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Control of a Variable Blade Pitch Wind Turbine Subject to Gust Wind and Actuators Saturation

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Abstract: This paper examines the dynamics and control of a variable blade pitch wind turbine during extreme gust wind and subject to actuators saturation. The mathematical model of the wind turbine is derived using the Lagrange dynamics. The controller is formulated using the Takagi–Sugeno fuzzy model and utilizes the parallel distributor compensator to obtain the feedback control gain. The controller’s objective is to obtain the generator electromagnetic torque and the blade pitch angle to attenuate the external disturbances. The (T–S) fuzzy controller with disturbances rejection properties is developed using the linear matrix inequalities technic and solved as an optimization problem. The efficacy of the proposed (T–S) fuzzy controller is illustrated via numerical simulations.

Keywords: wind turbine; (T–S) fuzzy model; parallel distributor compensator (PDC); linear matrix inequality (LMI); actuator saturation; disturbances



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1. Introduction

The dynamic and control of large and medium-size wind turbines remain a considerable challenge for scientists and engineers despite the substantial research done in the last few decades, for instance, considering the wind turbine complex nonlinear dynamics, the convoluted behavior of the wind, the maximum power that can be withdrawn from the system being constrained by the Betz Equation [1], and the overall performance affected by the disturbances.

The stability analysis in the presence of disturbances of a complex system was widely investigated; a synopsis of novel methods is cited in [2]. Concerning control system design applied to the wind turbine technology, an ample amount of literature is cited in [3–12]. Over the last decades, the design of controllers using fuzzy logic approach has been used widely as a substitute to traditional control technic especially for nonlinear systems [13]. The Takagi–Sugeno (T–S) fuzzy model is considered one of the most popular forms of fuzzy systems [14]. The stability analysis of a dynamic system represented by the (T–S) fuzzy model can be performed using a Lyapunov function approach [15]. Therefore, many control problems have been concluded, and some excellent results have been disclosed in the literature. The (T–S) fuzzy model was expanded to include systems undergoing external disturbances. A considerable amount of work was done to prove the stability of disturbed dynamic systems. For instance, Zheng et al. [16] developed an output feedback control for a (T–S) fuzzy system with multiple time-varying delays and unmatched disturbances. In [17], the author proposed a fuzzy sliding mode control method combined with a deep learning algorithm to approximate the dynamics model and to counteract the disturbances. The Takagi–Sugeno–Kang is used in [18] to derive a robust fuzzy control for a Magnetic Bearing System Subject to Harmonic Disturbances. Yan Cao et al. [19] proposed a robust H_∞ to reduce the disturbance of uncertain discrete-time fuzzy systems. Yoneyma [20] design a stable filter with disturbance attenuation of Takagi–Sugeno fuzzy systems with immeasurable premise variables. An innovative fuzzy-observer-design technic for Takagi–Sugeno fuzzy models with unknown output disturbances is presented in [21]. Vu and Wang [22] designed an observer and a Controller for Takagi–Sugeno (T–S) fuzzy systems

with an enlarged class of disturbances. In [23], a fuzzy disturbance observer controller is developed and applied to a nonlinear system under internal and external disturbances. A robust adaptive sliding-mode control for fuzzy systems with mismatched uncertainties and exogenous disturbances in which the uncertainties in state matrices are mismatched and norm-bounded. In contrast, the exogenous disturbances are assumed to be bounded with an unknown bound, which is estimated by a simple and effective adaptive approach is developed in [24]. In [25], the author analyzes the unknown slippage in wheeled mobile robots and proposes a fuzzy adaptive tracking control method to counteract the dynamic disturbances. Chen et al. [26] proposed a novel-function approximator; the authors use the Fourier series expansion and fuzzy-logic system to model unknown periodically disturbed systems. Then, an adaptive backstepping tracking-control scheme is developed. Other advanced methods like output feedback [27,28], neuro-fuzzy [29], genetic algorithm [30], model predictive [31], and interval type-2 fuzzy systems [32] were used.

This paper introduces a (T-S) fuzzy control method for disturbance rejection applied to a medium-size wind turbine subject to extreme gust wind and actuators saturation. The wind turbine is equipped with a blade pitch mechanism to adjust the blade pitch angle accordingly to minimize the effect of the disturbances mainly caused by the extreme variation of the wind. The controller is constructed based on the (T-S) fuzzy model of the wind turbine and utilizes the parallel distributed compensator (PDC) technique to obtain feedback gain. Note that the feedback gain is obtained while the initial condition is unknown but bounded. The control problem is formulated in terms of linear matrix inequalities and solved using an optimization technic such as the interior point method. A numerical simulation is provided to analyze the capability of the proposed controller.

