

Article

Genetically Optimized Pitch Angle Controller of a Wind Turbine with Fuzzy Logic Design Approach

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Abstract: An important engineering challenge is the design of a wind turbine's pitch angle controller. The dependability, safety, and power output maximization of a wind turbine are all impacted by this controller. In this study, a 2 MW doubly fed induction generator wind turbine's blade angle controller design with a novel fuzzy logic controller is tested in a simulated environment. The evolutionary algorithm technique is used to optimize the fuzzy logic controller with three inputs. A genetic algorithm is used to optimize the specified pitch angle controller for a number of coefficients. After the optimization process, the controller's performance is assessed in terms of power output, overshoot, and steady-state error characteristics.

Keywords: wind energy; wind turbine; pitch angle controller; genetic algorithm optimization; fuzzy logic



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1. Introduction

Traditional energy sources such as natural oil, gas, and coal have proven to be quite successful economic drivers. They are, however, hazardous to the environment and public health. Wind energy has grown in popularity in recent years due to its inherent features of being reusable and clean, in contrast to the quick depletion and increasing environmental risks of fossil fuels. Wind turbines are the primary equipment used in the energy industry to convert wind energy into electric energy. They cannot produce constant power without a proper regulation system, since wind speed fluctuates erratically. Therefore, researchers focused on the stability and dependability of control systems. The pitch angle is the primary control variable of the wind turbine control system. Its control is one of the dominant factors that determines the conversion efficiency of wind energy.

Wind varies dramatically in nature. As a result, wind turbines exhibit rapid variations in electric energy output [1]. Turbines are controlled in different ways defined by wind speed. The wind speed at which the turbine starts to produce energy is defined as the cut-in speed. Below cut-in wind speed, aeromechanical power cannot overcome the mechanical inertia of the power train, and the turbine does not operate. Cut-out speed is the wind speed at which a wind turbine ceases to operate. If the turbine reaches around cut-out wind speed, the automation system protects the turbine from mechanical damage by braking or shutting down the operation. Typically, there are three major operational regions for wind turbines [2]. In the second region, wind speeds are more than the cut-in value but less than the rated value, which is defined as the wind speed where the maximum turbine power is reached. The turbine should work to maximize power in this region [3]. In the third region, wind speeds are higher than the rated value but less than the cut-out value. Wind turbine output power is maintained at a nominal output value by using a blade pitch angle controller [4].

Pitch angle control is required when the generator rotating speed is kept constant and the wind speed exceeds the rated wind speed. Minor adjustments in pitch angle can have a

significant impact on power output. In order to maintain wind turbine output power at a desired nominal value, fuzzy logic approaches are widely employed in the literature. A fuzzy logic pitch angle controller is used directly in a number of investigations [4–11]. In addition to the direct fuzzy logic control (FLC), fuzzy logic proportional control [1,12–14], hybrid Proportional Integral (PI) fuzzy logic control [15–17], hybrid Proportional Integral Derivative (PID) fuzzy logic control [18–21], fuzzy predictive control [2,3], neuro-fuzzy control [22–24], and hybrid fuzzy sliding mode control [25] are also used for regulation at a nominal output power and to counteract fluctuations in power output.

Model predictive control, a predictive control that simulates future reactions, has been presented to enhance the performance of the wind turbine in order to predict future responses for the wind [26]. In addition, sliding mode control (SMC) is employed in the control field for wind turbines because of its effective operation and straightforward design. Additionally, it manages uncertainty brought on by unmodeled quantities, parametric fluctuations, and modeling approximations [27].

Another approach applied to wind turbines is that of genetic algorithms (GA). This methodology is used to search for optimum design or controller parameters. Research on airfoils [28,29] and the creation of a framework for floating offshore wind turbine support structures [30] are two examples of studies focusing on the best design parameters. The controller design is another area in which GA is employed. Integral gains are tuned [31], PI [32–34], and also PID controller parameters are optimized with the GA [35]. Feedback control can be employed with the GA for wind turbines [36–38]. GA can be used to search for a pitch variation law in order to optimize efficiency [39]. Wind speed estimator [40], tip speed ratio and pitch angle optimization for the maximization of the total power of wind farms [41] are other methods that use the GA to improve the performance of wind turbine systems.

FLC parameters can also be tuned with the GA in order to enhance the effectiveness of the controller. Wind turbine generators can be controlled with FLC and GA [42,43]. The pitch angle control of the turbine can be achieved with this control technique. In [44,45], the pitch angle control of a turbine is carried out with FLC and control parameters are tuned with genetic tuning. These fuzzy controllers employ generator power as input of the fuzzy controller. Likewise, in [46,47], pitch angle control is achieved with FLC and GA. In these control schemes, power error and the power error rate of change are used as inputs of the FLC system.

In this study, we use FLC with GA to control the pitch angle of a 2 MW wind turbine model described in [48]. We constructed a novel control system to employ three inputs for fuzzy logic control: error in generator power, power error rate, and generator speed. A genetic algorithm tunes fuzzy logic control parameters. We present the performance of the controller under fluctuating wind profile with simulation results. The organization of this paper is as follows. Section 2 describes the methodology of the wind turbine model, the fuzzy logic controller and the GA. Section 3 presents simulation results with discussions. Lastly, in Section 4, conclusions are put together.

