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Comparative Study of Control Methods for a 2MW Doubly-Fed Induction Generator Wind Turbine

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ABSTRACT

This paper presents a comparative study of two control methods for a 2MW Doubly-Fed Induction Generator Wind Turbine (DFIG-WT) using MATLAB Simulink. The Proportional-Integral-Derivative (PID) and Model Predictive Control (MPC) control methods were implemented and evaluated in terms of their ability to track reference signals, disturbances tolerance and stabilize the system under uncertain wind conditions. The performance of the control methods was assessed using a high-fidelity WT model that incorporates the dynamics of the wind turbine, the wind speed, and the control system. The results show that the MPC control method outperform the PID control method in terms of tracking accuracy and disturbance tolerance.

1. Introduction

Wind energy has emerged as an important source of renewable energy as it is abundant, widely distributed, and emits no greenhouse gases. Wind turbines are a crucial component of wind power generation, converting the kinetic energy of wind into electrical energy. Wind turbines come in different sizes and types, ranging from small-scale turbines used for residential or community power generation to large-scale turbines used for utility-scale wind farms Li *et al.,* [1]. Wind turbines are subject to a range of dynamic loads and disturbances that can affect their performance and structural integrity. Wind conditions are variable and unpredictable, and wind turbines must be able to operate in a wide range of wind speeds and directions. The aerodynamic forces acting on the rotor blades can cause fluctuations in the torque and power output of the wind turbine. Additionally, wind turbines are subject to mechanical vibrations and structural loads that can cause fatigue and damage to the turbine components according to Cui *et al.,* [2]. Effective control methods are therefore necessary to ensure safe and efficient operation of wind turbines. The control system of a wind turbine typically includes sensors to measure the wind speed and other operating conditions, actuators to adjust the pitch of the blades or the generator torque, and a control algorithm to determine the appropriate

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control inputs. The control algorithm must be able to track the desired power output or rotor speed while accounting for the nonlinear and uncertain dynamics of the wind turbine and the varying wind conditions supported by Zhang *et al.,* [3].

The PID controller is a widely used control method for wind turbines due to its simplicity and robustness, for instance, Zhou and Shen [4], and Schena [5] all mention that PID control is commonly used in wind turbine pitch systems. Additionally, Sarkar *et al.,* [6] and Aldair *et al.,* [7] use PID controllers in their pitch control systems for wind turbines. However, Xia *et al.,* [8] suggested that traditional PID control is commonly used for regulating the pitch of wind turbines, but it may struggle to achieve accurate control in situations where there is intense wind turbulence. Hence, to address the challenges posed by strong wind turbulence, a nonlinear PID control strategy has been developed for wind turbine pitch regulation. While this strategy ensures accuracy and stability, it may result in slower response times. Furthermore, Shao *et al.,* [9] have proposed a self-tuning PID control approach that utilizes reinforcement learning specifically for the pitch control of large wind turbines. In addition, Ngo *et al.,* [10] have conducted research on small-scale wind turbine systems and have proposed a pitch angle control method that combines a PID controller with fuzzy logic. The fuzzy-PID controller can compensate for the nonlinear characteristic of the pitch angle and wind speed. However, Liu *et al.,* [11] also stated that the nonlinearity and uncertainty of wind turbine dynamics can limit the effectiveness of PID control. There are also some researches that compares PID controller with other design techniques such as D. Izci *et al.,* [12] compares the performance of the reptile search algorithm (RSA) based PID controller design technique with other previously reported techniques such as gravitational search algorithm (GSA), particle swarm optimization (PSO), and bacterial foraging optimization (BFO) based PID controller design techniques. In this design procedure, RSA is used to tune the PID controller parameters for DFIG-based wind energy conversion systems. The objective is to minimize a cost function that represents the difference between the desired output and actual output of the system. The RSA algorithm is used to find optimal values for K_p, K_i, and K_d parameters of PID controller that minimize this cost function. The simulation results show that RSA-based PID controller outperforms other techniques in terms of settling time, overshoot, and steady-state error. This demonstrates that RSA is an efficient and reliable approach for tuning PID controllers in DFIG-based wind energy conversion systems. D. Izci *et al.,* [13] also proposed augmented hunger games search algorithm using a logarithmic spiral opposition-based learning technique (LsOBL-HGS) to optimize functions and design controllers in various real-world applications. In this paper, the algorithm was utilized to design a fractional-order proportional-integral-derivative (FOPID) controller for a magnetic ball suspension system. The LsOBL-HGS algorithm has been shown to outperform other optimization techniques such as grey wolf optimization (GWO), Harris hawk's optimization (HHO), and aquila optimization (AO) algorithms, as well as the original version of HGS in terms of both convergence speed and control performance. Additionally, the algorithm has been applied to solve other optimization problems such as feature selection, image segmentation, and power system optimization. The results showed that the LsOBL-HGS algorithm achieved better performance in terms of convergence speed and solution quality. Therefore, the LsOBL-HGS algorithm can be a useful tool for solving complex optimization problems. Furthermore, D. Izci *et al.,* [14] evaluate the performance of a newly developed algorithm, slime mould algorithm (SMA), for designing efficient PID controllers in regulating a direct current (DC) motor's speed and controlling the output voltage of an automatic voltage regulator (AVR) system. The integral of time multiplied absolute error (ITAE) was used as the objective function to optimize the system's dynamic response and stability. The proposed design approach of the PID controller for DC motor speed regulation outperforms other design approaches, with better transient stability, fast damping characteristics, and no overshoot. The proposed design approach of the PID controller for

