch control has several parameters. These parameters should be selected to achieve the best performance. Selecting the optimal parameters is not a straightforward task and needs a lot of trial and error procedures. Using optimization techniques not only determines the parameters of the controller, but also gives their optimal values. To find the optimal parameters the following two objective functions are considered:

$$J_1 = \int_0^{T_f} \left|e(t)\right| dt \tag{40}$$

$$J_2 = \int_0^{T_f} \left|\dot{\beta}(t)\right| dt \tag{41}$$

where T_f is the simulation time, the first objective function (40), is the integral of absolute error (IAE) that it's minimization leads to reduction of both transient and steady-state error by creating a uniform weight over error. The second objective function (41) is the integral absolute rate of the control signal (IARCS), which decreases the fluctuations of pitch control and thus reduces the mechanical loads. Therefore, fatigue damages will be decreased. These two cost functions are contradictory, i.e., decreasing/increasing IAE will increase/decrease IARCS. The best solution is to find the best trade-off between these two contradictory objective functions. In other words, when both objective functions are optimized together, the result can keep the generator and rotor speed at the nominal speed, and can also reduce the deviation of the pitch control, thus can mitigate fatigue damages. Consequently, we have the following multi-objective optimization problem:

$$\min_{Controller\ Parameters} J_1 \,\&\, J_2 \tag{42}$$

The multi-objective optimization in (42), is a highly nonlinear optimization problem and so does not have a closed-form solution. One of the useful approaches to solve this highly nonlinear optimization problem is to use evolutionary algorithms. Two effective multi-objective optimization algorithms are NSGA-II and MOPSO [55, 65-68]. To find the optimal parameters of the proposed adaptive robust controller, we use these two algorithms to solve the nonlinear multi-objective optimization problem in (42). It should be noted that since solving (42) by using evolutionary algorithms is numerical and stochastic, the obtained solutions are suboptimal. It is noteworthy that the proposed adaptive robust controller not only guarantees the closed-loop stability but also reduces IAE effectively and at the same time mitigates fatigue damages appropriately.

4- SIMULATION RESULTS AND VALIDATION

To study the performance of the proposed adaptive controller, we first apply it to the model described in Section 2, then use FAST simulator to validate the results. The model parameters are used from the National Renewable Energy Laboratory (NREL) offshore-Baseline $5\,MW$ wind turbine [56]. The average and variance of the wind speed are considered $15\,m/s$ and 1, respectively with the Kaimal wind spectrum [69]. Fig. 2 depicts the considered wind speed. For C_p, we used the lookup Table proposed by NREL instead of approximated functions, which is more practical. The block diagram of the proposed wind turbine control system is shown in Fig. 3.

To apply the pitch control in (25), an RBF neural network with five neurons in the hidden layer is considered. As stated in subsection 3.2, the parameters of the proposed adaptive pitch controller in subsection 3.1 are chosen by solving (42), using MOPSO and NSGA-II. The parameters of the MOPSO algorithm and NSGA-II are shown in Tables 1 and 2.

Remark 2. The number of iterations and the population size are selected after 20 experimental simulations. Crossover and mutation parameters are selected using [54] and [67]. It should be noted that based on discussions in [67] to have an effective balance between exploration and exploitation the

