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Control of wind turbine above rated wind speed using improved fuzzy logic and model predictive control

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This paper focuses on the design of improved fuzzy logic and model predictive control schemes employed for pitch angle regulation of wind energy conversion system (WECS). Due to rotation of earth, the speed of wind on the earth's surface changes continuously. As a result, the power generated from WECS varies. This generated power from WECS depends on cube of the wind speed and it leads to the power fluctuations. Pertaining to the stable power output from WECS under varying wind speed, a number of control techniques are developed in the literature over the last few years. Presently for regulation of output power fluctuations against variable wind speed environment, pitch angle control is extensively used. In view of handling the uncertainties owing to wind speed variations, this study exhibits the comparative performance of Improved Fuzzy logic control (IFLC) and Model predictive control (MPC) schemes by modeling and simulating the WECS via MATLAB/Simulink. The main control objective is to keep the power generation within the rated power of the generator against wind speed variation, which can be achieved by regulating the pitch angle and/or generator torque. To assess the capability of MPC scheme, the WECS is modeled and simulated under different wind speed test cases. From the obtained results, it is confirmed that the response of MPC is better than IFLC, in situation of wind speed variations.

Keywords: Wind Energy Conversion System; Improved Fuzzy Logic Control; Power quality; Model Predictive Control.

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1. INTRODUCTION

Because of increasing green energy awareness and crisis of depleting fossil fuels, the interest towards development of renewable energy systems goes on increasing in particular wind energy. Its annual growth rate is around 30% [1]. As the power extracted from the wind is proportional to the cube of wind speed, so the wind energy conversion system is of nonlinear in nature. Therefore in modern wind energy conversion systems (WECS), control system plays a vital role. In fact a variable speed variable pitch operation of a WECS is shown in Figure 1 [2]. The first region is related to low wind speeds and known as partial load regime (between cut-in wind sped, V_{ci} and rated wind speed V_r). As wind speed is low in this regime, the speed controller will regulate the speed of the rotor to maintain the tip speed ratio constant. So that power coefficient will be the maximum and the turbine efficiency will be increased. The next regime is known as full load regime and is related to medium and high wind speeds (between rated wind speed V_r and Cutout wind speed V_{co}). In this region the control objective is to control both output power and speed to their rated values by regulating the pitch angle and/or generator torque of wind turbine. In this region control of torsional torque is also important because of high wind speed and it is also controlled through the pitch angle.

The control design of a variable speed and variable pitch WECS is difficult because of its multiple inputs and multiple outputs in nature. Different types of control techniques are suggested for this problem. One of the classical control methods is Proportional-Integral [3-8] control. In Proportional-Integral (PI) controller it is to be interface with the process and adjust the controller parameter by trial and error method. By doing so, it controls both transient and steady state response. The simplicity and low cost of these controllers is also their weakness. Because of this most of the industrial controllers are used today are PID controllers.

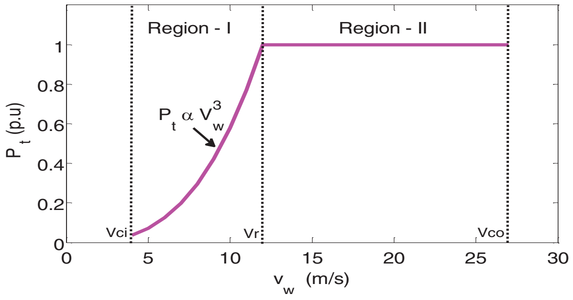


Figure 1 Power curve characteristics for WECS.

It may be noted that classical automatic control methods are inappropriate for handling complex or ill-defined systems. Intelligent systems which combine knowledge, techniques & methodologies from various sources are alternative approaches for resolving the imprecise dynamical behavior of such complex systems. The intelligent techniques such fuzzy inference systems provide a feasible alternative to capture the approximate, qualitative aspects of human reasoning and decision making processes. Fuzzy logic is expressed by means of the human language. Based on fuzzy logic, a fuzzy controller converts a linguistic control strategy in to an automatic control strategy and by using expert experience and knowledge database fuzzy rules are constructed.

These fuzzy rules along with fuzzification and defuzzification block are the key component of fuzzy inference system (FIS) which can effectively model human expertise in a specific application. Therefore Fuzzy control is a suitable choice for pitch angle control of wind energy conversion technology problems [9-13].