DC motor speed regulation using SMA was compared to other metaheuristic approaches such as Harris hawk's optimization (HHO), atom search optimization (ASO), and grey wolf optimization (GWO), and the comparative results showed that SMA is an effective algorithm for solving real-world engineering problems. Simulation results showed that the proposed approach produced better results in terms of transient stability, fast damping characteristics, and no overshoot compared to other metaheuristic algorithms. Furthermore, the frequency response performance of the controlled systems with the proposed approach was the best among the tested techniques.

Meanwhile, MPC is a promising alternative offering improved performance and robustness. For instance, Han and Gao [15] have suggested a solution to the issues of wind speed uncertainty and measurement noise in hydraulic wind turbine systems by using an MPC method with a dynamic Kalman filter. This approach is based on a linear parameter-varying model. Dickler *et al.,* [16] have concentrated on verifying the effectiveness of a linear time-variant MPC system in a full-scale field test of a 3 MW wind turbine. Suboh *et al.,* [16] develop a linear MPC controller to maximize the power production of DFIG wind turbines according to wind speed. Cui *et al.,* [2] have conducted a comparative analysis of two advanced control algorithms, which includes classical tracking MPC, to determine their effectiveness in optimizing the operation of wind energy conversion systems. While there are several studies that have evaluated the performance of PID and MPC control methods in wind turbine systems, few studies have compared the performance of these methods under varying levels of wind speed uncertainty. For instance, Han and Gao [15] propose a nonlinear dynamical model of the wind turbine and use LIDAR measurements to obtain scheduling variables for MPC, but do not compare the performance of PID and MPC under different levels of wind speed uncertainty. Similarly, Suboh *et al.,* [17] develop a linear MPC controller to maximize power production of DFIG wind turbines according to wind speed, but do not compare the performance of PID and MPC under different levels of wind speed uncertainty. Therefore, in this study, PID and MPC control methods for wind turbine control methods are observed and analysed. Specifically, the ability of these methods to track reference signals, reject disturbances and stabilize the system under varying wind conditions. Additionally, N.A *et al.,* [18] also conducted an investigation of MPC controller on wind turbine system during uncertainty but do not compare the PID and MPC controller. The study is conducted using a high-fidelity DFIG wind turbine model that incorporates the dynamics of the wind turbine, the wind speed, and the control system. The results of this study will provide valuable guidance for the development of more efficient and reliable wind turbine control systems.

The following is a summary of the key findings and contributions of this work:

i. This paper presented a comparison study between PID and MPC performances during ad hoc uncertainty in the wind turbine system with bounded disturbance.
ii. The presented method of MPC controller takes into consideration the states and controlled signals constraints.

The remainder of this paper is structured as follows. Section 2 explains the structure of the wind turbine system and the presented control method. The comparison analysis of PID and MPC control methods are discussed in Section 3. This paper comes to a close in Section 4.

2. Methodology

2.1 Mathematical Modelling of Wind Turbine

The Wind Energy Conversion System (WECS) captures the kinetic energy of the wind and converts it into mechanical energy using the wind turbine. In a wind energy conversion system (WCES), the mechanical energy generated by the wind turbine is transferred through the drivetrain shaft and converted into electrical energy by a generator. This electrical energy is then fed into the grid for consumption. Cui *et al.,* [2] have presented a schematic of the WECS in Figure 1.