2. Materials and Methods

2.1. Wind Generator Dynamic Model

A simplified dynamic model of the wind turbine and its drive train based on the two-mass system is illustrated in Figure 1. The drive train consists of a rotor, a generator, and a gearbox. The mathematical model based on this configuration has been used to design linear and nonlinear controller [33,34].

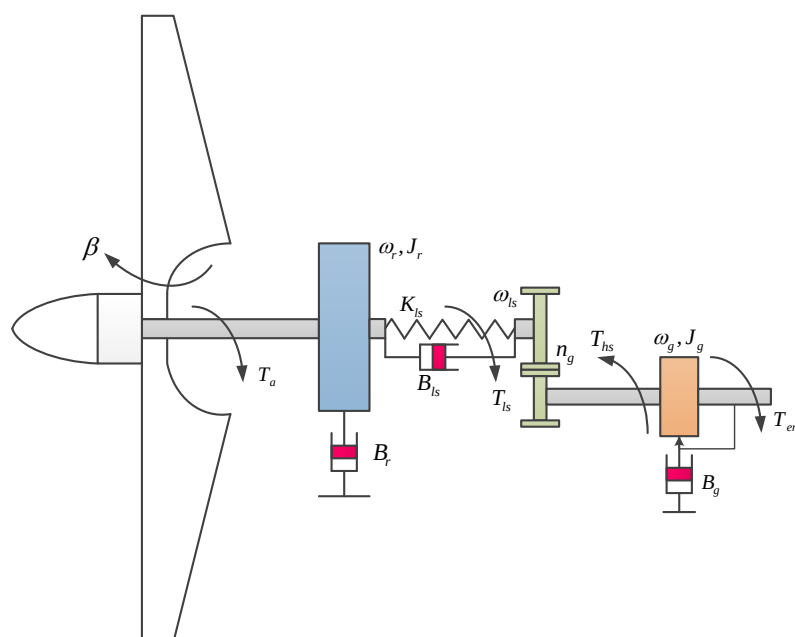


Figure 1. Wind turbine model.

With the assumptions that the moment of inertia of the gearbox and the damping effect of the blades can be ignored, the equations of motion are derived using Lagrange dynamics and written in the following form:

$$\begin{cases} J_r \dot{\omega}_r = T_a - T_{ls} - B_r \omega_r \\ J_g \dot{\omega}_g = T_{hs} - B_g \omega_r - T_{em} \\ \dot{\beta} = -\frac{1}{\tau} \beta + \frac{1}{\tau} \beta_d \end{cases} \quad (1)$$

where J_r , ω_r represents the moment of inertia and the angular velocity of the rotor, T_{ls} is the torque on the low-speed shaft, B_r is rotor damping coefficient, and T_a is the aerodynamic torque, it and can be modeled as

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

where ρ is the air density, R is the rotor radius, V is the wind speed, $C_q(\lambda, \beta)$ is the torque coefficient in which β is the blade pitch angle, and λ is tip speed ratio, and it can be written as

$$\lambda = R \frac{\omega_r}{V} \quad (3)$$

J_g , ω_g represents the moment of inertia and the angular velocity of the generator, B_g is generator damping coefficient, T_{em} is the electromagnetic torque, and T_{hs} is the high-speed shaft torque. It is worthwhile to mention that the third equation in Equation (1) represents the electromechanical pitch systems model where τ is a time delay constant and β_d is the desired pitch angle. It is worth mentioning without going into many details that the flux-weakening control technique, which is considered one of the most practical solutions [35–40], is used to limit the generator speed, to achieve an extended constant power range, to eliminate the use of multiple gear ratios, and to reduce the power inverter volt-ampere rating.

The low-speed shaft torque can be written as

$$T_{ls} = K_{ls}(\theta_r - \theta_{T_{ls}}) + B_{ls}(\omega_r - \omega_{ls}) \quad (4)$$

and for an ideal gearbox with a ratio n_g , the following relationship holds [41]:

$$n_g = \frac{T_{ls}}{T_{hs}} = \frac{\omega_g}{\omega_{ls}} = \frac{\theta_g}{\theta_{ls}} \quad (5)$$

Using Equations (1)–(5), the nonlinear model of the wind generator can be written in the following form.

