An Improved Supervised Fuzzy PI Collective Pitch Angle Control for Wind Turbine Load Mitigation

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Abstract. Wind energy is a promising energy vector, attracting the consideration of industrialists and scientists in the light of the current energetic-environmental challenges. Hence the need to develop control laws to extract maximum profit from wind turbines. In this context the following paper addresses the problem of wind turbine power limitation in full load region using a novel supervised fuzzy PI pitch angle control. The proposed controller schedule proportional and integral gains based on real-time measurement of pitch angle and its rate. The proposed control has been validated on Controls Advanced Research Turbine (CART) using Fatigue, Aerodynamics, Structures and Turbulence (FAST) simulator by considering 9 DOFs. The obtained results confirm that the proposed control law provides better power and speed regulation with best load reduction and damping to the flexible modes of wind turbine than baseline PI pitch controller.

Keywords: Wind turbine · Collective pitch control · Fuzzy · PI · FAST

1 Introduction

As a result of the large-scale environmental damage caused mainly by the overexploitation of fossil fuels, the world has realized the need for a generalized energy transition towards renewable resources [1, 2]. Indeed, by late 2019, global wind development has touched a cumulative installed capacity of 650 [GW], with an annual growth rate of 19%

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over the previous year. Offshore installation is taking 10% growth share with 6 [GW] added to global capacity in 2019 [3].

Horizontal axis wind turbines are the most common for commercial purposes, due to their simple design and highly aerodynamic efficiency. According to their speed, two types of horizontal axis wind turbines can be distinguished, which are, fixed and variable speed wind turbines. The latter are designed in order to operate under various wind speed conditions. One can distinguish three operating zones, namely:

- Region I: below cut-in wind speed.
- Region II (Partial Load): between cut-in wind speed and rated wind speed.
- Region III (Full Load): between rated wind speed and cut out wind speed as shown in Fig. 1.

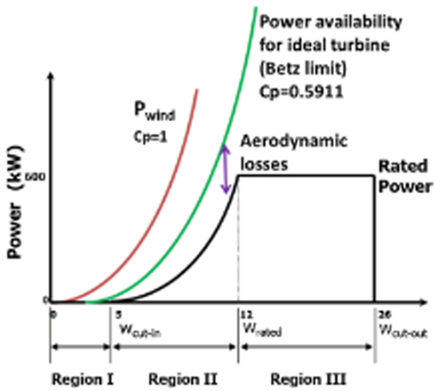

Fig. 1. Power curve of CART wind turbine [4]

When the wind speed is below its nominal value, the objective is to maximize power capture by acting on electromagnetic torque in order to ensure an optimal rotor speed tracking. While for high wind speeds, the pitch actuator is used to reduce the captured power and maintain it around its nominal value [4].

The control strategy consists of a feedback policy, commonly implemented controller corrects the measured error between rated power and the measured one [5–7], or, equivalently, the rotor speed error [8, 9]. Conventional PI controller is the most commonly used pitch controller. Unfortunately, PI is not robust against wind speed variation [10]. To compensate for the non-linearity effects, parameter variations or ill known dynamic behavior, various techniques are used, including PI gain scheduling [6, 10], which consists of correcting gains via an adaptive non-linear relationship between pitch angle and rotor speed in order to reduce the slip induced when the operating point is changed. One can see a modified fuzzy PI gain scheduling pitch angle control, in which authors substitute the nonlinear relationship with a fuzzy inference system. The main limitation of the proposed controller is that the last is a single input system, don't taking into consideration the interdependency of proportional and integral actions. fuzzy

PI gain scheduling [11]. Fuzzy logic control [6, 7, 12], obtained results show that the fuzzy command gives a better result compared to PI controller and considerably reduces structural loads. However, its main disadvantage in the proper choice of rules and the form of membership functions, but it remains one of the most widely used techniques, as it does not require knowledge of the mathematical model and works perfectly well with unknown systems. Learning-based control such as neural networks [13], ANFIS [14], the disadvantage of learning-based techniques is that they require the acquisition of quality data, containing sufficient information on the dynamics of the system, in order to achieve good results.