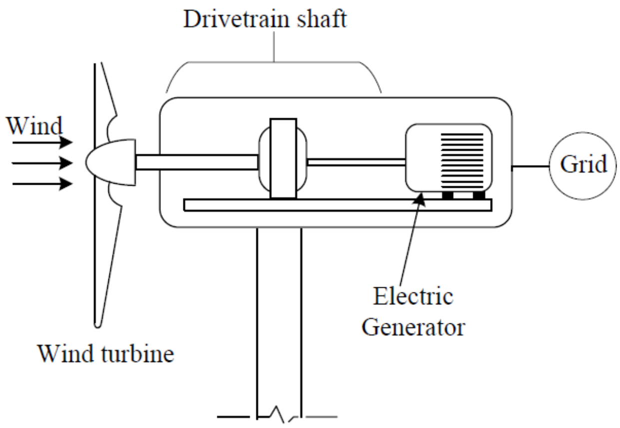

Fig. 1. WCES schematic mode

The generated mechanical energy by the wind turbine can be adopted by Zhang *et al.,* [3] and Nahooji *et al.,* [19]:

$$P_{mech} = 0.5\rho\pi R^2 V_m^3 C_p(\lambda, \theta) \tag{1}$$

in wind energy conversion systems, air density is typically denoted by ρ, and the generator rotor radius is represented by R. The wind speed is expressed as and V_m in meters per second. The coefficient of performance of the turbine, denoted by $C_p(\lambda, \theta)$, is a non-linear function of the blade pitch angle, θ, and the tip-speed ratio (TSR), λ. The relationship between C_p and λ, θ for the 2 MW wind turbine used in this study are illustrated in Figure 2 which is plotted from the following equations:

$$\left.\begin{aligned} C_p &= 0.5\left(\frac{0.98}{\lambda_i} - 0.4\theta - 5\right)e^{\frac{16.5}{\theta}} \\ \frac{1}{\lambda_i} &= \frac{1}{\lambda + 0.08\theta} - \frac{0.035}{\theta^3} \end{aligned}\right\} \tag{2}$$

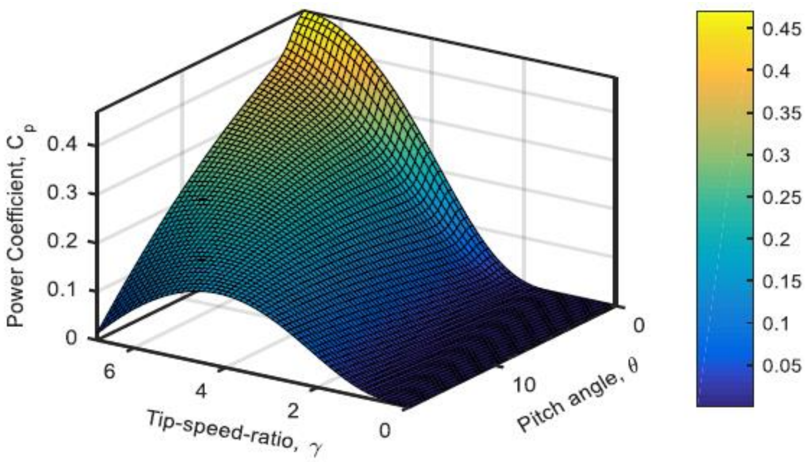

Fig. 2. Power coefficient variation [20]

where TSR defines the ratio between the tangential speed of the blade tip and the wind sp. It is used to describe the relationship between the speed at which the blades are rotating and the speed of the wind that is passing over them and can be expressed as:

$$\lambda = \frac{\omega_t R}{V_t} \tag{3}$$

where the terms ω_t refers as the rotational speed. The wind turbine generator electromechanical behaviour is modelled as a single lumped mass system and can be defined as:

$$J_m \frac{d\omega_m}{dt} = 0.5(T_e - T_m - D_m \omega_m) \tag{4}$$

where, inertia, rotational speed, and viscous damping in wind turbines are represented by J_m, ω_m and D_m respectively. The electrical torque of the generator is denoted by T_e while the mechanical torque can be expressed as

$$T_m = \frac{P_m}{\omega_m} \tag{5}$$

Due to the presence of a gear ratio, n_g in a gearbox, the rotor speed is connected to the dynamic rotational speed, which is represented as $\omega_t = \eta_g \omega_m$.