2. Methodology

Modeling of a wind turbine is a critical part of wind turbine engineering as it affects many disciplines. There are several simulator options employed in research and development. There are two major types of wind turbine models in the literature: a doubly fed induction generator (DFIG) type with a gearbox, and a direct drive type without a gearbox. In this study, the controller algorithm is designed and optimized for a 2 MW wind turbine with a DFIG type generator. The system is modeled in order to build controllers and observe the impacts of numerous engineering factors. The mathematical model is generated in the MATLAB Simulink environment. The model can simulate thermal and electrical grid aspects, power output, and controller effects.

2.1. Modeling of a Turbine

The mathematical model of a wind turbine can be defined by the torque equation of its rotor. (1) below expresses the main dynamics of a turbine rotor [4].

$$T_t = \frac{1}{2} \rho \pi R^3 \frac{C_p(\lambda, \beta)}{\lambda} V_w^2. \quad (1)$$

Here ρ denotes the air density [kg/m^3], R stands for the radius of the rotor (m), V_w is the wind speed [m/s], β is the pitch angle, and λ is the tip speed ratio [4].

Power coefficient (C_p) is one of the most crucial parameters for wind turbines. The function converts the parameters pitch angle and the tip speed ratio to a constant between 0 and 0.6. The constant that the function affects is the generated aeromechanical power of a turbine. The power coefficient is calculated as,

$$C_p(\lambda, \beta) = C_1 \left(C_2 \frac{1}{\lambda} - C_3 \beta - C_4 \right) e^{\frac{-C_5}{\lambda}} + c_6 \lambda, \quad (2)$$

where

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

and $C_1 = 0.5$, $C_2 = 116$, $C_3 = 0.4$, $C_4 = 5$, $C_5 = 21$, $c_6 = 0.0068$ [49].

Figure 1 shows the curves for the power coefficients for a modern horizontal axis wind turbine. They are functions of pitch angle and tip speed ratio. As shown in power curve in Figure 1, the pitch angle variable plays a crucial role in maximization of the turbine power.

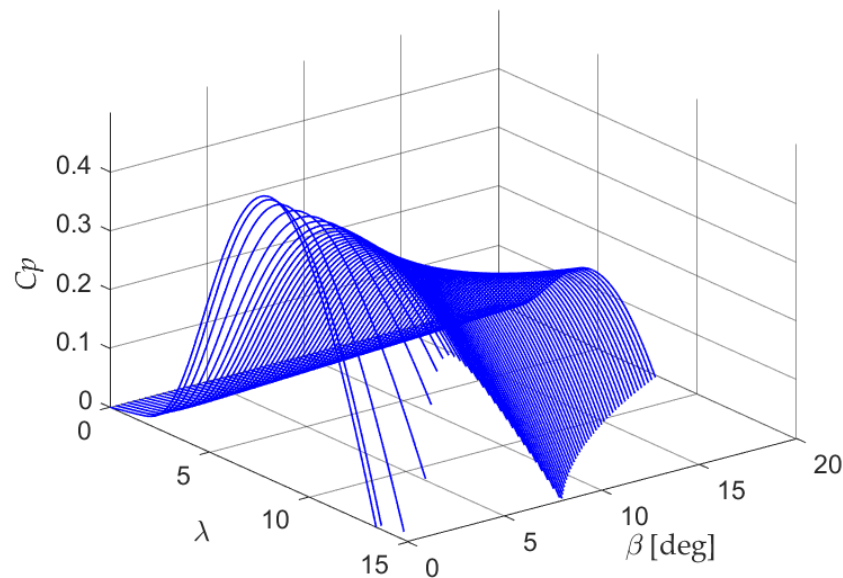


Figure 1. Power coefficient diagram of a modern wind turbine.

Figure 2 presents the block diagram of a conventional wind turbine. As can be seen from the figure, the pitch angle reference is supplied for a nonlinear turbine plant where the output is generally the rotational speed of the generator. In the following sections of this study, the purpose of the proposed controller is to keep the rotational speed of the generator stable.

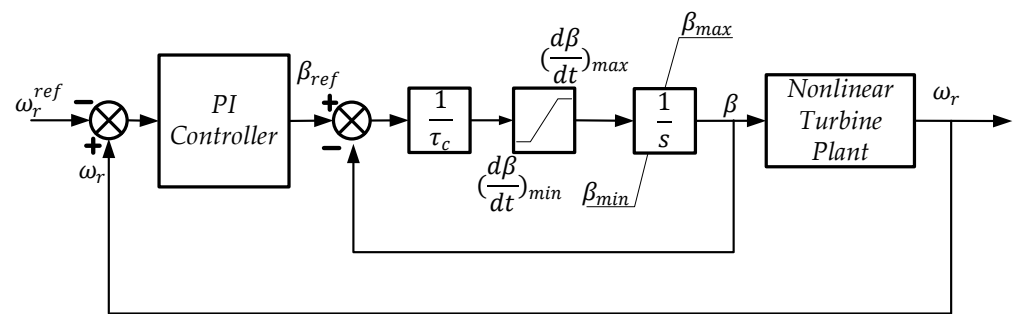


Figure 2. Typical PI control block diagram of a wind turbine pitch angle controller.