As a solution to overcome the limitation of baseline PI, PI gain scheduling controller being described in [10] and the fuzzy gain scheduling proposed by [9], the present paper proposes a new supervised fuzzy PI collective pitch angle control for wind turbine. The rest of the paper is structured as follows, the system modeling is briefly described in Sect. 2. The proposed controller is detailed in the Sect. 3. Then main results are discussed in Sect. 4. Finally, drawn conclusion are presented in the last section.

2 Wind Turbine Modeling

Wind turbines are mechatronic systems that convert the captured kinetic energy of the wind into electric energy. Typically, the aerodynamic torque of a wind turbine is given by (1), such as [15]:

$$T_a = \frac{P_a}{\omega_r} = \frac{1}{2\lambda}\rho\pi R^2 C_p(\lambda, \beta)v^2 \tag{1}$$

where P_a [W] is the wind power, $\rho\left[\mathrm{kg}\cdot m^{-3}\right]$ is the air density, R[m] is rotor radius and $v\left[\mathrm{m}\cdot \mathrm{s}^{-1}\right]$ denotes wind speed. The nonlinear coefficient $C_p(\lambda, \beta)$ depending on tip-speed ratio λ and blade pitch angle β[°] shown in Fig. 2 given by a lookup table developed by National Renewable Energy Laboratory (NREL) [2, 16].

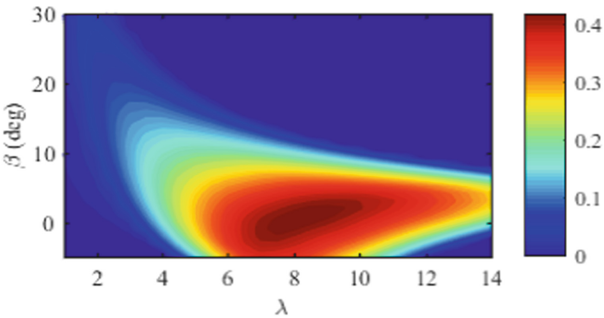

Fig. 2. Power coefficient contours of CART wind turbine

The one mass model is expressed as follows:

$$J_t\dot{\omega}_r = T_a - D_t\omega_r - T_g \tag{2}$$

where $J_t\left[\mathrm{kg}\cdot\mathrm{m}^2\right] = J_t = J_r + n_g^2 J_g$ denotes the turbine total inertia $D_t\left[\mathrm{N}\cdot\mathrm{m}\cdot\mathrm{rad}^{-1}\cdot\mathrm{s}^{-1}\right] = D_t = D_r + n_g^2 D_g$ is the turbine total external damping and $T_g[\mathrm{N}\cdot\mathrm{m}] = T_e n_g$ is generator torque in the rotor side.

The generator is modeled by a first-order system, defined by the following differential equation [4]:

$$\dot{T}_e = -\frac{1}{\tau_{Te}} T_e + \frac{1}{\tau_{Te}} T_e^{ref} \tag{3}$$

where $\tau_{Te} = 0.01\,[s]$ is the time constant of the generator and T_e^{ref} is the reference electromagnetic torque [4].

Pitch actuators for wind turbines can be either hydraulic or electric motors. It is necessary to alter the pitch angle of a blade in order to regulate the produced power and keep it on its rated value [6]. A first-order actuator model is adopted to represent the actual electric motor drive installed in CART.

$$\dot{\beta} = -\frac{1}{\tau}\beta + \frac{1}{\tau}\beta_{ref} \tag{4}$$

where τ_β is a time constant that depends on pitch actuator.