2.1.1 DFIG-WT model

This study focuses on the investigation of a 2 MW DFIG-WT where the base value used is 2MVA. The parameters of this system are presented in Table 1 in per unit. The machine equations utilized in this study are expressed in a synchronously rotating d-q reference frame, which is based on the approach suggested by Suboh *et al.,* [20] can be written as follows.

Table 1
Parameters for 2MW DFIG-WT

Parameter	Value
J_m	4.5207 s
Gear ratio, n_g	84.15
D_m	0.01
R_s	0.0049 p.u
R_r	0.0055 p.u
L_m	3.9530 p.u
L_{ss}	4.0454 p.u
L_{rr}	4.0525 p.u
Rotor radius, r	37.5 m

$$\left.\begin{aligned} \varepsilon\frac{di_{dr}}{d_t} &= (L_mV_{ds} - L_sV_{dr}) + \big(L_m\omega_s\psi_{qs} - L_s(\omega_s - \omega_m)\psi_{qr}\big) + (L_sR_ri_{dr} - L_mR_si_{ds}) \\ \varepsilon\frac{di_{ds}}{d_t} &= (L_mV_{dr} - L_rV_{ds}) + \big(L_r\omega_s\psi_{qs} - L_s(\omega_s - \omega_m)\psi_{qr}\big) + (L_sR_si_{ds} - L_mR_ri_{dr}) \\ \varepsilon\frac{di_{qr}}{d_t} &= \big(L_mV_{qs} - L_sV_{qr}\big) + \big(L_m\omega_s\psi_{ds} - L_s(\omega_s - \omega_m)\psi_{qr}\big) + \big(L_sR_ri_{qr} - L_mR_si_{qs}\big) \\ \varepsilon\frac{di_{qs}}{d_t} &= \big(L_mV_{qr} - L_rV_{qs}\big) + \big(L_r\omega_s\psi_{ds} - L_mL_s(\omega_s - \omega_m)\psi_{qr}\big) + \big(L_rR_si_{qs} - L_mR_ri_{qr}\big) \end{aligned}\right\} \tag{6}$$

where, $\varepsilon = (L_m^2 - L_rL_s)/\omega_s$.

Based on this approach, it is possible to obtain the electrical torque and output power respectively as follows:

$$T_e = \psi_{qr}i_{dr} - \psi_{dr}i_{qr} = \psi_{ds}i_{qs} - \psi_{qs}i_{ds} \tag{7}$$

$$P_{out} = T_e\omega_m \tag{8}$$

The use of a DFIG is widespread in wind farms due to its numerous advantages, including variable speed, independent control of active and reactive power, cost efficiency, and potential improvements in the quality of generated power, among others as stated by Gholami *et al.,* [21].

2.2 Proportional-Integral-Derivative Control

The PID controller is a commonly used type of controller in which the input variables are the proportion (P), integration (I), and differential (D) of the deviation from the desired set point. These input variables are used to calculate the control function, which produces an output signal that acts on the controlled target (T) to bring it closer to the desired set point according to Baburajan and Silpa [22]. This controller operates on a linear basis and the principles are illustrated in Figure 3.

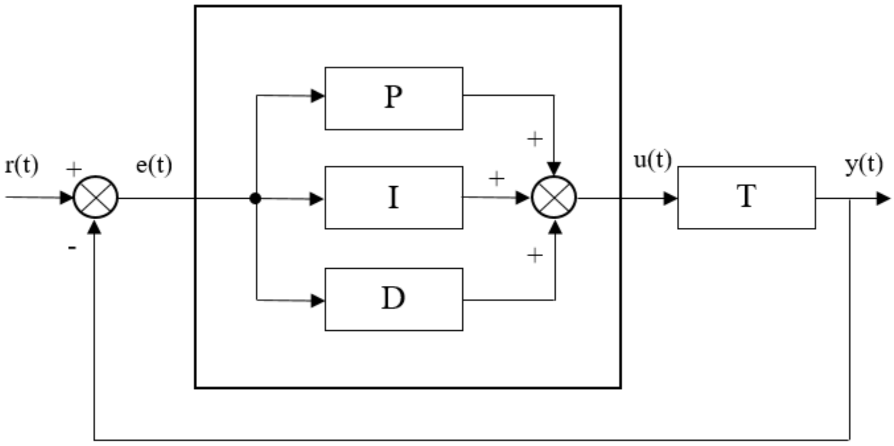

Fig. 3. Block diagram of PID controller [22]

The control input to the plant is produced by the PID controller, and this output can be represented in the time domain as follows:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_p \frac{de}{dt} \tag{9}$$