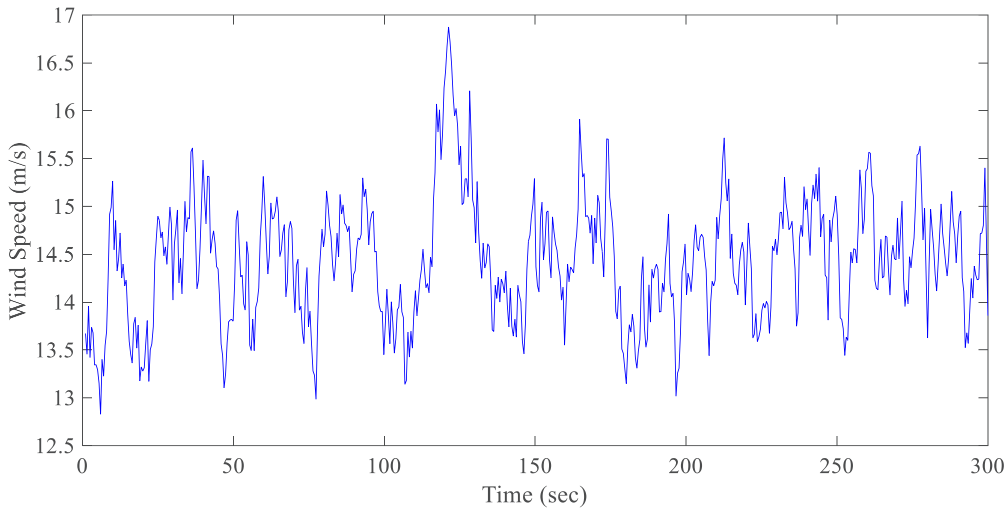

Fig. 2. Wind speed profile

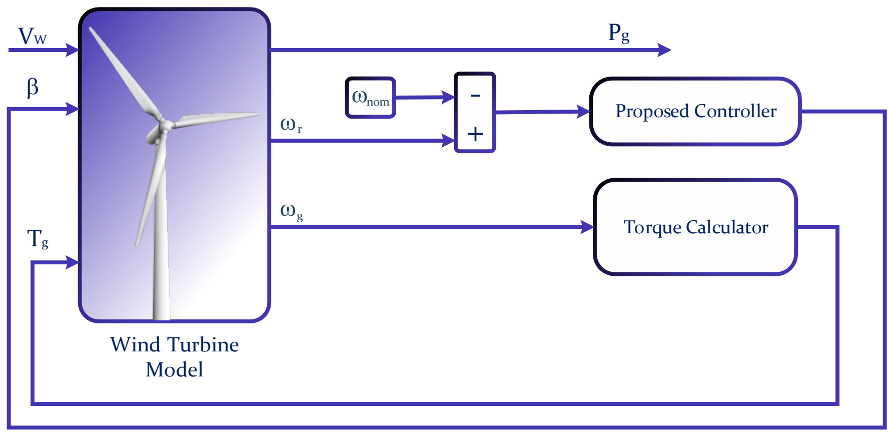

Fig. 3. The block diagram of a wind turbine control system

Table 1. MOPSO parameters

Number of Iterations	100
Population Size	50
Repository Size	50
Number of Grids per Dimension	5
Leader Selection Pressure	2
Deletion Selection Pressure	2

Table 2. NSGA-II parameters

Number of Iterations	100
Population Size	50
Crossover Percentage	0.8
Mutation Rate	0.08
Crossover Distribution Index	0.5 to 20
Mutation Distribution Index	0.5 to 20

crossover and mutation indices are increased linearly. Other parameters of MOPSO are selected via trial and error to achieve the best performance.

The Pareto fronts of both algorithms are shown in Fig. 4. To determine the best multi-objective optimization algorithm, we can apply the seven-point metric as an effective method to compare the multi-objective algorithms [65]. For each algorithm set A, which contains seven points is considered as follows:

$$A = \{[0, J_{2,\max}], [0, \frac{2}{3} J_{2,\max}], [0, \frac{1}{3} J_{2,\max}], [0,0], [\frac{1}{3} J_{1,\max}, 0], [\frac{2}{3} J_{1,\max}, 0], [J_{1,\max}, 0]\}, \tag{43}$$