Rigorous tuning, increase in number of controllers and computational time are the major drawbacks of PI and fuzzy logic controllers. To overcome these problems an advanced method of control technique is developed known as model predictive control [14]. Paper [15-18] describes about the model predictive control application in wind energy conversion system. In paper [15], researchers describes about the comparison between model predictive control with linear quadratic Gaussian (LQG) and linear quadratic regulator (LQR) control. They are also suggested that as compared to LQG and LQR, MPC can handle constraints more effectively. Unnecessary shut down of wind turbines due to over speed limits which leads to grid loss can be avoided by systematic use of system constraints and predicted behavior through MPC controllers is elaborately discussed in paper [16]. In paper [17-18] authors describes about power tracking in optimal manner and better load mitigation compared to PI controller. In our paper we have first compared MPC with IFLC and classical PI controller using step wind speed. Then a detailed robust comparison is done between PI, Improved fuzzy logic controller and model predictive controller by using simulated wind speed through MATLAB/SIMULINK based WECS model.

This paper is organized as follows. The mathematical modeling of WECS is discussed in section 2. Different control algorithm applied to the wind turbine pitch angle control is presented in section 3. Simulation results of different control mechanism are discussed in section 4, followed by the conclusions in Section 5.

2. WECS MODELING

In a wind energy conversion process, wind power is extracted from the wind speed through different control components and the schematic control block diagram for a horizontal axis variable speed WECS is shown in Figure 2 [18]. Basically it is consists of five different blocks. The mathematical equations for each block are derived first then their SIMULINK models are developed from it.

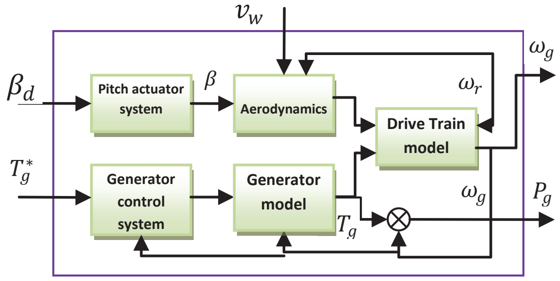


Figure 2 Control model of WECS.

2.1 Aerodynamic system

The aerodynamic torque developed by the rotor disc is given by [2]

$$T_t = P_t/\omega_t \tag{1}$$

where ω_t is rotational speed of wind turbine. P_t is power available at rotor of wind turbine and it is expressed by

$$P_t = P_w C_p(\lambda, \beta) \tag{2}$$

where C_p is the power coefficient and its theoretical limit is 0.593. This limit is known as Betz limit. P_w is the power available with the wind speed. Theoretically its magnitude is

$$P_w = \frac{1}{2}\varsigma \pi R^2 v_w^3 \tag{3}$$

where ς is the air density, R is the radius of turbine blade and v_w is the effective wind speed.

The power coefficient $C_p(\lambda, \beta)$ is also known as efficiency coefficient and it is a function of tip speed ratio λ and blade pitch angle β. Mathematically

$$C_p(\lambda, \beta) = 0.5176(116/\lambda_i - 0.4\beta - 5)e^{(-21)/\lambda_i} + 0.0068\lambda \tag{4}$$

$$1/\lambda_i = 1/(\lambda + 0.08\beta) - 0.035/(\beta^3 + 1) \tag{5}$$

The ratio between effective wind velocity and the blade tip speed is known as tip speed ratio (TSR) λ.

$$\lambda = (\omega_t R)/v_w \tag{6}$$

A three dimensional plot of power coefficient $C_p(\lambda, \beta)$ and its top view is shown in Figure 3 and Figure 4. Power characteristics with variable speeds are shown in Figure 5. From Figure 3, it is found that Power coefficient changes with variations of tip speed ratio and these are reaches to their peak or maximum, for a single value of λ with a specific value of pitch angle.

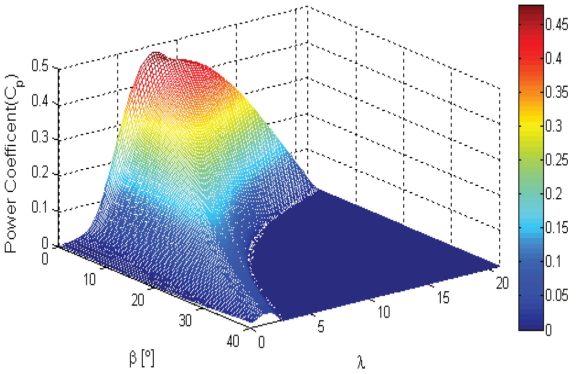


Figure 3 Power coefficient C_p curve.

2.2 Generator model

Basically induction generators are used in WECS for its low cost and rugged construction. In an induction generator, mechanical response is slower than electric response because electric time constant is negligible compared to the mechanical time constant [19]. So to make it simple the generator torque can be manipulated and is approximated by a first order system with time constant τ_g.

$$\dot{T}_g = -\frac{l}{\tau_g} T_g + 1/\tau_g T_g^* \tag{7}$$

where T_g^* is the actuator's output and used as reference value for generator system.