$$\begin{cases} \dot{\omega}_r = \frac{1}{J_r} \left[-K_{ls} \theta_r + \frac{K_{ls}}{n_g} \theta_g - (B_{ls} + B_r) \omega_r + \frac{B_{ls}}{n_g} \omega_g + T_a \right] \\ \dot{\omega}_g = \frac{1}{J_g} \left[\frac{K_{ls}}{n_g} \theta_r - \frac{K_{ls}}{n_g} \theta_g + \frac{B_{ls}}{n_g} \omega_r - \left(\frac{B_{ls}}{n_g} + B_g \right) \omega_g - T_{em} \right] \\ \dot{\beta} = -\frac{1}{\tau} \beta + \frac{1}{\tau} \beta_d \end{cases} \quad (6)$$

where, $x = [\theta_r \ \theta_g \ \omega_r \ \omega_g \ \beta]^T$ represents the state vector, and $u = [T_{em} \ \beta_d]^T$ is the the control input vector. Note that the torque coefficient $C_q(\lambda, \beta)$ can be approximated as follows [41]:

$$C_q(\lambda, \beta) = \frac{1}{\lambda} \left[c_1 \left(\frac{c_2}{\lambda_1} - c_3 \beta - c_4 \right) e^{\frac{-c_5}{\lambda_1}} + c_6 \lambda \right] \quad (7)$$

where

$$\frac{1}{\lambda_1} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1 + \beta^3} \quad (8)$$

2.2. Takagi–Sugeno Fuzzy Model

A nonlinear dynamic system with disturbances is represented by the following (T–S) fuzzy model:

Model Rule i : IF $z_1(t)$ is about $\mu_{i1}[z_1(t)]$, ..., $z_p(t)$ is about $\mu_{ip}[z_p(t)]$, THEN

$$\begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) + D_i \varphi(t) \\ y(t) = C_i x(t) \end{cases} \quad (9)$$

where $\mu_{ij}[z_p(t)]$ is the grade of the membership of $z_p(t)$, x represents the state vector, u is the control input vector, y is the output vector, $(i = 1, 2, \dots, r)$ specifies the number of fuzzy rules, and $\varphi(t)$ represents the disturbance. A_i , B_i , D_i , and C_i are known constant matrices with appropriate dimensions. The firing strength of each rule can be determined using T -norm product as follows:

$$w_i[z(t)] = \prod_{j=1}^p \mu_{ij}[z_p(t)] \quad (10)$$

and the normalized membership functions are computed as

$$h_i[z(t)] = \frac{w_i[z(t)]}{\sum_{i=1}^r w_i[z(t)]} \quad (11)$$

connecting all the rules, the (T–S) fuzzy model takes the following form:

$$\Sigma_{T-S} : \begin{cases} \dot{x}(t) = \sum_{i=1}^r h_i[A_i x(t) + B_i u(t) + D_i \varphi(t)] \\ y(t) = \sum_{i=1}^r h_i C_i x(t) \end{cases} \quad (12)$$

There are many advantages of using fuzzy logic controllers over conventional controllers. For instance, if the (T–S) fuzzy model is derived using the sector nonlinearity approach [42], it will provide a way to obtain an exact representation of the full nonlinear model as a weighted combination of linear submodels, where the nonlinearities of the system are shifted into the membership functions. Moreover, the advantage of the fuzzy logic controller is its aptitude for dealing with nonlinearities and uncertainties. Other advantages of the Fuzzy logic controller, to mention a few, can be illustrated as follows:

- They are cheaper to develop, they cover a wider range of operating conditions, and they are more readily customizable in natural language terms.
- They are quick to comprehend conceptually, the ideas underlying them are fundamental.
- They are flexible, they enable emerging Fuzzy structures to be applied to their features by applying new information to established rules.
- They are tolerant of incorrect data, complex uncertainty, and unmodeled dynamics.

Because of these advantages, (T–S) fuzzy model structures are an ideal basis for the design of controllers and observers.

In this paper, we derive an approximated (T–S) fuzzy model Equation (12) by linearizing the nonlinear model equations around different operating points and using predefined fuzzy membership functions to combine the linear submodels to an overall nonlinear model.

For instance, when the rotor is operating around the nominal speed, the aerodynamic torque might be estimated as

$$T_a \approx \frac{\partial T_a}{\partial \omega_r} \omega_r + \frac{\partial T_a}{\partial \beta} \beta + \frac{\partial T_a}{\partial V} V \quad (13)$$

Considering the following premises variable represented by two rules each:

$$\begin{cases} \omega_r \in [0.1 \ 3] \text{ rad/s} \\ \beta \in [0 \ 30] \text{ deg} \\ V \in [0 \ 30] \text{ m/s} \end{cases} \quad (14)$$

and the state vector $x = [\theta_r \ \theta_g \ \omega_r \ \omega_g \ \beta]^T$, and the control input vector $u = [T_{em} \ \beta_d]^T$, then the dynamic model represented by Equation (6) takes the form of Equation (9). The matrices A_i , B_i , D_i , and C_i in Equation (9) are obtained by local approximation in fuzzy partition space of the premise variables ω_r , β , and V , and is shown below.