3 Supervised Fuzzy PI Collective Pitch Angle Control

One of the problems with the variable-fixed speed control is the one reported by A.D. Wright in [10]. In fact, when the operating point changes the performance of the controller decreases significantly, because each operating point requires particular gains. In order to overcome this problem, authors have proposed a PI gain sequencing technique, which allows the gain to be corrected from a nonlinear relationship based on the measurement of the pitch angle, thereby solving the problem of slipping when the operating point is changed.

In order to improve this gain scheduling technique, we propose a new supervised fuzzy PI pitch angle control, that is conceptually in accordance with the PI gain scheduling controller proposed by the reference herein [10], although the adaptation is provided by a fuzzy inference system (FIS) that allows the PI gains correction based on the real-time measurement of pitch angle its rate. The proposed control law, which bloc is diagramed in Fig. 3 is given as follows:

$$\beta_d = \left(K_P.K_{\beta_P}\varepsilon\right) + \left(K_I.K_{\beta_I}\int_0^t \varepsilon(\tau)\,d\tau\right) \tag{5}$$

where $\varepsilon = \omega_r - \omega_{ref}$ is the rotor speed error and K_P, K_{β_P}, K_I, K_{β_I} are respectively proportional gain, fuzzy proportional gain corrector, integral gain and its corrector. The main improvements of the proposed Fuzzy PI controller are the following:

- Gain correction using human expertise, without the need for complex mathematical relationships.

- Consideration of pitch rate, resulting in reduced loads on pitch actuators.
- Each controller action is corrected separately, taking into account gains interdependency.
- The proposed controller does not need the aerodynamic sensitivity depending on aerodynamic torque measurement. Even if theoretically the aerodynamic torque is easily calculated, its measurement for field wind turbines remains difficult.

The principle of fuzzy logic control is to design a controller emulating the human reasoning in its behavior. This type of controller has already proved its effectiveness against strongly nonlinear, or even mathematically unknown, systems. This is achieved by assigning linguistic variables to fuzzy subsets, making it easier to set up fuzzy rules deduced from expertise.

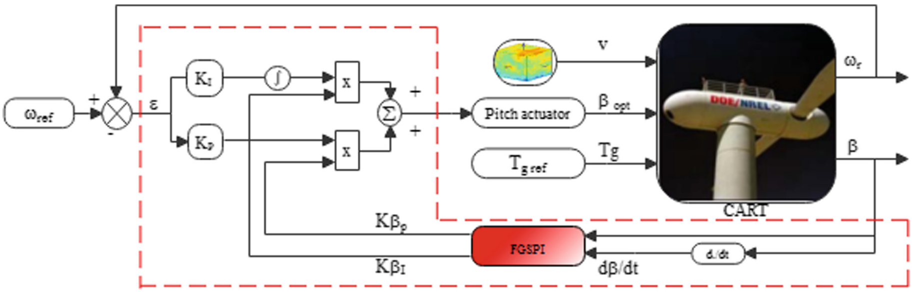

Fig. 3. Bloc diagram of the proposed supervised fuzzy PI collective pitch angle controller

Table 1. Fuzzy rules

Gains		K_{β_p}			K_{β_I}		
β		N	ZO	P	N	ZO	P
$d\beta/dt$	N	S	B	B	B	S	S
	ZO	B	B	B	S	B	S
	P	B	S	B	S	B	S

Regarding the proposed supervised fuzzy PI collective pitch angle controller, we opted to reduce the number of Membership Functions (MFs) for reasons of stability and practical implementation. The fuzzy MFs for inputs, namely, pitch angle β and pitch rate $d\beta/dt$ being shown in Fig. 4a, b, are linguistically labeled as follows: N: Negative, P: Positive, ZO = Zero, S = Small and B = Big. During preliminary tests of the proposed controller, we observed that using the triangular membership function gives more sensitivity as inputs approached zero. The fuzzy range [−1,1] with a symmetric distribution to zero. For outputs K_{β_P} K_{β_I}, sigmoidal function labeled S = small and a Z-shaped function labeled B = big are used for each one, as one can see in Fig. 4c, d. The proposed FGSPI is a Mamdani type fuzzy inference system managed on a knowledge basis using the fuzzy rules of the IF-THEN type, given by (6). Table 1 summarizes the 18 rules scheduling the fuzzy output.