The power generated P_g by the generator is given by:

$$P_g = T_g \omega_g \tag{8}$$

where ω_g is rotational speed of the generator.

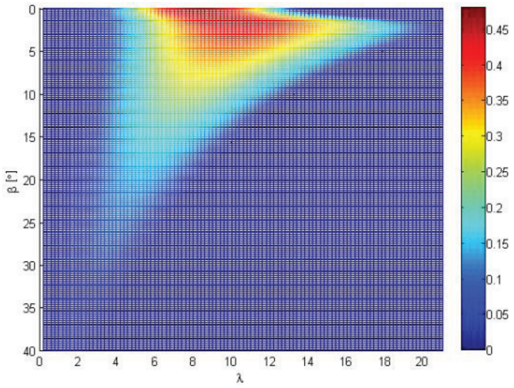


Figure 4 Top view curve for $\lambda v/s\beta$ derived from Figure 3.

2.3 Actuator dynamics

The actuator model describes the dynamic behavior between the pitch demand from the pitch controller to the actuation of this demand. The actuator can be modeled as first order dynamics with time constant τ:

$$\dot{\beta} - l/\tau\beta + 1/\tau\beta_d \tag{9}$$

where β_d is the blade pitch angle reference value.

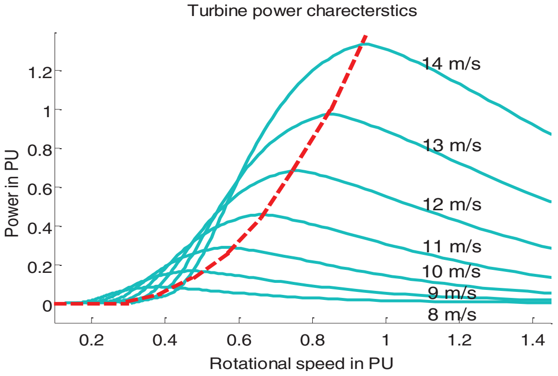


Figure 5 Rotational speed v/s Turbine Power Characteristics.

2.4 Drive train model

A Drive train model can be represented by two mass system with a flexible shaft [20] connect to it. Its equations are

$$\frac{d\omega_t}{dt} = -\frac{i}{J_t} T_{tw} + \frac{1}{J_t} T_t \tag{10}$$

$$\frac{d\omega_g}{dt} = \frac{1}{J_g} T_{tw} - \frac{1}{J_g} T_g \tag{11}$$

$$\frac{dT_{tw}}{dt} = k_s i \omega_t - k_s \omega_g - \left(\frac{i^2 B_s}{J_t} + \frac{B_s}{J_g} \right) T_{tw} + \frac{i B_s}{J_t} T_t + \frac{B_s}{J_g} T_g \tag{12}$$

$$T_{tw} \overset{\text{def}}{=} k_s \omega_{tw} + B_s (i \omega_t - \omega_g) \tag{13}$$

Here, turbine and the generator inertia constants are J_t and J_g respectively; ω_{tw} is the shaft twist angle; i is the gear ratio; K_s, B_s are the shaft stiffness and damping coefficients respectively.

2.5 Wind speed model

Because of non-stationary in nature, measurement/prediction/generation of wind speed is a difficult task. Weather forecasting researchers [21] are used different methods for development of wind speed. In our study wind speed $v_w(t)$ is designed by superposing two frequency components [2]. The two components are, a low-frequency component $v_m(t)$ and a turbulence component $v_t(t)$. Wind shear, rotational sampling effects and tower shadow are included in the wind speed model

$$v_w(t) = v_m(t) + v_t(t) \tag{14}$$

Equations from (1) to (14) represent the wind turbine model equations. By summing up these equations WECS model is formulated. The main nonlinearity is due to presence of turbine torque expression in equation (1). After linearzing the turbine torque expression we get

$$\Delta T_t = L_\omega \Delta\omega_t + L_v \Delta v_w + L_\beta \Delta\beta \tag{15}$$

$$L_\omega = \frac{\partial T_t}{\partial \omega_t},\ L_v = \frac{\partial T_t}{\partial v_w},\ L_\beta = \frac{\partial T_t}{\partial \beta} \tag{16}$$