$$A_i = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ -\frac{K_{ls}}{J_r} & \frac{K_{ls}}{n_g J_r} & \frac{1}{J_r} \left[\frac{\partial T_a}{\partial \omega_r} - (B_{ls} + B_r) \right] & \frac{B_{ls}}{n_g J_r} & \frac{1}{J_r} \frac{\partial T_a}{\partial \beta} \\ \frac{K_{ls}}{n_g J_s} & -\frac{K_{ls}}{n_g^2 J_s} & \frac{B_{ls}}{n_g J_s} & -\frac{1}{J_s} \left[\frac{B_{ls}}{n_g^2} + B_g \right] & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau} \end{bmatrix}$$

$$B_i = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ -\frac{1}{J_s} & 0 \\ 0 & 0 \frac{1}{\tau} \end{bmatrix}; D_i = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{J_r} \frac{\partial T_a}{\partial V} \\ 0 \\ 0 \end{bmatrix}; C_i = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}; i = 1, 2, \dots, 8$$

2.3. Fuzzy Controller Design

Consider the dynamic system represented by the following fuzzy model.

$$\Sigma_{T-S} : \begin{cases} \dot{x}(t) = \sum_{i=1}^r h_i [A_i x(t) + B_i u(t) + D_i \varphi(t)] \\ y(t) = \sum_{i=1}^r h_i C_i x(t) \end{cases} \quad (15)$$

Furthermore, in this paper, we assume that the following inequalities can describe the actuators amplitude constraints.

$$\|u\|_2 \leq \delta \quad (16)$$

Furthermore, the initial condition is unknown but bounded such that.

$$\|x(0)\| \leq \sigma \quad (17)$$

2.4. Parallel Distributed Compensation Control

Wang et al. [43] introduced the Parallel Distributed Compensation (PDC) which can be used to design a fuzzy controller from a given (T-S) fuzzy model. A full state feedback control law for each model rule is designed from the corresponding rule of the (T-S) fuzzy model. The control rule is represented as follows:

Control Rule i : IF $z_1(t)$ is $\mu_{i1}[z_1(t)]$, ..., $z_p(t)$ is $\mu_{ip}[z_p(t)]$, THEN.

$$u_i(t) = -K_i x(t) \quad i = 1, 2, \dots, r \quad (18)$$

where K_i represents the control feedback gain matrix. The complete control input is formulated as follows:

$$u(t) = - \sum_{i=1}^r h_i K_i x(t) \quad (19)$$

Note that the PDC controller described by Equation (19) has a simple form and is easy to implement.

2.5. Controller Structure

The disturbance rejection can be realized by minimizing the H_∞ norm of the system, i.e.,

Minimize: γ

Subject to

$$\sup_{\|\varphi(t)\|_2 \neq 0} \frac{\|y(t)\|_2}{\|\varphi(t)\|_2} \leq \gamma \quad (20)$$

The fuzzy controller design is formulated as an optimization problem using linear matrix inequalities (LMIs). The feedback gains K_i stabilizing the system given by Equation (12), and satisfying the control input constraint Equation (16), and unknown bounded initial condition Equation (17), and minimize the H_∞ -norm can be achieved by solving the following linear matrix inequalities (LMIs). We refer the reader to [44] to see the detailed proof.

Minimize: γ^2

Subject to

$$X \geq \sigma^2 I \quad (21)$$

$$\begin{bmatrix} X & M_i^T \\ M_i & \delta^2 I \end{bmatrix} \geq 0 \quad (i = 1, 2, \dots, p) \quad (22)$$

$$\begin{bmatrix} M(1,1) & -\frac{1}{2}(D_i + D_j) & \frac{1}{2}X(C_i + C_j)^T \\ -\frac{1}{2}(D_i + D_j)^T & \gamma^2 I & 0 \\ \frac{1}{2}(C_i + C_j)X & 0 & I \end{bmatrix} \geq 0 \quad (23)$$

where

$$M(1,1) = -\frac{1}{2}(XA_i^T - M_j B_i^T + A_i X - B_i M_j + XA_j^T - M_i^T B_j^T + A_j X - B_j M_i)$$

such that $i, j = 1, 2, \dots, r, i \leq j$, and X is a positive definite matrix. If a feasible solution exists, the feedback gain can be computed as

$$K_i = M_i X^{-1} \quad (24)$$

The design process can be summarized as shown in the following Figure 2.