2.2. DFIG Type Wind Turbine Configuration and Modeling

Wind turbines consist of a number of subsystems named mechanical, electromechanical and electrical submodules. The aerodynamic subsystem is also to be considered. All subsystems and modules have their dedicated controllers. The controllers for pitch and torque, however, have the most dominant roles.

As shown in Figure 3, wind turbines comprise a variety of subsystems from many technical disciplines, and most of them require distinct controllers. Torque controllers are often used to adjust the power of DFIG type generators, whereas pitch controllers are utilized to control the rotor speed. The classification of operating regions is significant for wind turbine technologies since wind regime graphs provide many critical descriptions for the turbine, including operating speed, maximum power, and maximum attainable aeromechanical power. The wind profile is separated into three regions based on wind speed. Operational regions are referred to as (1) cut-in, (2) rated and (3) cut-off. Turbines typically begin to generate power when the wind speed reaches a threshold speed (cut-in speed). The wind turbine control system operates in the MPPT (Maximum Power Point Tracking) state until the time when the rated wind speed is reached. As the wind speed increases, the pitch mechanism maximizes the power generation from the accessible aeromechanical power. In the rated speed region (between cut-in and rated wind speeds), the pitch system regulates the pitch angle at zero degrees. In the cut-off region (between rated and cut-off wind speeds), the pitch angle is controlled in order to keep the power at its rated value. Beyond the cut-off speed, the automation system uses the pitch angle by regulating or locking at a certain value with blades parallel to the incoming wind, with the objective of halting the wind turbine [8]. The controller proposed in this paper can be employed in all control roles mentioned above.

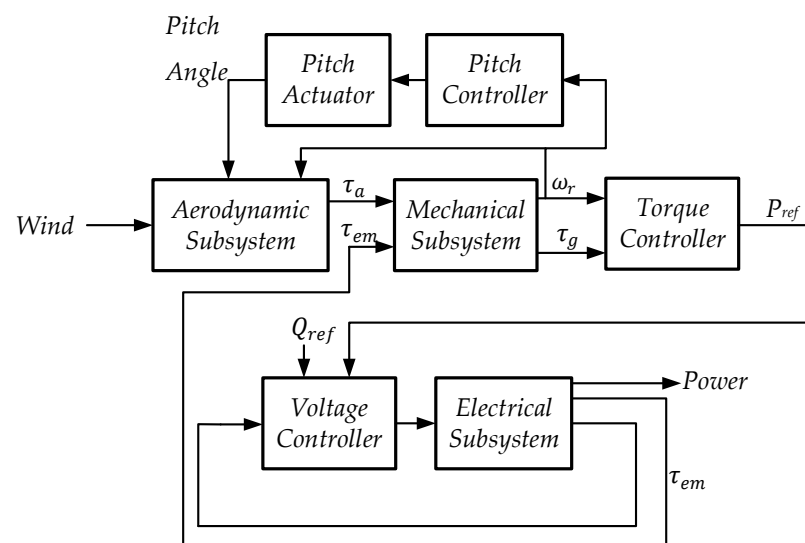


Figure 3. Wind Turbine Block Diagram.

Modeling aerodynamic, mechanical, electromechanical effects, and grid side converters in a simulation is significant in the performance comparison of controllers. The model of a 2 MW DFIG type variable speed and variable pitch wind turbine in MATLAB/Simulink is employed. A wind profile above the rated speed is employed. This particular wind profile aims at studying how abrupt wind changes and pitch control affects power regulation.

2.3. Fuzzy Logic Controller

The advantage of a fuzzy controller is its remarkable inference capability based on fuzzy information. Changes to the control rules and suitable membership functions, reasoning processes, and choices can enhance the features of the controlled system. Fuzzy control has been frequently utilized in variable pitch control to reduce the negative impacts of nonlinear components and the challenge of changing system parameters. The design of the control scheme is crucial, including the selection of input and output variables and membership function parameters. Figure 4 shows the fuzzy control system block diagram.

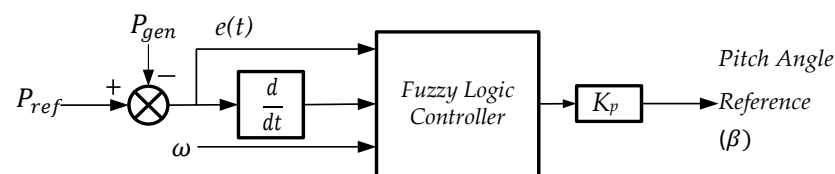


Figure 4. Control System Block Diagram.