The symbol 'Δ' is used for representing the deviation of a variable from its operating point. The operating point of WECS can be completely defined by $\bar{v}_w$. The linearized state space representation of the wind energy conversion system with state vector, control input and measured output can be written in following manner

$$x \overset{\text{def}}{=} \begin{bmatrix} \Delta\omega_t \\ \Delta\omega_g \\ \Delta T_{tw} \\ \Delta T_g \\ \Delta\beta \end{bmatrix} \in \mathbb{R}^5 \text{ is the state vector}$$

$$u \overset{\text{def}}{=} \begin{bmatrix} \Delta T_g^* \\ \Delta\beta_d \end{bmatrix} \in \mathbb{R}^2 \text{ is the control input and}$$

$$y \overset{\text{def}}{=} \begin{bmatrix} \Delta\omega_g \\ \Delta P_g \end{bmatrix} \in \mathbb{R}^2 \text{ is the measured output.}$$

$$\dot{x}(t) = Ex(t) + F_u u(t) + F_v \Delta v_w(t) \tag{17}$$

$$y(t) = Gx(t) \tag{18}$$

$$E \tag{19}$$

$$= \begin{bmatrix} \frac{L_\omega}{J_t} & 0 & -\frac{i}{J_t} & 0 & \frac{L_\beta}{J_t} \\ 0 & 0 & \frac{1}{J_g} & -\frac{1}{J_g} & 0 \\ k_s i + \frac{iB_s}{J_t} L_\omega & -K_s & -\left(\frac{i^2 B_s}{J_t} + \frac{B_s}{J_g}\right) & \frac{B_s}{J_g} & \frac{iB_s}{J_t} \\ 0 & 0 & 0 & -\frac{1}{\tau_g} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau} \end{bmatrix} \tag{20}$$

$$F_u = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \frac{1}{\tau_g} & 0 \\ 0 & \frac{1}{\tau} \end{bmatrix}, \quad F_v = \begin{bmatrix} \frac{L_v}{J_t} \\ 0 \\ \frac{iB_s}{J_t} L_v \\ 0 \\ 0 \end{bmatrix} \tag{21}$$

$$G = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & \overline{T}_g & 0 & \overline{\omega}_g & 0 \end{bmatrix} \tag{22}$$

The different parameters [18] of the wind energy conversion systems used in this paper work are shown in Table 1.

Table 1 Parameters of WECS.

Sl. Parameter No.	Unit	Value	
01	Rated turbine power, P$_{t,rat}$	[MW]	2
02	Rated rotor speed, $_{t,rat}$	[rad/s]	3.0408
03	Blade radius, R	[m]	33.29
04	Pitch actuator constant, τ	[s]	0.1
05	Max. blade pitch, β_{max}	[deg]	45^o
06	Min. blade pitch, β_{min}	[deg]	0^o
07	Max, blade pitch rate,	[deg/s]	10^0
08	Min, blade pitch rate,	[deg/s]	-10^0
09	Gear ratio,	[–]	74.38
10	Generator inertia,	[kg.m^2]	56.29
11	Rotor inertia,	[kg.m^2]	1.86e6
12	Generator time constant, τ_g	[s]	20e-3

3. CONTROLLER DESIGN

3.1 Improved fuzzy logic control (IFLC)

Classical control methods can perfectly be applicable to linear systems. But power systems are of non-linear in nature and linearization problems will also occur in it. Therefore control law of variable speed wind turbine could not perform well with these methods. So the use of fuzzy control methods can overcome these problems. Fuzzy logic control is derived from fuzzy theory introduced by Zadeh in 1965. It is one of the soft computing tools that can take automatic decisions like human beings. A fuzzy logic based controller and its different stage block diagram is shown in Figure 6. It consists of an input stage, a processing stage and an output stage. The input or fuzzification stage translates the input crisp data in to the fuzzy representation incorporating the vagueness & imprecision in a natural language, for further processing in FLC. The processing or the rule evaluation stage is carried out for each appropriate rule and generates a result for each, then combines the results of the rules. Using the Centroid Method the output or the defuzzification stage then converts the combined result back into a specific control output value.

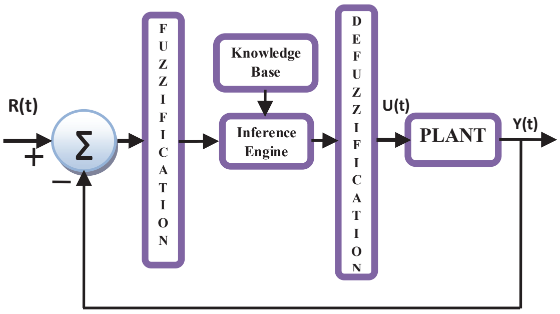


Figure 6 Block diagram of Fuzzy controller.