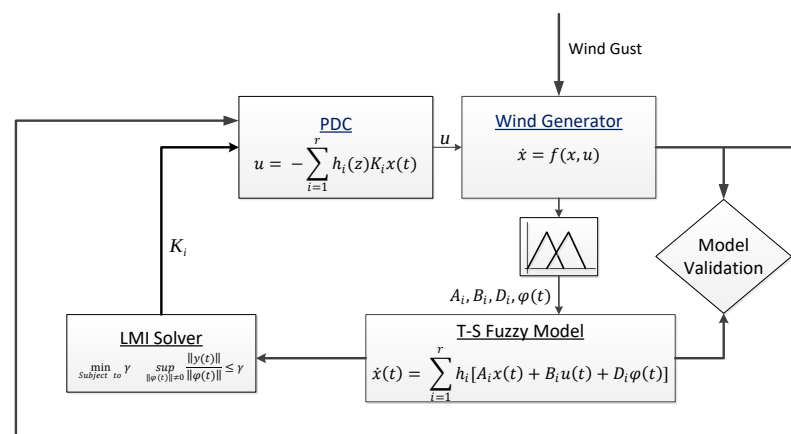


Figure 2. Flowchart of the design and controller process.

3. Results

3.1. Fuzzy Model Validation

The performance of the fuzzy controller depends on the accuracy of the fuzzy model which in return depends on the number of fuzzy rules used to approximate the nonlinear dynamic model. On the other hand, many rules will increase the computational cost. Fuzzy systems modeling has been verified to be universal approximators [45]. Nonetheless, for the approximation to be accurate, a large number of fuzzy rules is needed, in particular when the input membership functions are defined on a space with high dimensions. In general, a large rule number may lead to inefficiency and difficulty in system implementation. A fuzzy system with many rules may be hard to design and have high computation complexity, and poor convergency in parameter tuning [46].

A numerical simulation of the nonlinear model represented by Equation (6) was conducted and compared to validate the (T-S) fuzzy model described by Equation (12) using a set of 2 rules for each premise variable and a constant control input $u = [0 \ 0.1]^T$ and initial conditions $x_0 = [0 \ 0 \ 0.8 \ 0.8 \ 0]^T$. The membership functions of the rules 1, 2 are illustrated in Figure 3 and the physical parameters of the wind turbine are shown in Table 1.

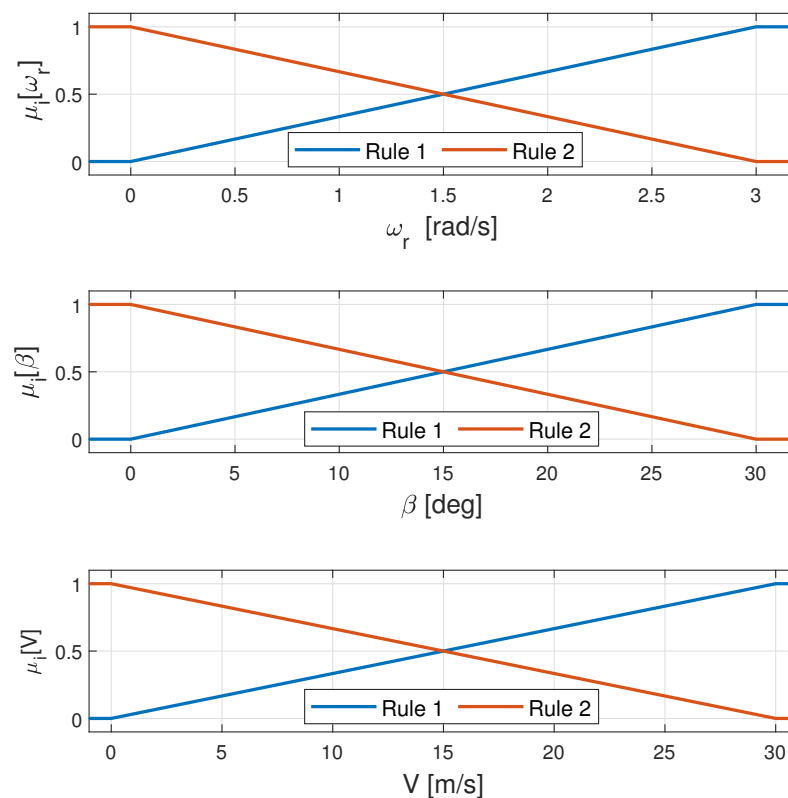
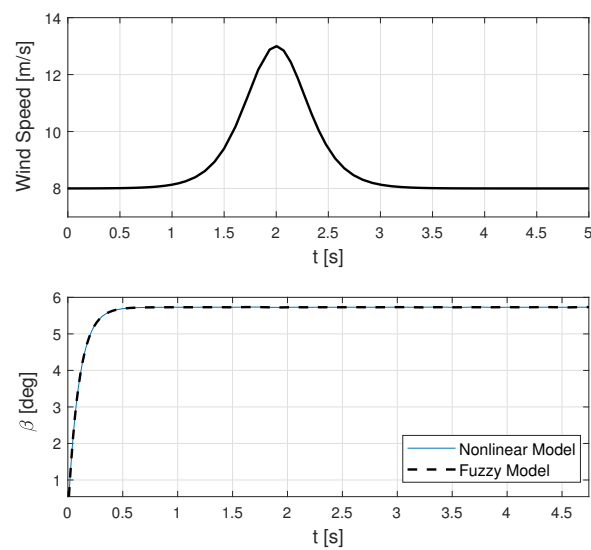
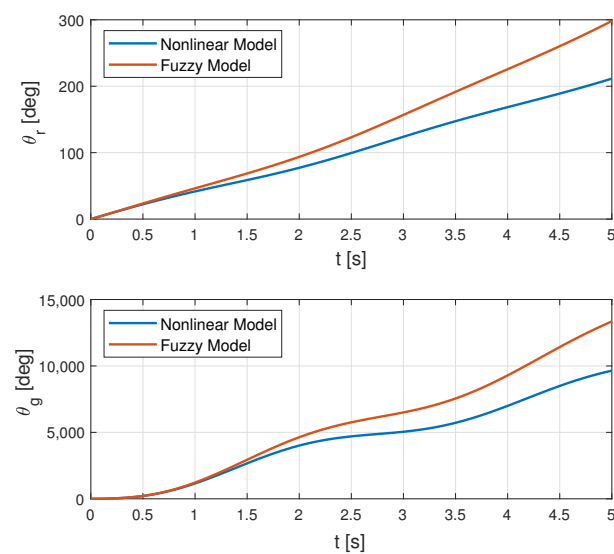