Power error, change in power error, and generator speed are chosen as controller inputs. The purpose of the controller is to steadily keep power at its reference. Power error and change in power error during one computational cycle are selected as inputs for power regulation. These variables are defined as power error and change in power error.

$$e_p[k] = P_{ref}[k] - P_{gen}[k], \quad (4)$$

$$\Delta e_p[k] = e[k] - e[k - 1]. \quad (5)$$

Here $e_p[k]$ is power error, $P_{ref}[k]$ is generator power reference, k is discrete time step, $P_{gen}[k]$ is generator power, and $\Delta e_p[k]$ is the change in power error. A third input variable is also used, namely, the deviation of the generator speed from its nominal value, $d_{w_g} = w_{g-nominal} - w_g$. Any modification on the pitch angle β will affect the generator speed. The generator speed, on the other hand, determines the turbine power. The inclusion of our third variable provides the controller with the freedom of tuning its action with the instantaneous generator speed. When the power error requires an increase in generator speed, and when this speed is already excessive, a moderate action on pitch angle variation can be taken. If instantaneous generator speed is not considered in the control output decision, however, a large pitch angle would be commanded. Triangle membership functions with overlaps are utilized to build the fuzzy sets of inputs, as shown in Figures 5–7. The membership functions of power error and change in power error can be seen in Figures 5 and 6. The membership functions of generator speed deviation d_{w_g} are presented in Figure 7. Negative Big (NB), Positive Big (PB), Negative Medium Big (NMB), Positive Medium Big (PMB), Negative Medium (NM), Positive Medium (PM), Negative Small (NS), Positive Small (PS), Zero (ZE) are the linguistic variables. Membership function variables are unknown and calculated with the GA.

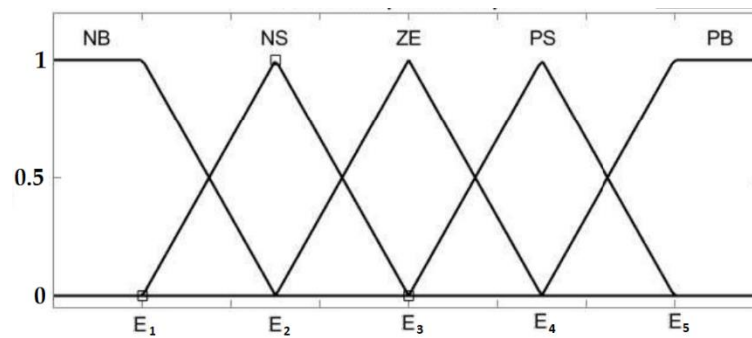


Figure 5. Fuzzy control membership functions for generator power error.

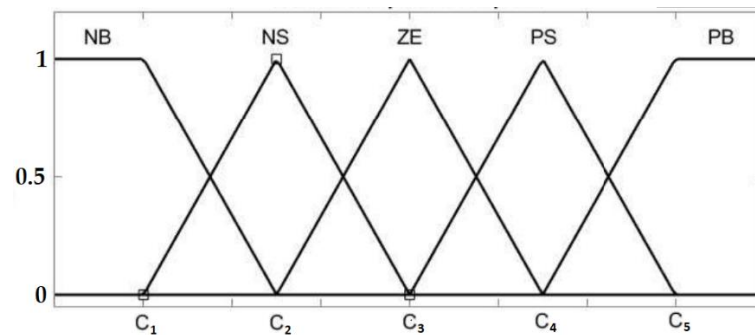


Figure 6. Fuzzy control membership functions for change in generator power error.

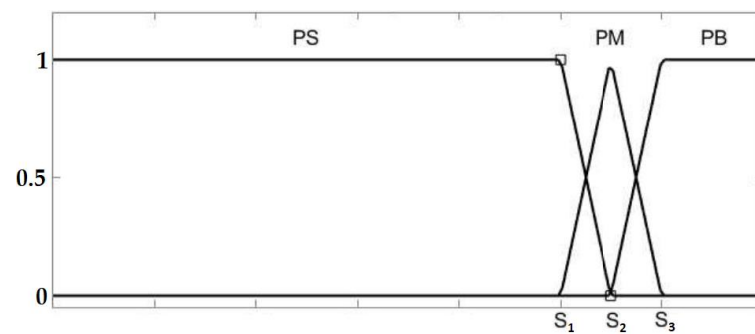


Figure 7. Fuzzy control membership functions for deviation in generator speed.

The singleton membership functions of the output are presented in Figure 8. This figure shows negative big (NB), negative medium big (NMB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), positive medium big (PMB) and positive big (PB) rule strengths.

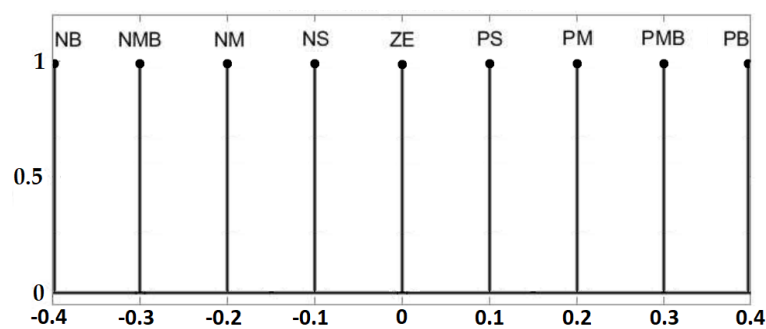


Figure 8. Fuzzy control membership functions for output pitch angle.

Fuzzy logic rules are of the following structure:

$$R_i: \text{ If } e_{w_g}(k) \text{ is } A_i \text{ and } e_p(k) \text{ is } B_i \text{ and } \Delta e_p(k) \text{ is } C_i \text{ then } \Delta\beta(k) \text{ is } D_i \quad (6)$$

where A_i, B_i, C_i are fuzzy sets of input variables and D_i is a fuzzy singleton corresponding to a rule strength. The fuzzy system computes the necessary change $\Delta\beta(k)$ in the pitch angle in the next computational step. The final value of this angle is obtained by cumulatively adding the fuzzy system outputs each cycle.