$$\textbf{IF } \beta \text{ is N and } d\beta/dt \text{ is N, } \textbf{THEN}, \; K\beta_p \text{ is B and } K\beta_I \text{ is S} \tag{6}$$

The output of the Mamdani type fuzzy inference system consists of several weighted fuzzy sets. Each component of the weight vector corresponds to a specific rule. In order to transition from the fuzzy domain to the numerical domain, the center of gravity method is used. Accordingly, the output is equal to the weighted sum of the numerical values of the corresponding labels, as follows:

$$CG = \frac{\sum_{i=1}^{m} \mu_i c_i}{\sum_{i=1}^{m} \mu_i} \tag{7}$$

where c_i is the center of gravity of the i^{th} MFs μ_i and M the number of fuzzy rules. After tuning of the proposed FIS, the obtained fuzzy surface is shown in Fig. 4e, f.

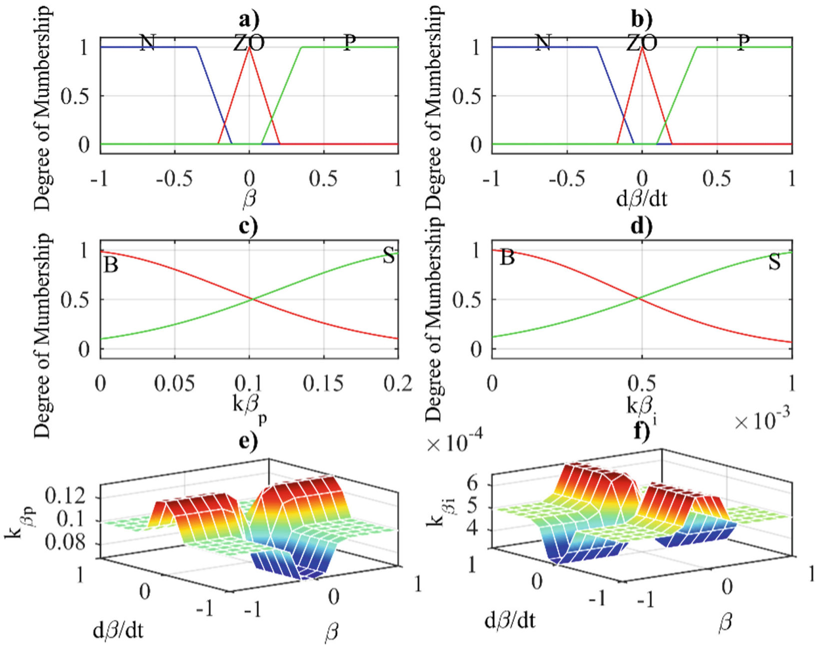

Fig. 4. MFs and fuzzy surfaces, **a)** β, **b)** $d\beta/dt$, **c)**$K\beta_p$, **d)** $K\beta_I$ **e)** Fuzzy output $K\beta_p$, **f)** Fuzzy output $K\beta_I$

4 Result and Discussions

In order to highlight the effectiveness of the proposed supervised fuzzy PI controller, the latter were validated by the FAST simulator [17] shown in Fig. 5, using the parameters of the CART shown in Fig. 6, located located at National Wind Technology Center (NWTC). Its characteristics are described in [10, 18]. Simulations were performed by enabling first flapwise blade mode (2×1 DOF); second flapwise blade mode (2×1 DOF), first edgewise blade mode (2×1 DOF), rotor-teeter (1 DOF), drivetrain rotational-flexibility (1 DOF), generator mode (1 DOF).