Figure 3. Fuzzy membership function.

The results of the simulation of the nonlinear and the fuzzy model shows that with a set of eight rules, the (T-S) fuzzy model present an adequate approximation, however the result can be improved further by adding more rules. The plots of the wind speed, blade pitch, the angular displacement, and the angular velocity of the rotor and the generator are presented in Figures 4–6.

Table 1. Parameters of the wind turbine.

Parameters	Symbole	Values
Rotor radius	R	21.65 m
Rotor inertia	J_r	34.4 kg·m ²
Generator inertia	J_g	34.4 kg·m ²
Shaft damping coeff	B_{ls}	9500 N·m/rad·s ⁻¹
Shaft stiffness coeff	K_{ls}	2.691 × 10 ⁵ N·m/rad·s ⁻¹
Rotor friction coeff	B_r	27.36 N·m/rad·s ⁻¹
Generator friction coeff	B_g	0.2 N·m/rad·s ⁻¹
Gearbox ratio	n_g	43.165
Air density	ρ	1.225 kg/m ³
time delay	τ	0.1 s
torque coeffs	$c_1 \dots c_6$	0.5176, 116, 0.4, 5, 21, 0.0068

**Figure 4.** Wind speed and blade pitch angle.**Figure 5.** Angular displacement.

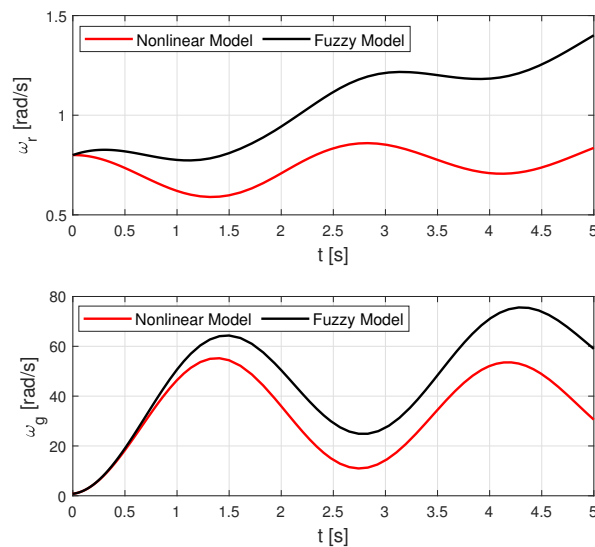


Figure 6. Angular velocity.