The FLC rule base is presented as in Table 1. It reflects 75 rules (R_1, \dots, R_{75}) in the structure described in (6). For instance, if generator power error value is NB, change in generator power error is NS and deviation of generator speed from its nominal value is PB, the FLC output is PS which means $\beta[k]$ should be increased by 0.1 deg.

Table 1. Fuzzy Logic Control Rules.

e_P		NB			NS			ZE			PS			PB		
d_{w_g}		NM	ZE	PM	NM	ZE	PM	NM	ZE	PM	NM	ZE	PM	NM	ZE	PM
Δe_P	NB	NB	NS	PS	NB	NS	PS	NB	NS	PM	NB	PM	PMB	NMB	PMB	PB
	NS	NB	NS	PS	NB	NS	PS	NB	ZE	PMB	NMB	PM	PMB	NMB	PMB	PB
	ZE	NB	NS	PS	NB	ZE	PM	NMB	ZE	PMB	NMB	PM	PB	NM	PMB	PB
	PS	NB	NS	PM	NMB	ZE	PM	NMB	ZE	PB	NM	PMB	PB	NM	PMB	PB
	PB	NMB	ZE	PM	NMB	ZE	PM	NM	PS	PB	NM	PMB	PBPB	NM	PMB	PB

For each rule a truth value T_i is computed with the product inference technique:

$$T_i = \mu_{e_p}(e_p(k)) \mu_{\Delta e_p}(\Delta e_p(k)) \mu_{d_{w_g}}(d_{w_g}(k)) \quad (7)$$

The necessary change in the pitch angle β is computed by the center average defuzzification rule:

$$\Delta\beta = \frac{\sum_{i=1}^{75} T_i D_i}{\sum_{i=1}^{75} T_i} \quad (8)$$

The output of the fuzzy logic controller is multiplied by a tuning coefficient, K_p , to obtain the pitch angle:

$$\Delta\beta[k] = K_p \Delta\beta[k], \quad (9)$$

The main feature of the rule base in Table 1 is to increase β when the power is below the reference value, and to lower it when there is excess power. This action is, however, moderated by two factors: change of power and deviation of generator speed. If power is to be increased and the change of power is positive, β is increased less when compared with the case with zero or negative change of power. Also, if the generator speed is in excess of the nominal value, power increase is targeted with a very small increase in β . The overall rule base acts as a dual goal control mechanism, aiming to keep power in generator speed at their reference and nominal values, respectively.

2.4. Genetic Algorithm Optimization of Fuzzy Logic Control

A population-based algorithm is employed in GA. Each population member has a fitness value, representing the relative value of the objective function. The greater fitness value of a member, the more likely it will become a next-generation parent. Various methods, such as a roulette wheel, tournament and ranking, are utilized to choose the proper individuals from the formed population. In this study, the tournament method is employed as a selection method. Tournament selection has various advantages over other options of selection methods for genetic algorithm. It is practical to code and works on parallel architectures [50].

The crossover technique creates new population members from two existing ones. The crossover rate defines the number of population members who will be crossed. This ratio varies depending on the design process and the task at hand. The crossover ratio used is 80% in this study. This is a quite commonly implemented value in the literature, and has been selected for this reason [51].

The fitness function represents how close each member of the population is to the solution. The function tolerance value is selected as 1×10^{-6} as convergence criteria for the objective function, and the fitness function is selected as integral time absolute error (ITAE), defined as follows.

$$ITAE = \sum_{l=0}^k |e(l)|. \quad (10)$$

Here, $e[t]$ is power error and t is time. The GA optimization is utilized to compute optimum membership function values for FLC. The optimized variables can be seen in Figures 6–9. These variables are E_1, E_2, E_3, E_4 and E_5 for membership functions of power error, C_1, C_2, C_3, C_4 and C_5 for membership functions of change in power error, S_1, S_2 and S_3 for membership functions of generator speed and the scaling factor K_p . Table 2 presents optimization results for these parameters and allowed intervals. These intervals are found with a trial-and-error method in order to find approximate regions in which the controller performs adequately.