In this paper, we have developed a two input, two different output Mamdani type fuzzy controllers for a variable speed wind turbine. Initially a fuzzy set of two inputs and one output for each control variable are designed by using triangular membership functions (MFs) with overlapping. Because of overlapping it is easy to implement, quicker to process and provides more sensitivity to the variables when they approach to zero. Overlapping is a key feature of fuzzy systems. Membership functions are used as a means of controller tuning. It is chosen in such a way that this reflects the characteristics of the input variables and meets the requirement of the controller. For both pitch angle and generator torque, 3 inputs and 3 output membership functions [2] are described in Table 2 by using 09 Fuzzy-if-then rules. In input and output membership functions, the linguistic variables used are –L (negative large), -M (negative medium), -S (negative small), +S (positive small), +M (positive medium) and +L (positive large).

Table 2 Rules of fuzzy system.

Change in Error (Δe)	**Error (e)**		
	-L	Z	+L
-L	-L	-S	+L
Z	-M	Z	+M
+L	-S	+S	+L

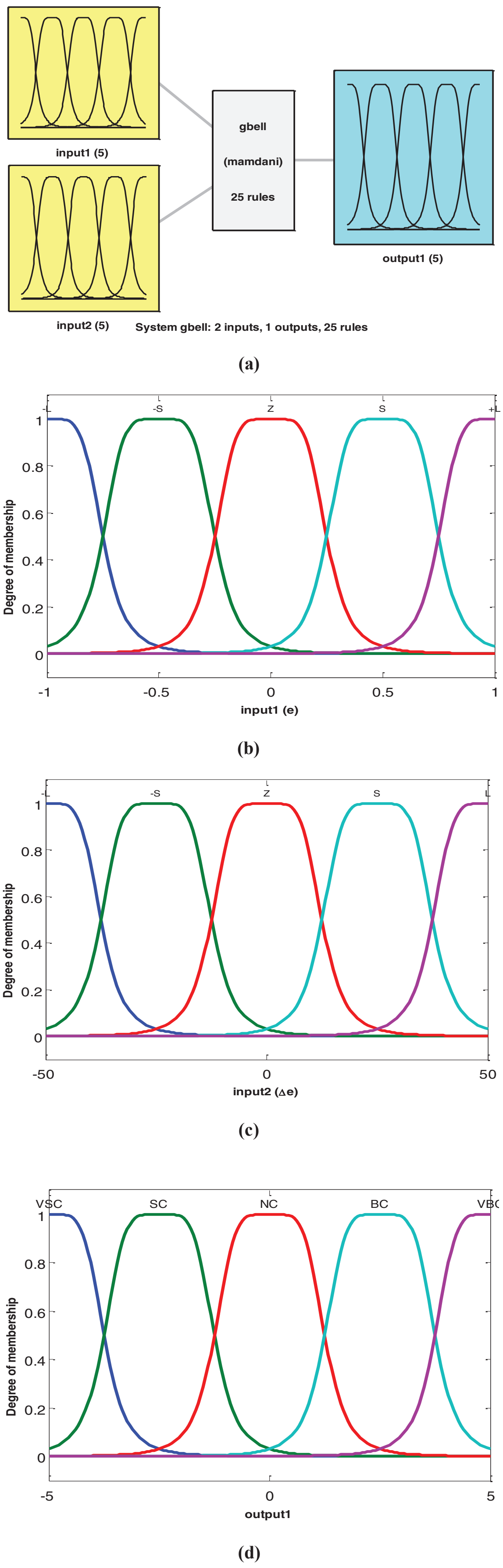
Table 3 Rules of improved fuzzy system.

Change in Error (Δe)	**Error (e)**				
	-L	-S	Z	S	L
-L	SC	SC	BC	VBC	VBC
-S	SC	SC	SC	NC	NC
Z	BC	SC	NC	BC	BC
S	VBC	NC	BC	BC	VBC
L	VBC	VBC	BC	VBC	VBC

The control performance of the system will be affected when MFs and rule base of fuzzy controller is changed. To improve the performance of fuzzy controller, the triangular MFs are changed with 'gbell' MFs. Also five input and output MFs were taken in place of three input and output MFs. Finally it is compared with the triangular MFs of fuzzy controller given in [2]. It is observed that 'gbell' MFs are very much improved by adopting appropriate rule base according to the pitch angle of wind turbine. The Fuzzy-if-then rules used in 'gbell' controller is given in Table 3. The fuzzy set all MFs, input MFs and output MFs for WECS is shown in Figure 7. Figure 8 depicts the generator out power comparison for Fuzzy and IFLC.

3.2 Model predictive control (MPC)

Model predictive control is effectively used in different industrial applications due to its capability to handle MIMO control



(a)

(b)

(c)

(d)

Figure 7 (a) Fuzzy structure (b) (c) Input MFs (d) Output MFs.