The tracking error (e) in a PID controller is defined as the difference between the desired input value (r) and the actual output (y). This error signal is sent to the controller, which calculates the derivative and integral of the error to generate a control signal (u). The control signal is produced by adding together the proportional gain (K_p) multiplied by the magnitude of the error, the integral gain (K_i) multiplied by the integral of the error, and the derivative gain (K_d) multiplied by the derivative of the error. The plant then uses this control signal (u) to adjust its output and produce a new output value (y), which is compared to the desired input value to generate a new error signal for the controller. This process repeats until the plant's output closely matches the desired input value. The transfer function of the PID controller can be expressed using the Laplace transform, as suggested by Baburajan and Silpa [22]

$$K_p + \frac{K_i}{s} + K_d s = \frac{K_d s^2 + K_p s + K_i}{s} \tag{10}$$

A proportional controller (K_p) can decrease the rise time and partially reduce steady-state error, but it can't eliminate it completely. An integral controller (K_i) can eliminate steady-state error for constant or step inputs, but it may lead to slower transient response and oscillations. A derivative controller (K_d) can improve system stability, decrease overshoot, and enhance transient response.

2.3 Model Predictive Control

MPC involves the use of a process model to predict the future behaviour of the plant at every sampling instance. The control vector is optimized by MPC, and only the first element in the optimal control sequence is applied to the plant, while the remaining sequence is ignored. This entire process is repeated at each sampling moment. As explained by Aslam and Sohaib [23], Figure 4 shows the fundamental structure of MPC.

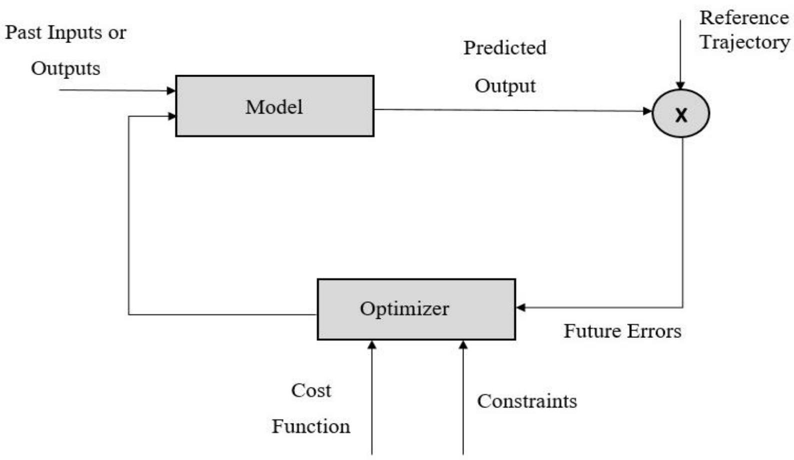

Fig. 4. Basic structure of MPC

MPC requires two main components for implementation: the system model and the optimizer. When constraints are present, the optimizer is a mathematical function that optimizes the control signal by minimizing the cost function. The optimized control signals are then fed as future inputs into the plant's system model to estimate the output. The difference between the estimated output and the desired reference value is fed back to the optimizer, which then optimizes the next input. This iterative process continues indefinitely. In this study, the cost function used for the proposed MPC is based on output tracking, as suggested by Suboh *et al.,* [17].

$$J(Z_k) = \sum_{j=1}^{n_y} \sum_{i=1}^{p} \left\{ \frac{w_{i,j}^{y}}{s_j^{y}} \left[\omega_{dj}(k+i|k) - \omega_{rj}(k+i|k) \right] \right\}^2 \quad (11)$$

where each notation represents;
k = current control interval
p = prediction horizon
n_y = number of plant output variables
$\omega_{rj}(k+i|k)$ = predicted value of plant output
$\omega_{dj}(k+i|k)$ = reference value of plant output
s_j^y = scale factor for plant output
$w_{i,j}^y$ = tuning weight for plant output
Z_k = QP decision, given by

$$Z_k^T = [u(k|k)^T \quad u(k+1|k)^T \cdots u(k+p-1|k)^T \quad \in_k]$$

Then, MPC will solve the following optimization problem at each sampling;

$$\min_{u_k} J(Z_k) \text{ subject to}$$

$$u_{min} < U_k < U_{max}$$

To ensure that the hardware limitations are met, the variables being controlled are usually assigned with minimum and maximum constraints.