All simulations were carried out using the wind speed profile shown in Fig. 7a. It has been performed using Turbsim [19]. It consists of 10 min turbulent wind series, with a mean value of $\overline{v} = 18\left[\mathrm{m}\cdot\mathrm{s}^{-1}\right]$ at hub-height. The turbulence is introduced via Kaimal spectra with an intensity of 10%. Figure 7b shows the distribution of the wind speed profile. It can be seen that varies approximately from 15 to 21 [$\mathrm{m}\cdot\mathrm{s}^{-1}$] with a high frequency of values in the range [17–19], which can be explained by the moderate turbulence intensity. Figure 7c shows the measured rotor speed signal, we observe that both controllers provided good regulation of the rotor speed around its nominal value of 41.7 [rpm], with a notable superiority of the proposed supervised PI controller over the baseline PI. It can be seen that the PI controller exhibits more oscillations with a speed varying between 40.21 and 42.95 [rpm] resulting in a large structural load on the rotor shaft (Low Speed Shaft) with a variance of 0.45 [rpm]. This was reduced to 0.35 [rpm] by correcting the gains using the proposed supervised fuzzy PI controller.

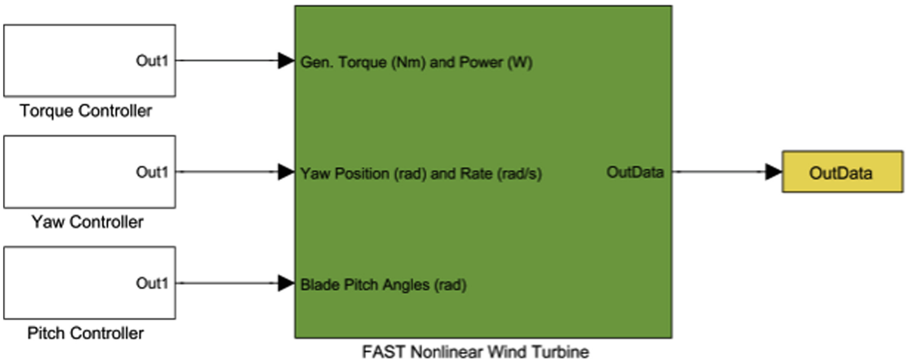

Fig. 5. FAST simulator Simulink blocs

We should notice that PI controller is not suitable for variable wind speed. This is explained by the fact that this controller is synthesized from a linearized model around a specific operating point. Whereas the proposed controller provides a real-time correction of the gain according to the change of the operating point, leading to a controller similar in dynamics to a series of local controllers, which are responsive to wind speed changes. Figure 7d shows the measured electrical power. The performance of the proposed controller is reflected in its ability to provide a good regulation of the produced electrical power around its nominal value of 600 [kW], with a small variance of 5.14 [kW]. T will

Fig. 6. CART wind turbine (From [20] with permission)

Table 2. Statistical comparison of control strategies

Criterion	Performance	
	PI	Proposed
$\min\omega_r[\mathrm{rpm}]$	40.21	40.71
$\max\omega_r[\mathrm{rpm}]$	42.95	42.55
$\overline{\omega}_r[\mathrm{rpm}]$	41.71	41.70
$\mathrm{std}\omega_r[\mathrm{rpm}]$	0.45	0.35
$\min P_e[\mathrm{kW}]$	578.59	579.96
$\max P_e[\mathrm{kW}]$	619.63	619.49
$\overline{P}_e[\mathrm{kW}]$	599.99	599.93
$\mathrm{std}P_e[\mathrm{kW}]$	8.34	5.14
$\min\beta[°]$	3.00	0.00
$\max\beta[°]$	18.58	15.33
$\overline{\beta}[°]$	14.06	13.09
$\mathrm{std}\beta[°]$	1.80	0.79
min $(d\beta/dt)$	−3.24	−8.09
max $(d\beta/dt)$	20	20.00
moy $(d\beta/dt)$	0.02	0.00
std $(d\beta/dt)$	1.15	0.47

lead to higher quality energy with fewer harmonics, allowing stability for an eventual connection of the machine to the grid. Figure 7e, g shows the obtained pitch angle and its Power Spectral Density (PSD) spectrum, it can be seen that the supervised fuzzy PI