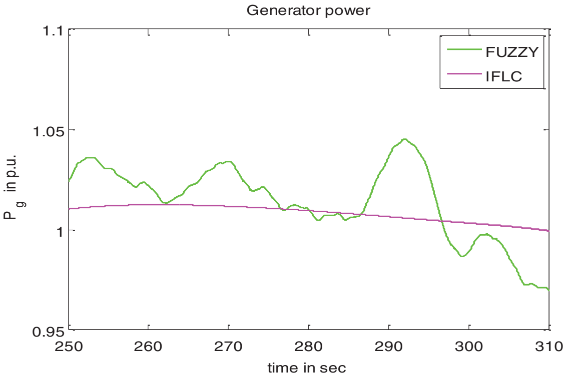


Figure 8 Output power comparison using Fuzzy and IFLC.

problems with constraints of the system variables. Because of this, it is successfully applied in electrical power systems, control engineering, process engineering and medical diagnosis etc. Model predictive controllers depend on dynamic model of the process. This dynamic model can be obtained by system identification or from input-output data of plant tests. MPC uses explicit internal model of the plant to generate prediction of the future plant behavior by solving the optimization problem. In this optimization process it allows the current time slot to be optimized, while keeping future time slots in account. It has the ability to predict the future events and can take control actions accordingly.

The fundamental thought behind model predictive controller is shown in Figure 9. This figure explains the curves of reference trajectory, set point trajectory, plant output, predicted plant output, past input control action and future input control action with current plant state is sampled at time ‘t’.

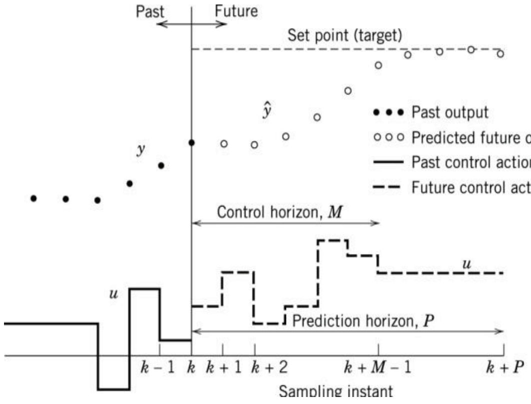


Figure 9 Fundamental concepts behind MPC.

A set point trajectory is that trajectory to which the output will follow it ideally. Reference trajectory is different from the set point trajectory. The reference trajectory approaches the set point exponentially from the current output value. The figure also gives information that by manipulating the control input ‘u’ in such a manner {at present time ‘k’ and predicted time $(k + j)$}, the control output ‘y’ and predicted control output ‘$\hat{y}$ will track the set point trajectory in an optimal way after a certain amount of samples known as prediction horizon P. Manipulation of control input is done over a certain number of samples known as control horizon M. Control horizon is less than prediction horizon.

Prediction model, Objective function and Constraints are the major components of MPC based system design. For design of prediction model, linearized, discrete time, state space dynamic model is used first. It is given by

$$x(k+1) = Ex(k) + F_u u(k) + F_v d(k) \tag{23}$$

$$y(k) = Gx(k) + H_v d(k) \tag{24}$$

where $x(k) \in \mathbb{R}^5$ is the state vector, $u(k) \in \mathbb{R}^2$ is the unit vector and $y(k) \in \mathbb{R}^2$ is the output vector at the sampling instant ‘k’. The reason for using this standard form is mainly that it connects well with the standard theory of linear system theory. Fictitious unmeasured disturbance is represented by $d(k)$. The computation of a control law of MPC is based on minimization of the following objective function [14].

$$J = \sum_{j=1}^{P} \hat{y}(k+j) - r(k+j)^2 + \rho \sum_{j=1}^{M} \Delta u(k+j-1)^2 \tag{25}$$

where $\hat{y}(k+j)$ is the output prediction at time j from present measurement time k. $r(k+j)$ indicates that the reference trajectory depends on the conditions at time k. $u(k+j-1)$ is the calculated control input based on prediction at time $(j-1)$ and ρ is weighing factor that balances between input and output cost.