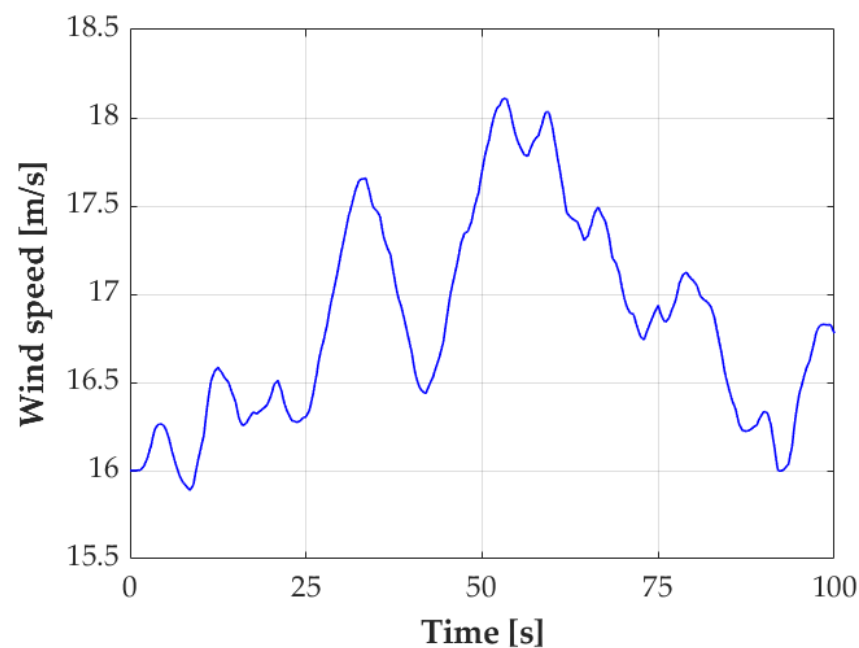


Figure 9. Wind speed.

Table 2. Fuzzy logic control parameters optimized by GA.

Variable	Interval	Value	Variable	Interval	Value
E_1	$[-4.2, -1.3]$	-3.076	C_3	$[0, 0]$	0
E_2	$[-3.6, -1.15]$	-2.746	C_4	$[0.00003, 0.00033]$	0.00003
E_3	$[-3, -1]$	-2.416	C_5	$[0.00006, 0.00066]$	0.00006
E_4	$[-2.85, -0.4]$	-2.085	S_1	$[-0.111, 0]$	-0.013
E_5	$[-2.7, 0.2]$	-1.755	S_2	$[-0.088, 0.022]$	0.002
C_1	$[-0.000066, -0.0006]$	-0.00006	S_3	$[-0.066, 0.044]$	0.018
C_2	$[-0.000033, -0.0003]$	-0.00003	K_p	$[19, 21]$	19.997

3. Implementation Results and Discussion

In this section, simulation results are presented with and without the tuning of the fuzzy control parameters by a conventional (without optimization parameters update between population iterations) GA system. Our motivation in using a straightforward (conventional) GA parameter tuning approach in this paper is as follows. A number of metaheuristic optimization techniques could be applied as alternatives to the conventional GA approach employed in this paper. Examples of these approaches are MPA (Marine Predator Algorithm) [52], PSO (Particle Swarm Optimization) [53], GSA (Gravitational Search Algorithm) [54], CS (Cuckoo Search) [55], FA (Firefly Algorithm) [56], CMA-ES (Covariance Matrix Adaptation Evolution Strategy), BO (Bonobo Optimization), BA (Bat Algorithm), BSO (Brain Storming Optimization), and TLBO (Teaching Learning Based Optimization). These approaches, as standard or with modifications, are capable of introducing online (between optimization iterations) optimization parameter updates. These updates can achieve superior convergence properties, for example, by increasing the reached fitness or by reducing the number of necessary iterations, and hence the computation time. [57] provides valuable comparison results. BO algorithm can be employed to regulate the yaw angle in the context of horizontal axis wind turbines [58]. Ref. [52] presents a MPA implementation on power flow optimization in the field of power generation. The alternative optimization technique and GA with online optimization parameter updates [59] do have the potential of outperforming the conventional GA (GA without parameter updates). However, there are a number of fuzzy control systems reported in the wind turbine control literature, many of which are tuned by conventional GA systems. Our work aims at creating another example in this category to be compared with such work. It is yet to be mentioned that the genetic tuning of a three-dimensional fuzzy control rule base contrasts the literature by adding one more complication level to the tuning task at hand. Reported in the wind energy field previously are two-dimensional fuzzy control rule bases adjusted via GA. It may also be argued that the straightforward implementation of the classical GA can be considered as a merit when compared with more complicated optimization systems.

The controller is simulated with significantly fluctuating wind data obtained from a wind field for 100 s. Table 3 shows various parameters of the turbine.

Table 3. Turbine parameters adapted from [60].

Parameter	
Nominal Output Power	2 MW
Working Mode	Grid Connected
Cut-in wind speed	3 m/s
Nominal wind speed	12 m/s
Cut out wind speed	25 m/s
Rotor Diameter	82.6 m
Rotor Swept Area	5359 m ²
Nominal Rotor Speed	15.8 rpm
Gear Box Rate	1:94.7
Generator Pole Pair	2
Generator Type	DFIG
Generator Synchronous Speed	1500 rpm
Generator Voltage	690 V
Nominal Generator Speed	220 rad/s

As shown in Figure 9, region three wind speed 5 m/s over the nominal speed is simulated and the controller response is observed. Another purpose of the controller is to achieve the desired power output in the shortest time and for the most prolonged duration.

The controller performance is measured with criteria such as settling time, overshoot, rise time, and steady-state error. As presented in Figure 10, the system reaches the steady state at around 10th second with the maximum power output. The magnitude of the power fluctuations without genetic tuning are 0.015 MW. With genetic tuning, this magnitude drops to 0.005 MW. Similar previous studies were not conducted in region three with wind speeds over 50% above the nominal wind speed [1,4]. This, however, is the case in the presented work. In this research, controller performs under highly fluctuating wind speed, whereas previous similar studies [1,4] had more steady profiles.