3. Results

The MATLAB Simulink software was utilized to develop and test the system, with dedicated PID and MPC controllers designed for the $V_m = 7$ m/s operating point. To assess and compare controller performance, two case studies were conducted: one without uncertainties and another with wind speed uncertainties present in the system.

3.1 Controller Analysis at Normal Wind Speed

The data that has been collected is the output value of the rotor speed, ω_r, coefficient of performance, C_p, and the power output, P_o. All simulation results during normal wind speed are shown in Figure 5(a) Rotor speed, Figure 5(b) Coefficient of performance and Figure 5(c) Output power. During normal wind speed, $V_{m=}$7 m/s, all of the output values achieved the desired value which are $\omega_r = 0.6801$ p.u, $C_p = 0.4708$ p.u and $P_o = 0.2185$ p.u.

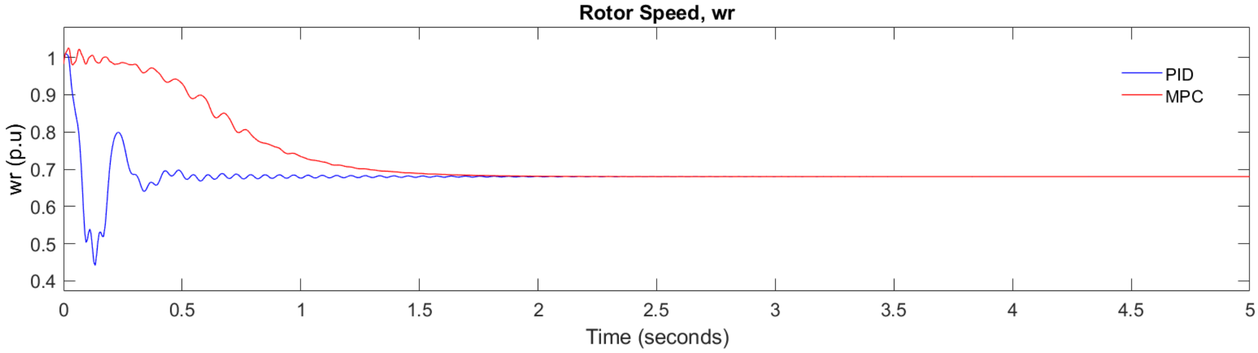

Fig. 5. (a) Rotor speed

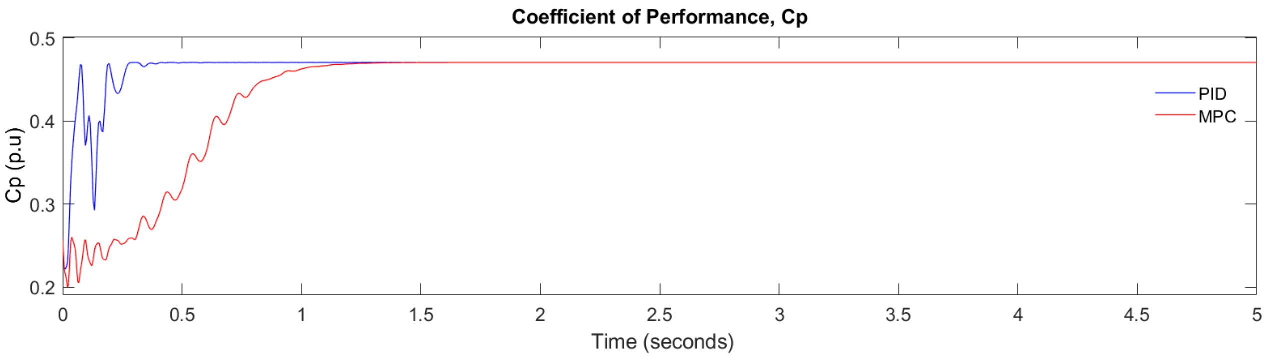

Fig. 5. (b) Coefficient of performance

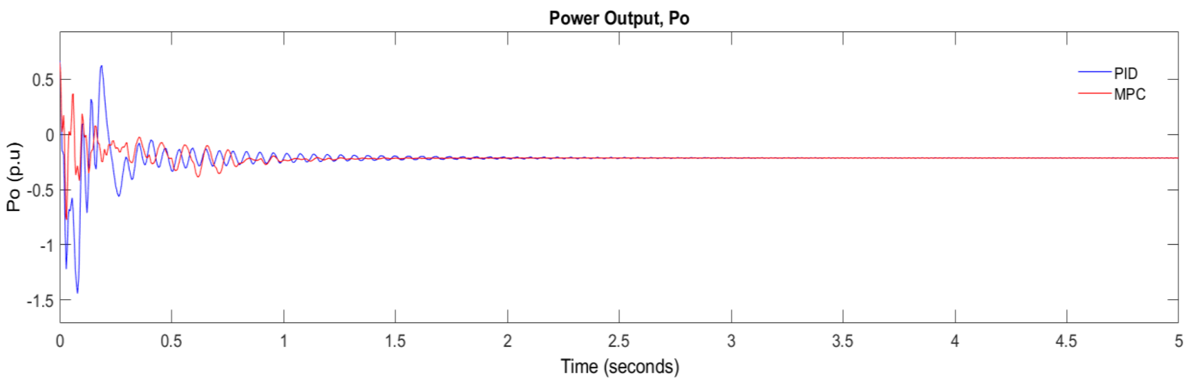

Fig. 5. (c) Output power

However, as can be seen, there are higher overshoot shown by the PID controller at the beginning of the starting point and the PID controller take a longer time to stabilize. The comparison of the overshoot (%), settling time (s), rise time (ms) and fall time (ms) between MPC and PID controller are