With input and output constraints:

$$u_{\min} \le u(k+j) \le u_{\max}$$
$$\Delta u_{\min} \le \Delta u(k) \le \Delta u_{\max}$$
$$y_{\min} \le y(k+j) \le y_{\max}$$

where $j = 1, 2, 3, \ldots \ldots \ldots$

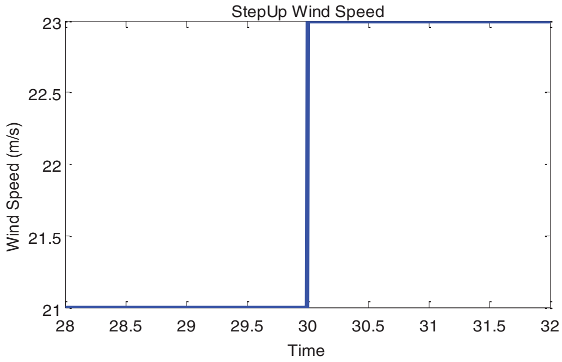
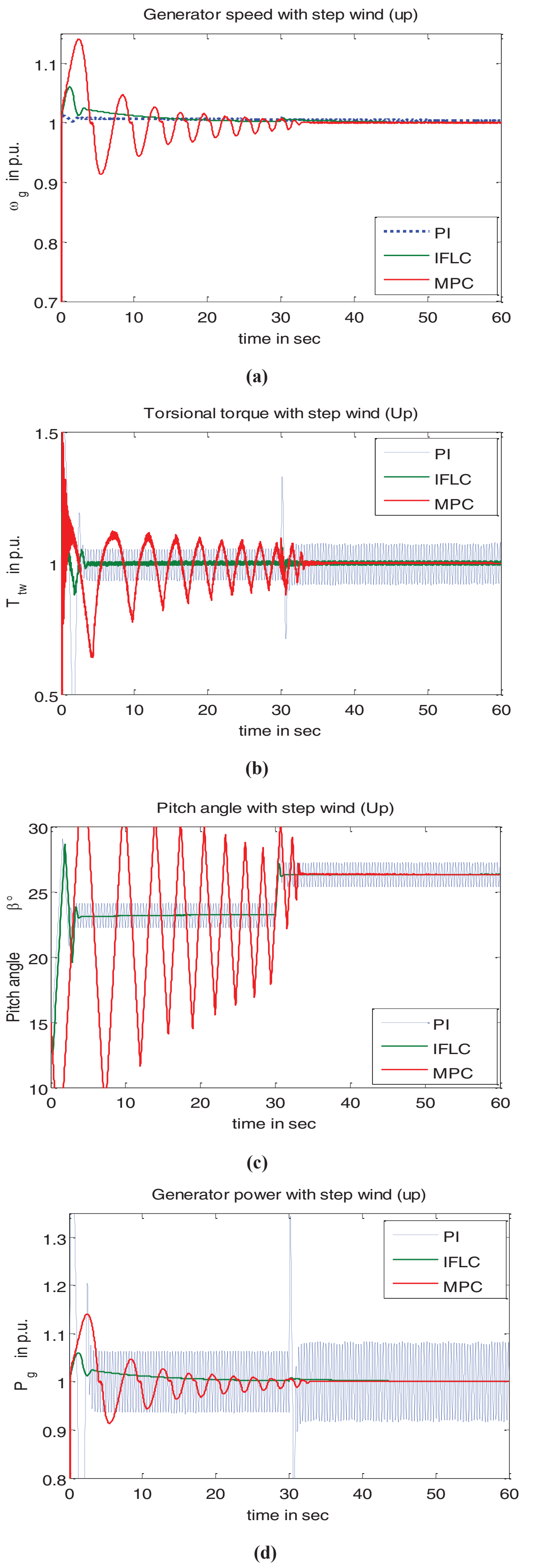


Figure 10 Step wind speed (up).

4. RESULTS AND DISCUSSIONS

This section presents detailed results of the MATLAB/SIMULINK based software simulation, which is carried out for a variable speed wind turbine for different test step wind speeds (up and down) with above rated using different controllers such as Proportional-Integral, Improved Fuzzy



(a)

(b)

(c)

(d)

Figure 11 Step wind (up) response for (a) Generator speed (b) Torsional torque (c) Pitch angle (d) Generator power.

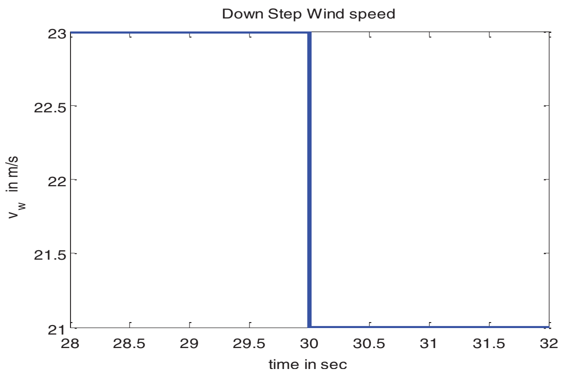


Figure 12 Step wind speed (down).