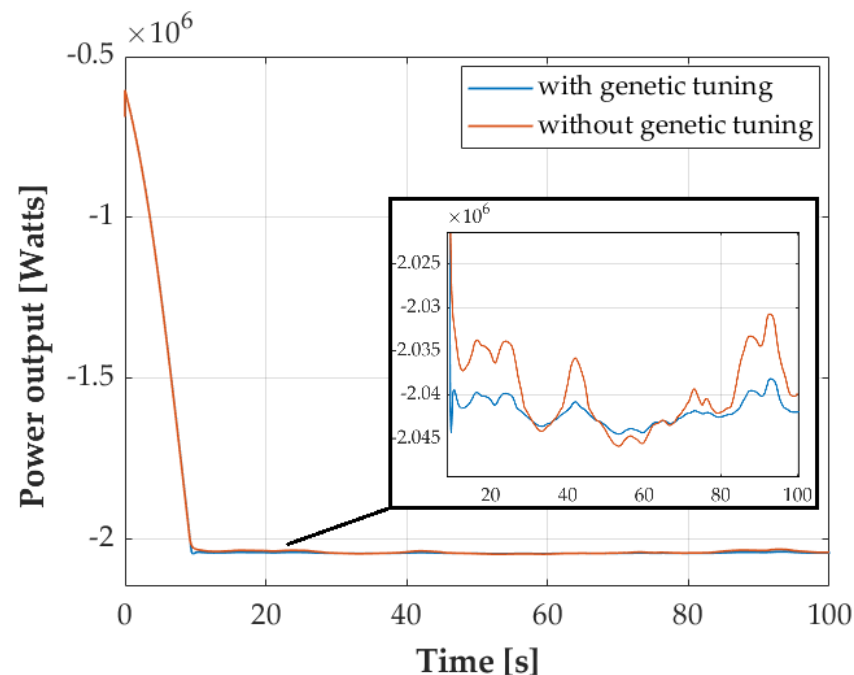


Figure 10. Power output with (blue line) and without (red line) using genetic algorithm.

In Figure 10, the maximum power is achieved after the transient phase is completed, and the change in power error is decreased approximately 50 percent with the genetic algorithm. As presented in Figure 11, better performed overshoot in change of error in power is achieved with genetic algorithm. In study [4] which employs fuzzy logic control without genetic algorithm optimization, there are significant errors in power and power error rate of change.

The response time of the controller is extended, and therefore after the generator rotational speed reaches 220 rpm, the controller starts acting, and the pitch angle departs from zero. After the initial step response of the pitch angle, the controller varies the pitch angle smoothly to regulate the rotational speed of the generator at 220 rpm, since this speed is the nominal speed of the 2 MW wind turbine as stated in Table 3. As the wind speed severely changes, the pitch angles of the blades react accordingly. Figure 12 depicts the controller's output pitch angle regime with and without genetic tuning. Note that the genetic tuned results in the curve, which exhibits a peak at about the 10th second. The abrupt behavior indicates an increased control effort compared with the fuzzy controller without genetic tuning. It should be kept in mind, however, that the speed of the blades and aero-structural stability of the turbine are related. Therefore, speed limitation is applied to safeguard the system from unstable behavior. The pitch angle speed limit in our simulations is set to 5 degrees/s.

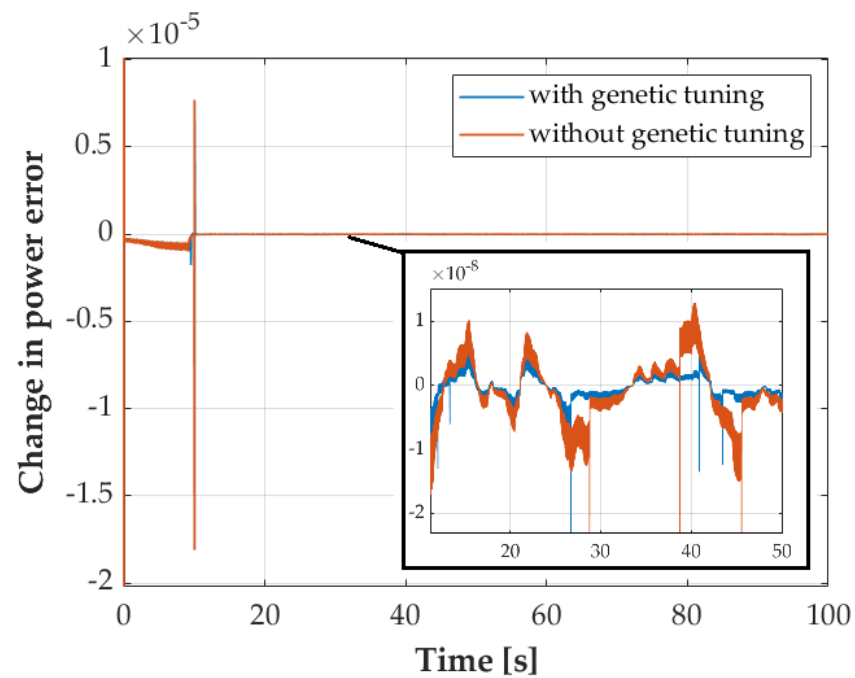


Figure 11. Change in power error with (blue line) and without (red line) using genetic algorithm.