shown in Table 2. A lower rise time indicates that the system responds more quickly to changes in the input or disturbances, and it takes less time for the output to reach and settle within a specified range around its desired or steady-state value. This is often associated with a more agile and responsive control system. On the other hand, a higher rise time indicates a slower response and a longer time to reach the desired output range. A higher rise time can be indicative of sluggish or slow control system performance.

Table 2
Simulation result during normal wind speed, $V_m = 7$ m/s

Controller		ω_r	C_p	P_o
Model Predictive Control (MPC)	Output value (p.u)	0.6801	0.4708	0.2185
	Overshoot (%)	1.919	0.641	2.530
	Settling time (s)	2.262	1.053	2.022
	Rise time (ms)	-	42.179	4.210
	Fall time (ms)	527.557	-	3.648
Proportional-Integral-Derivative (PID)	Output value (p.u)	0.6801	0.4708	0.2185
	Overshoot (%)	2.028	0.065	97.479
	Settling time (s)	2.734	0.856	3.288
	Rise time (ms)	22.623	43.001	8.179
	Fall time (ms)	24.700	-	8.450

3.2 Controller Analysis at Normal Wind Speed During Uncertainty

The simulation is carried out by introducing ad hoc uncertainty into the wind turbine system for both MPC and PID controllers. All the simulation results during uncertainty are shown in Figure 6(a) Rotor speed, 6(b) Coefficient of performance and 6(c) Output power.