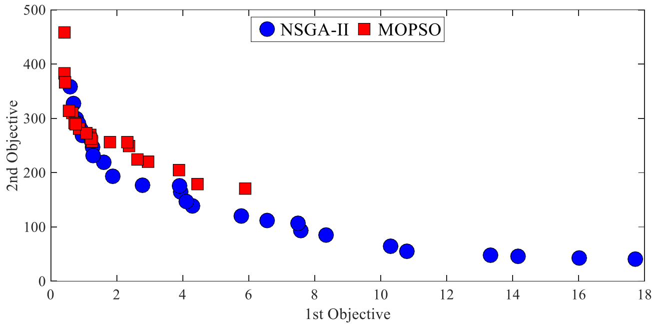

Fig. 4. NSGA-II and MOPSO Pareto fronts

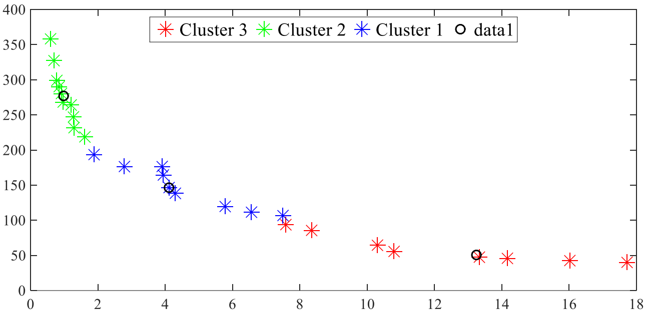

Fig. 5. Clustered NSGA-II Pareto front

Table 3. NSGA-II based optimized parameters

	C_1	C_2	C_3
γ_{1i}	[69.5964 95.0665 34.4425 98.0850 11.0527]	[4.8861 85.9207 5.9180 46.8156 9.4319]	[0.7040 0.6267 0.8622 0.5882 0.7209]
σ_i	[0.1589 0.0317 0.0400 0.0224 0.0218]	[0.5154 0.0100 0.7207 0.8019 0.8693]	[0.9853 0.9793 0.9821 0.9985 0.9997 1.004]
γ_2	16.9461	93.8741	1.0000
ς	0.1000	0.0456	0.1105
k	1.8974	1.1129	0.6294

where, $J_{1\max}$ and $J_{2\max}$ are respectively the maximum values of the cost functions (40) and (41) obtained by the algorithms. The seven-point metric for each algorithm is defined as:

$$M_{7\text{point}}(\text{algorithm}) = \frac{\sum\limits_{x \in PF(\text{algorithm})} \min\limits_{y \in A} \left\| x - y \right\|}{\left| PF(\text{algorithm}) \right|}, \qquad (44)$$

where, $PF(\text{algorithm})$ is the Pareto front for each algorithm and $\left|PF(\text{algorithm})\right|$ is cardinality number of $PF(\text{algorithm})$. Obviously, the algorithm that possesses the smaller $M_{7\text{point}}$ has better performance [70]. In our project, the value of $M_{7\text{point}}$ for the MOPSO algorithm is 90.7441 and is 32.5921 for NSGA-II. Thus, the NSGA-II has a better performance than the MOPSO algorithm. Therefore, the simulations are accomplished using only the results obtained via NSGA-II.

Each member in the Pareto front based on the designer's need is an optimal response for the system. To depict the results by simulations, using clustering method proposed in [71], we categorize the responses into 3 clusters and use the center for each cluster as the representative for the simulation purposes (Fig. 5). Thus, we have three solutions that can cover the Pareto front effectively. Table 3, demonstrates the three centers i.e., the three sets of optimal parameters for the proposed adaptive robust pitch control.

To study the results, two cases are considered: in Case 1, the proposed optimal adaptive robust pitch controller is applied to the model in Section 2. In Case 2, to validate the results the proposed controller is applied to FAST simulator developed by NREL.

Case 1. Application of the proposed optimal adaptive robust pitch controller on the model in section 2:

To show the effectiveness of the proposed optimal adaptive pitch controller it is applied to the 2-mass model presented