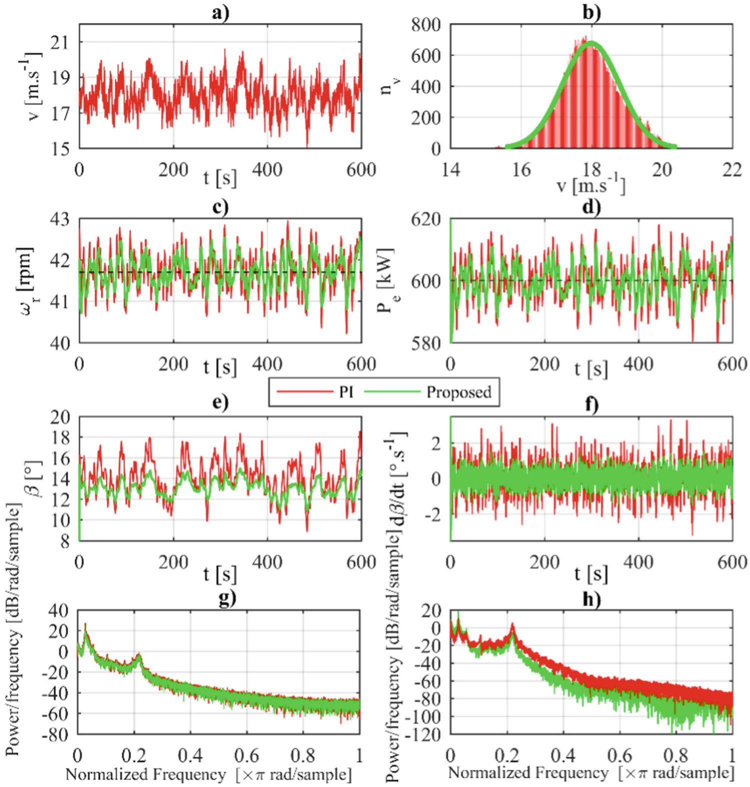

Fig. 7. Results. **a)** Wind speed,$\overline{v} = 18\left[\mathrm{m} \cdot \mathrm{s}^{-1}\right]$,**b)** Wind speed distribution, **c)** Rotor speed, **d)** Electrical power, **e)** Pitch angle**, f)** *PSD (β),* **g)** Pitch rate**, h)** *PSD (dβ/dt)*

control action has significantly reduced the oscillations, which contributes to the reduction of the forces on the blades, which not only ensures a good regulation, but also contributes to the longevity of the blades, which are continuously subjected to important aerodynamic loads. The same remark can be made about the pitch rate signal in time domain and its power spectral density illustrated by Fig. 7f, h. We notice that the pitch rate did not exceed the physical limits imposed by the manufacturer of 20 $[° \cdot \mathrm{s}^{-1}]$, with a reduction of the power of the control signal of a value in the vicinity of 4 [dB], with the ability of the proposed controller to attenuate the 1P component amplitude. Detailed statistical analysis of obtained results is given in Table 2.

5 Conclusion

The main concern for wind turbines control when the wind is above its nominal value is to maintain the electrical power around its rated one. In this context, a new supervised fuzzy PI pitch angle controller is proposed. The use of fuzzy reasoning to online adjust gains. Obtained results showed that this technique is more efficient compared to baseline PI controller. The adaptation policy must be understood as a set of local linear controllers acting each one around a specific point, which gives a good robustness against non-linear systems. In order to validate the proposed control law, the FAST simulator was used. Using the parameters of the CART wind turbine with 9 DOFs show that the proposed method gives a better result with a notable load reduction and damping to the flexible modes of wind turbine working in full load region.

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