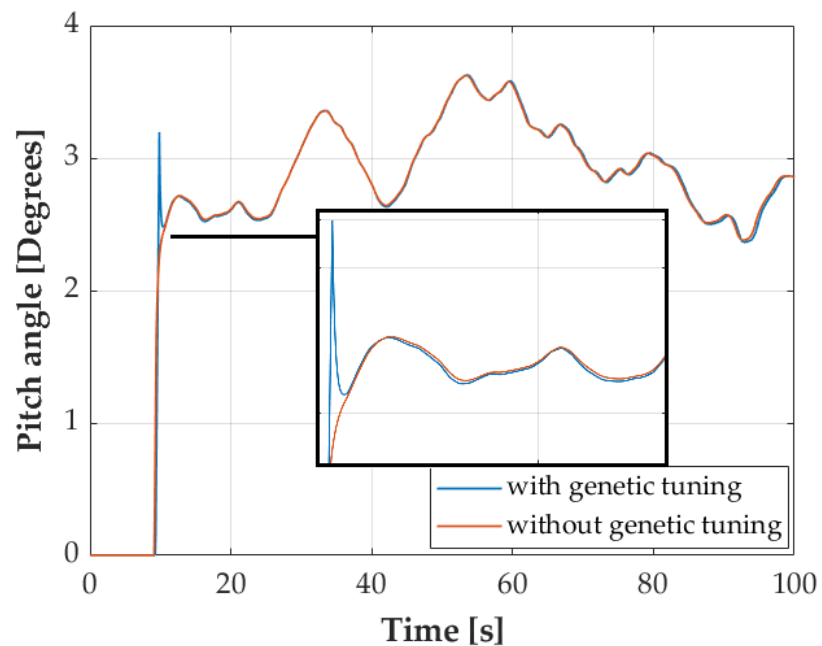


Figure 12. Pitch angle with (blue line) and without (red line) using genetic algorithm.

Figure 13 presents the response of the generator under the mentioned wind regime. Rotor speed fluctuations in the FLC with the GA optimization are about 0.3 rad/s, while those in the FLC without the optimization are about 0.6 rad/s. This indicates that the fluctuation problem is effectively solved by the genetic algorithm.

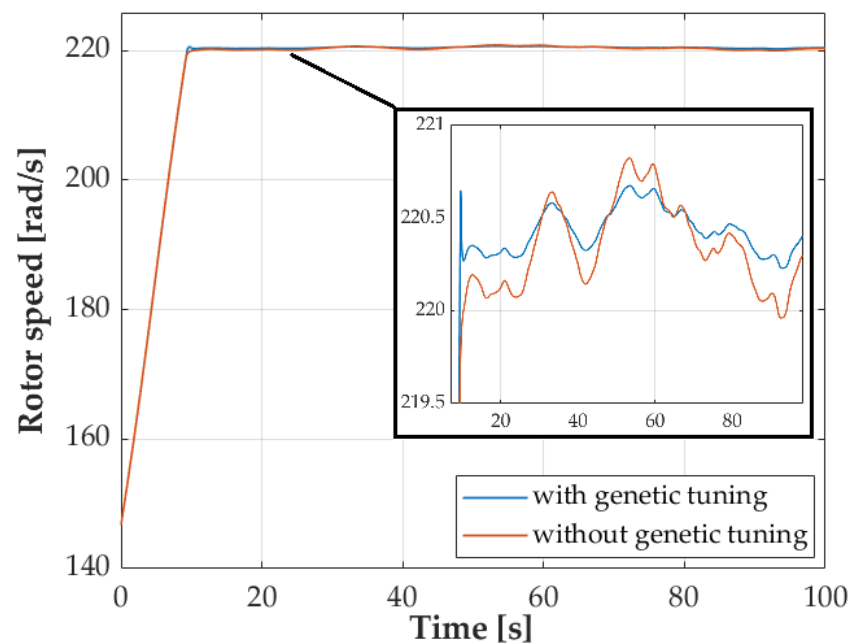


Figure 13. Rotor speed with (blue line) and without (red line) using genetic algorithm.

Moreover, with the GA optimization over the proposed fuzzy logic controller, a controller with a shorter settling time performance when compared with the previous studies is obtained [4]. In addition, as has been indicated previously in Figures 10–13, less fluctuation in generator speed, a smoother pitch angle curve and 30% less fluctuation in power production is achieved. The decreased settling time will increase the annual energy production.

However, the requirement of tuning with offline simulations can be considered as a disadvantage of genetic tuning methodology. This wind turbine model is very detailed and requires a moderate amount of computational power and time. Still, it is successful in tuning the fuzzy system with the three-dimensional rule base.

4. Conclusions

This study employs a DFIG configuration 2 MW wind turbine model to perform controller design with FLC techniques and genetic tuning. A novel control system is developed that uses three inputs for fuzzy logic control. Generator power error, power error rate and generator speed are used as inputs. A genetic algorithm adjusts fuzzy logic control parameters. Multiple simulations conducted in MATLAB/SIMULINK demonstrate optimized FLC performance.

Controller performance is crucial in maximizing the annual energy production. An ideal set of FLC parameters is produced by GA adjustment. With a quicker settling time and less power fluctuation, optimized FLC outperformed hand-tuned and existing conventional FLC approaches.

It is possible to think of implementation on experimental setups as future work. Also, comparisons with other optimization techniques can be carried out in simulation platforms.

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