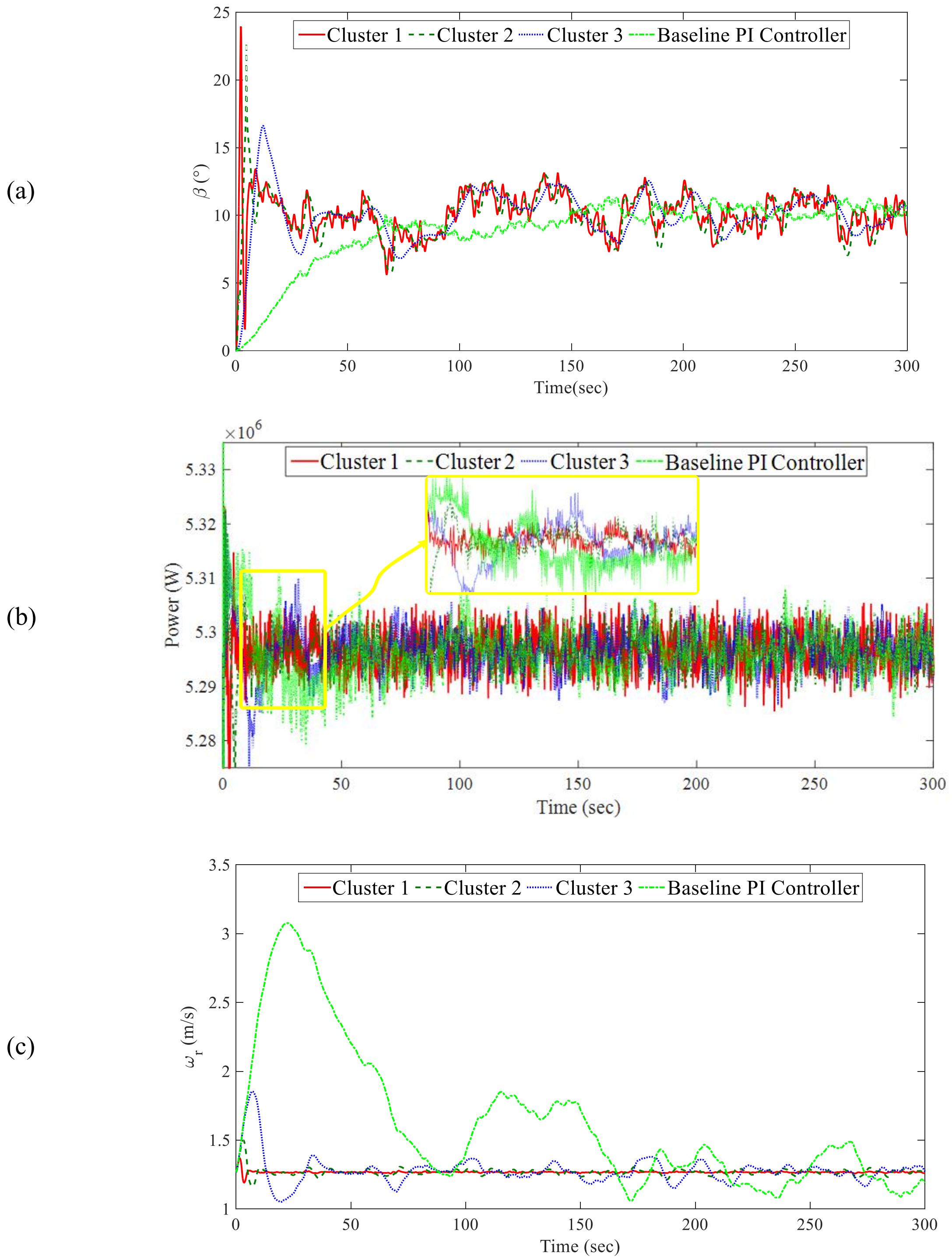

Fig. 6. Simulation results of the proposed optimal adaptive robust controller on the NREL 5 MW wind turbine (a) pitch angle (control signal), (b) output power and (c) rotor speed.

in section 2. Three controllers are considered: the proposed adaptive robust pitch controllers with optimal parameters using the center of clusters 1, 2 and 3 in Table 3. In order to show the effectiveness of our proposed optimal adaptive robust pitch controller, we make a comparison between our controller and the baseline PI controller designed by NREL [56]. It should be noted that the baseline PI is a gain scheduling controller, which its gains are functions of wind speed. Thus, baseline PI controller should know the wind speed to have a satisfactory response. However, our proposed method does not need to know the wind speed, and due to its adaptiveness and robustness, it can cope with this uncertainty. Fig. 6 demonstrates the pitch angle (control signal), output power and the rotor speed of the wind turbine for the different controllers.

For better comparison, the results are quantified and

Table 4. Comparison of the controllers on 2-mass model

Costs / Clusters	$J_1 = \int_0^{T_f} \lvert e(t) \rvert dt$	$J_2 = \int_0^{T_f} \lvert \dot{\beta}(t) \rvert dt$	$\frac{1}{T_f}\int_0^{T_f} P_g(t)dt\ (MW)$	$\frac{1}{T_f}\int_0^{T_f} \omega_r dt$
Proposed Adaptive Controller (Cluster 1)	1.0004	331.1691	5.2958	1.2673
Proposed Adaptive Controller (Cluster 2)	2.9659	218.4042	5.2959	1.2692
Proposed Adaptive Controller (Cluster 3)	18.9209	88.5776	5.2961	1.2797
Baseline PI Controller	122.4610	113.6587	5.2958	1.6000
Reference Value	0	0	5.2966	1.2671