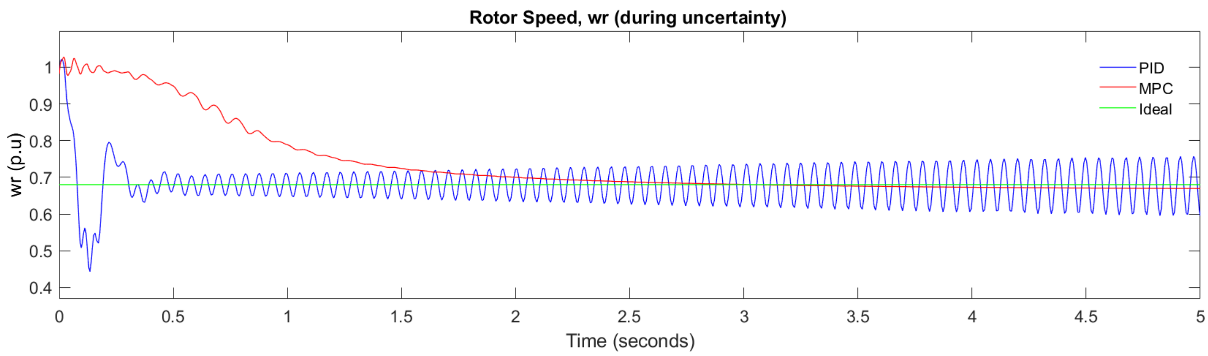

Fig. 6. (a) Rotor speed

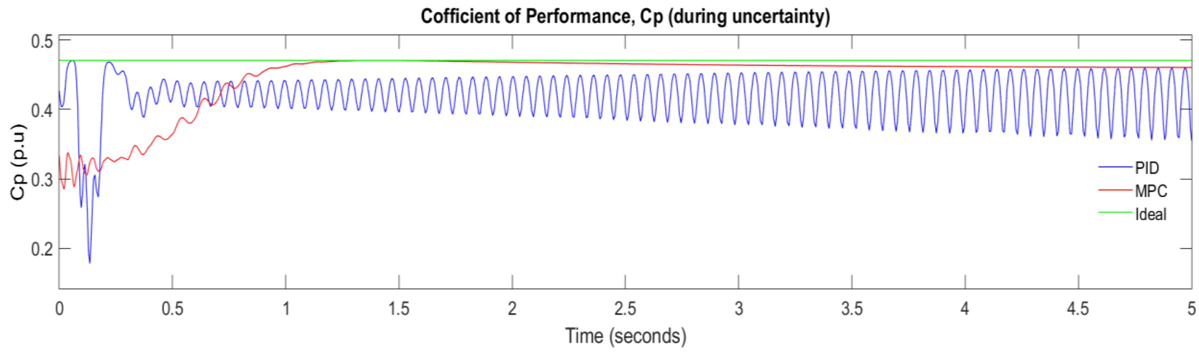

Fig. 6. (b) Coefficient of performance

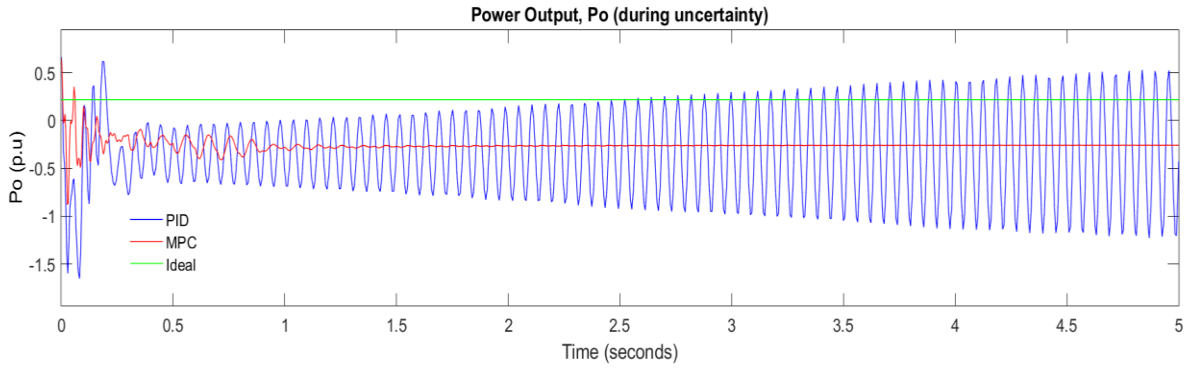

Fig. 6. (c) Output power

The data are recorded in Table 3. While both controllers do not achieve the desired value for ω_r, C_p, and P_o, however, MPC controller are able to generate the nearest output value from the desired value and efficiently stabilize the system. Even though the output power, P_o of the PID controller is higher than the MPC controller but it is also higher than the ideal output power which might harm the hardware installation.

Table 3
Simulation result during ad hoc uncertainty

Controller		ω_r	C_p	P_o
Model Predictive Control (MPC)	Desired output value (p.u)	0.6801	0.4708	0.2185
	Output value (p.u)	0.6662	0.4598	0.2593
	Overshoot (%)	1.999	8.088	58.602
	Rise time (ms)	-	22.049	8.491
	Fall time (ms)	43.484	-	4.936
Proportional-Integral-Derivative (PID)	Desired output value (p.u)	0.6801	0.4708	0.2185
	Output value (p.u)	0.7570	0.3357	0.4715
	Overshoot (%)	0.488	0.350	0.205
	Rise time (ms)	18.401	39.286	15.964
	Fall time (ms)	17.963	16.213	21.148

4. Conclusions

In this study, a DFIG wind turbine was modelled and simulated using MATLAB Simulink to analyse and compare both PID and MPC controllers in terms of its efficiency in handling ad hoc uncertainty in the wind turbine system. The effectiveness of both controllers was initially assessed by exposing them to a standard wind speed, and it was observed that both the PID and MPC controllers were able to generate the desired output, but PID controller took a longer time to achieve the steady-state value and had a higher overshoot compared to the MPC controller. For the second case studies, where ad hoc uncertainty is added into the system, MPC controller could not achieve desired output but only the nearest and shows better efficiency. However, PID controller shows higher overshoot and cause the system to be unstable throughout the simulation. Based on the analysis, it can be concluded that MPC controllers are more efficient and reliable for wind turbine system than PID controller.

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