3.2. Numerical Results

The efficacy of the fuzzy controller Equation (19) is tested by considering the wind speed input profile $6 \text{ m/s} \leq V \leq 30 \text{ m/s}$ as shown in Figure 7.

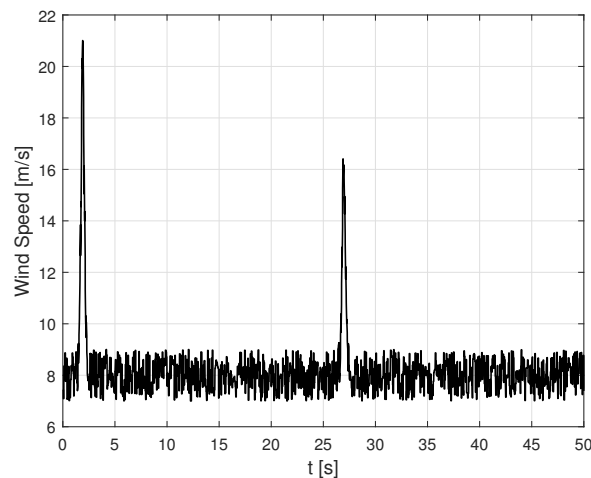


Figure 7. Wind Speed.

Note that the dynamic model of the wind turbine does not consider the deflection of the blades, so in the simulation, we use the static wind speed instead. However, more accurate scenarios should investigate the use of effective wind speed. The MATLAB toolbox YALMIP [47] is used to solve the LMIs in Equations (21)–(23). YALMIP is a solver used to model and solve optimization problems typically occurring in systems and control theory. It is important to mention that one way to tune the controller is by solving the LMIs in Equations (21)–(23) using different conditions. For instance, if the maximum actuators amplitude δ are known, we can modify the condition in Equation (16) accordingly and solve the LMIs in Equations (21)–(23) to obtain the control law that satisfies the parameters of the chosen actuator. This flexibility gives the proposed fuzzy controller great advantages over a traditional controller. Another approach is to obtain a feasible solution using different initial conditions by modifying the parameter σ in Equation (21).

The results of the simulation are shown in Figures 8–10. It is evident that the proposed controller is able to stabilize the wind generator subject to extreme and sudden gust wind reaching 75 km/h.

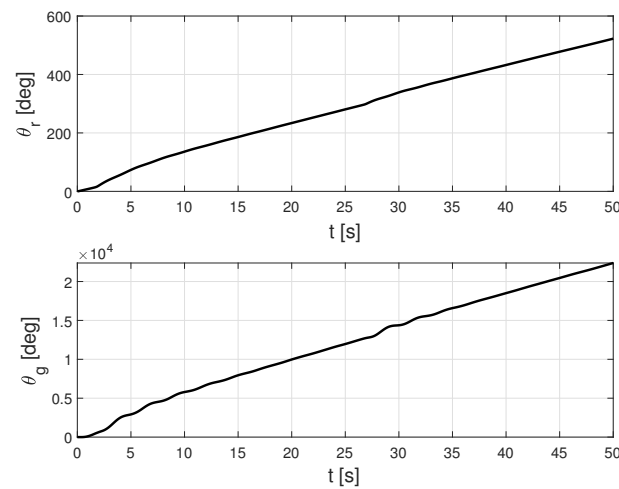


Figure 8. Angular displacement.

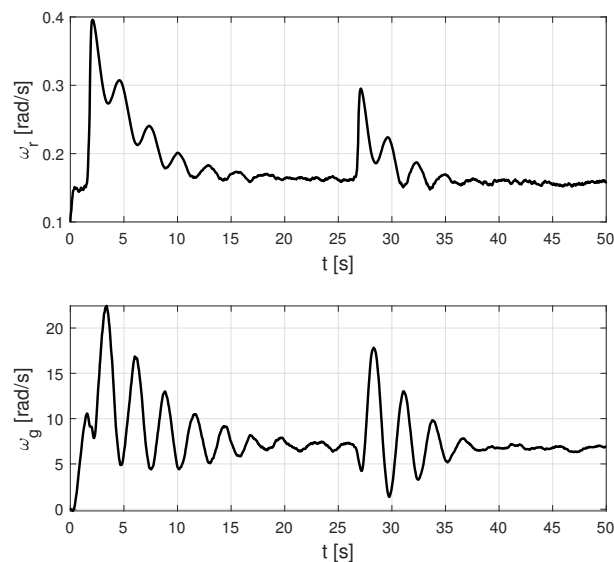


Figure 9. Angular velocity.