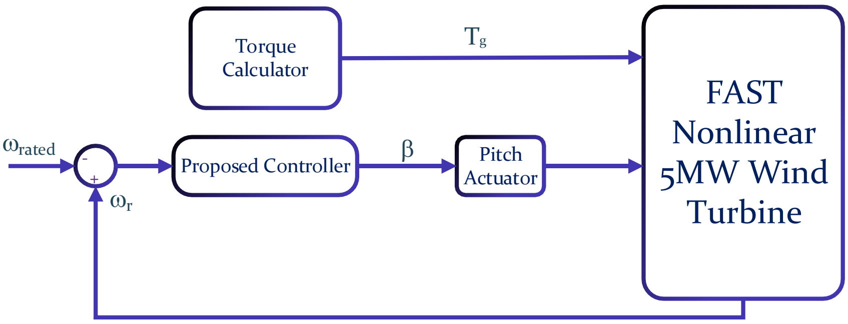

Fig. 7. Block diagram of the FAST simulator

presented in Table 4. From Fig. 6 and Table 4, it can be seen that if the error reduction is more important for the designer, cluster 1 has the best performance, and if mitigating the fatigue damages is more important, cluster 3 is the most satisfactory. As can be seen, the value of both cost functions is high for the baseline PI controller. This controller is not satisfactory in error reduction, but its performance in load mitigation is acceptable.

Case 2. Application of the proposed optimal adaptive robust pitch controller on the FAST simulator:

To validate the results, the FAST simulator is implemented. FAST (Fatigue, Aerodynamics, Structures, and Turbulence) simulator, is a comprehensive code, which can simulate several degrees of freedom of a wind turbine. FAST can give a noble approximated model even in high-frequency noises, made by NREL [68], and it is used by wind turbine designers to determine extreme and fatigue loads. The block diagram of the FAST simulator, using the proposed controller is shown in Fig. 7. The wind profile, the same as in Case 1, with average $15\,m/s$ speed is considered. The simulation parameters are chosen as same as Case 1. The performance of the proposed optimal adaptive robust pitch controller using the representative of clusters 1, 2 and 3 as its parameters is studied. Fig. 8 shows pitch angle (control signal), output power and rotor speed applying in the FAST simulator for different controllers. The results are also numerically compared in Table 5. Fig. 8 and Table 5 demonstrate the validity and practicality of the proposed optimal adaptive robust pitch controller. Furthermore, it can be seen that there is a trade-off between the error reduction and mitigating the fatigue damages, and the designer can choose one of the clusters based on the requirements. The baseline PI controller is not satisfactory in error reduction, but in mitigating the fatigue damage the results for baseline PI controller are tolerable, as similar to Case 1,

5- CONCLUSION

In this paper, an optimal adaptive robust pitch controller has been proposed for variable-speed wind turbines. Adaptive neural networks have been utilized based on the universal approximation theorem to cope with nonlinearities. A continuous adaptive robust structure has also been proposed to overcome the approximation error. All of the adaptive laws have been derived using the Lyapunov synthesis approach, and have proved all the signals involved are semi-globally uniformed and ultimately bounded. To derive optimal values for the parameters of the proposed adaptive robust pitch controller a suitable multi-objective optimization problem is defined. This multi-objective optimization, which is highly nonlinear is solved by two effective multi-objective optimization algorithms called MOPSO and NSGA-II. The performance of the proposed optimal adaptive robust pitch controller has been compared with the performance of the baseline PI controller developed by NREL using the standard NREL $5\,MW$ wind turbine model. Simulationresults demonstrate the effectiveness and applicability of the proposed optimal adaptive controller. To validate the results FAST (Fatigue, Aerodynamics, Structures, and Turbulence)

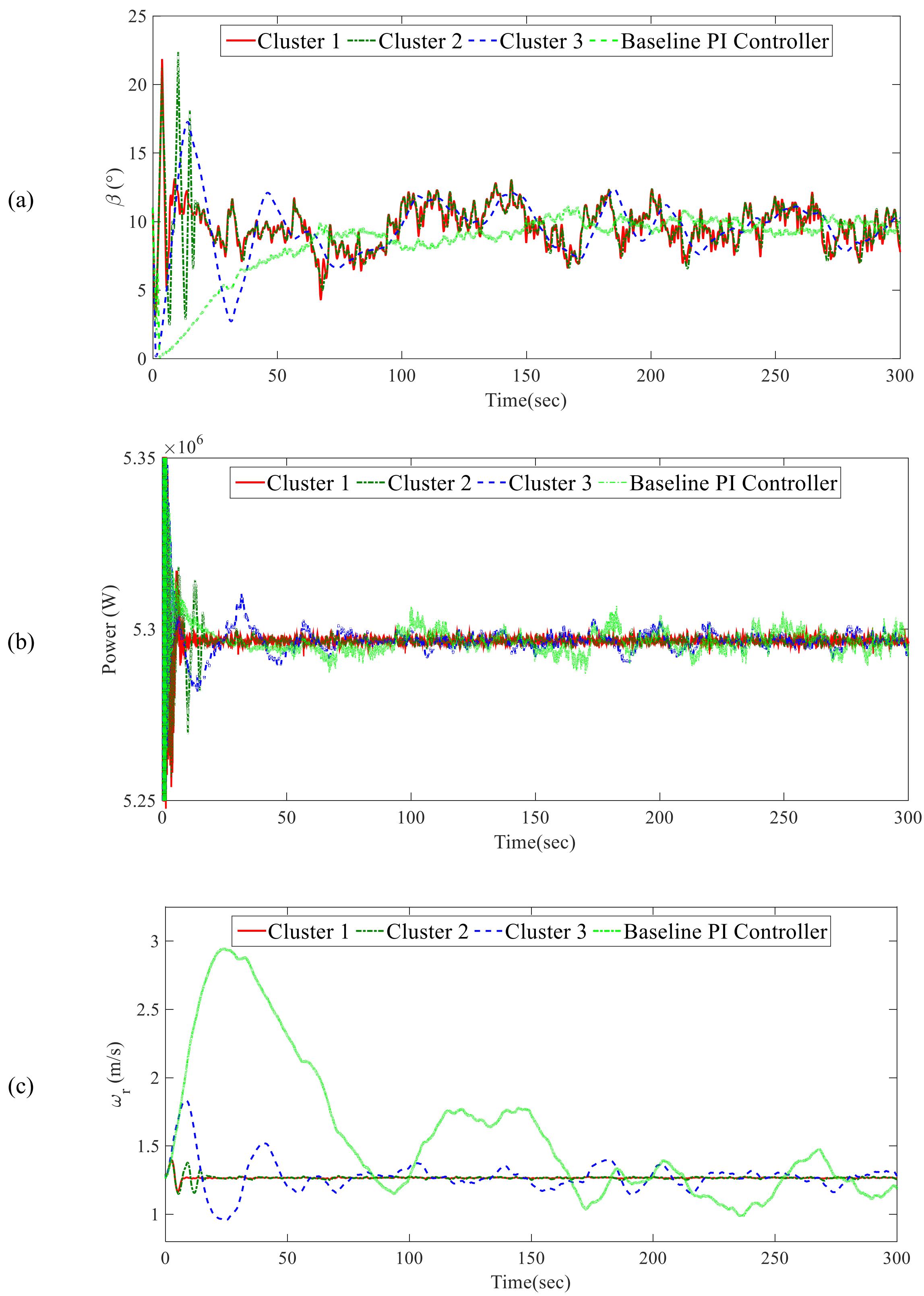

Fig. 8. FAST implementation results of the proposed optimal adaptive robust controller on the NREL 5 MW wind turbine (a) pitch angle (control signal), (b) output power and (c) rotor speed

Table 5. Comparison of the controllers on FAST simulator

Costs / Clusters	$J_1 = \int_0^{T_f} \lvert e(t) \rvert dt$	$J_2 = \int_0^{T_f} \lvert \dot{\beta}(t) \rvert dt$	$\frac{1}{T_f}\int_0^{T_f} P_g(t)dt\ (MW)$	$\frac{1}{T_f}\int_0^{T_f} \omega_r dt$
Proposed Adaptive Controller (Cluster 1)	1.0552	439.3883	5.1971	1.2673
Proposed Adaptive Controller (Cluster 2)	2.2526	373.1864	5.1941	1.2675
Proposed Adaptive Controller (Cluster 3)	22.3545	100.0287	5.1950	1.2771
Baseline PI Controller	125.5175	238.4595	5.2829	1.5821
Reference Value	0	0	5.2966	1.2671

simulator has been utilized.

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