As it is shown in the Figure 11, by comparing the desired blade pitch β_d with the actual blade pitch β we conclude that the proposed fuzzy controller performance is satisfactory. Considering for instance the absolute error $\Delta\beta = ||\beta_d - \beta|| = 0.7031^\circ$.

In addition, it is essential to acknowledge that the proposed (T-S) fuzzy controller has certain advantages over traditional controllers, for instance, the actuator amplitude saturation, which depends on the value of δ in Equation (16), and the initial condition described by Equation (17) are solved simultaneously. This advantage allows the design engineer to choose the best actuator to perform the task appropriately. Finally, the (T-S) fuzzy controller has a simple form and is easy to implement (see Equation (19)).

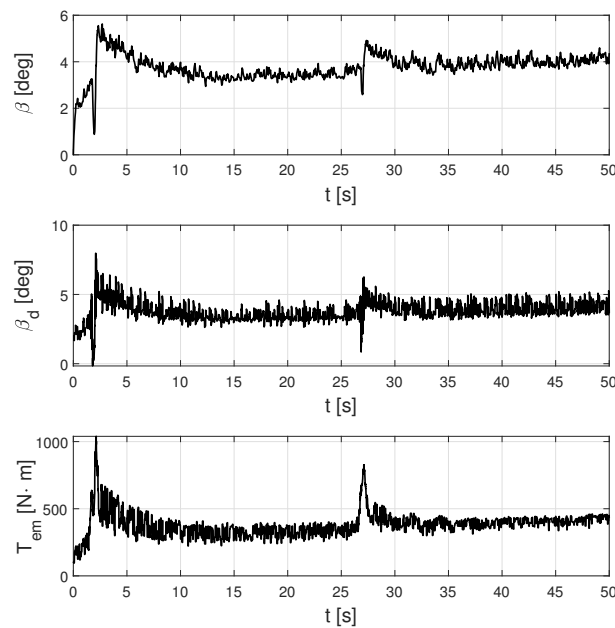


Figure 10. Blade pitch angle, desired blade pitch angle, and electromagnetic torque.

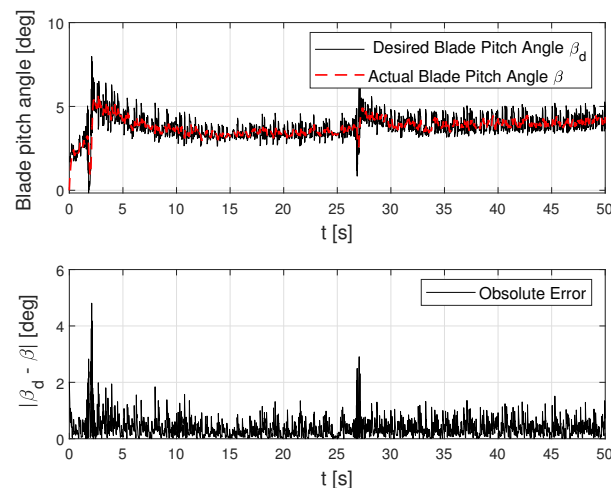


Figure 11. Absolute error of the desired and actual blade pitch angle.

4. Conclusions and Future Work

This paper applied a (T-S) fuzzy controller with disturbance rejection properties to a medium-size wind turbine operating in extreme gust wind conditions. The design procedure of the fuzzy controller is accomplished using the Takagi–Sugeno (T-S) fuzzy model, and the control law is realized by solving a set of linear matrix inequalities (LMIs). The controller performs the required task considering the actuators' amplitude constraints, and the stability is guaranteed with unknown bounded initial conditions. Numerical simulations demonstrate the performance of the proposed fuzzy controller.

It is important to mention that this paper does not analyze the effect of wind gusts on the tower supporting the wind generator, nor the deflection of the blade was taken into account. The stress and the deflection of the tower and blades should be carefully studied. Thus, a complete dynamic model involving the dynamic effect of the tower and the deflection of the blades should be developed. For instance, more accurate scenarios should use the effective instead of the static wind speed described in [48] by the following equation.

$$v_e = v - (\dot{y}_T + \dot{y}_B) \quad (25)$$

where y_T and y_B represents the deflection of the tower and the deflection of the blades respectively. In other words, the static wind speed is corrected by the tower and blade motion effects. Another avenue to investigate is the description of the generator dynamics included in the complete wind turbine system model. When advanced control designs have to be investigated, an explicit generator model might be required. In this situation, a simple first-order delay model can be sufficient, as described in [48] by the following equation.

$$\dot{T}_g = -\frac{1}{\tau_g}T_g + \frac{1}{\tau_g}T_{gd} \quad (26)$$

where T_{gd} represents the desired generator torque and τ_g the delay time constant.

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