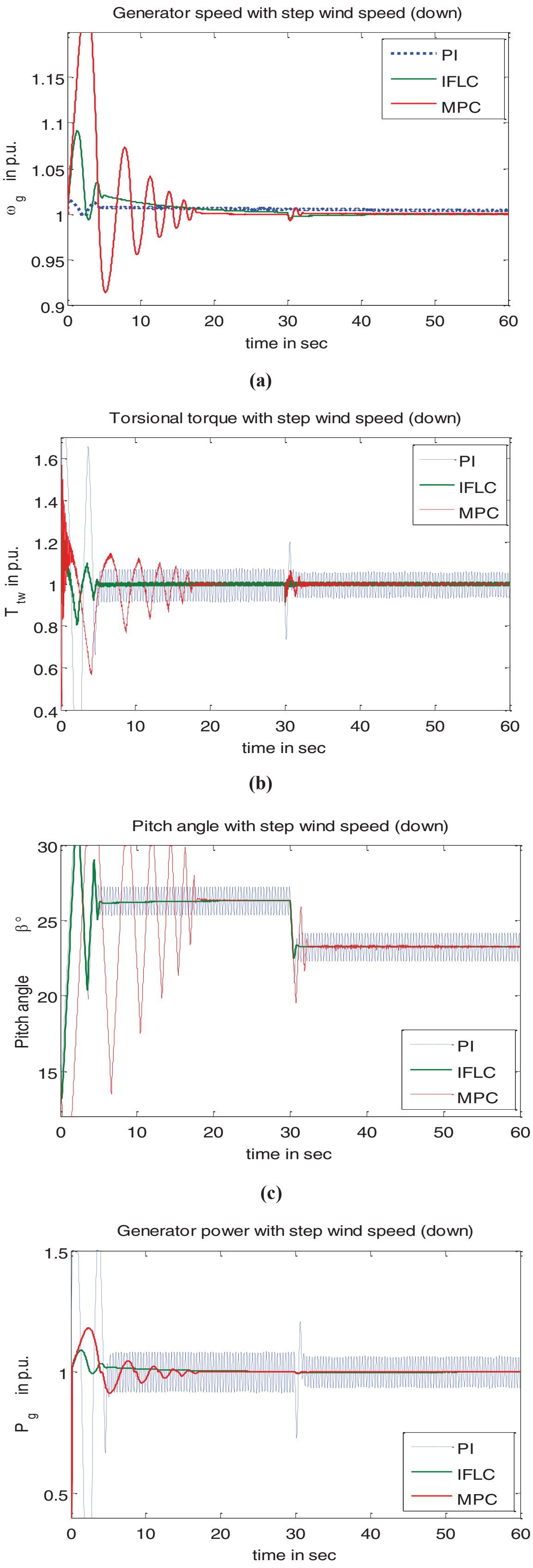
logic and MPC controller. For model predictive control, MPC model was simulated based on a linearized model of the system given in previous chapter with an operating wind speed $\bar{v}_w$ of 20 m/s. In this simulation sampling time T_s, prediction horizon length P and control horizon length M is taken as 50 ms, 20 and 10 respectively.

A wind speed in the form of step variation is shown in Figure 10 and Figure 12. In these figure a step change (up as well as down) will occur at the instant of 30 sec with a magnitude of two. By applying this step wind speed, the generator speed, torsional torque, pitch angle and generator speed is shown in Figure 11 and Figure 13. These simulations are carried out for 60 seconds to compare the PI, IFLC and MPC controllers.

A simulated wind speed is shown in Figure 14, which is comprised of a fast variation wind and a slow variation wind as given in equation (14). In this case the wind speed ranges between 18 m/s to 22m/s, with an average of 20 m/s. Finally Generator speed, Torsional torque, Pitch angle and Generator power is compared using PI, IFLC and MPC for above rated wind speed as shown in Figure 15 to Figure 18.

From Figures 11 and 13, it is found that, in classical control method the fluctuation in power output, drive train torsional torque and pitch angle is very high as compared to IFLC. In case of IFLC, the power output fluctuation is reduced completely after reaching the target value. Drive train torsional torque fluctuates around the target value after reaching their i.e. fluctuation is not eliminated completely. Similarly pitch angle fluctuation is also reduced. In case of generator speed, oscillation is reduced for IFLC.

Similarly from Figure 11 and 13, we found MPC controller works well to control generator power, drive train torsional torque and the generator speed. The controller acts very fast to reach around the target value. As the drive train torsional torque oscillation is low, so its effect will occur on the generated power of the wind turbine i.e. the power quality [22] will be improved. So it increases the life span of mechanical parts of the wind energy conversion system. But in case of pitch angle control, it oscillates more in the initial periods, and then it settles quickly to unit value. Finally in Figures 15 to 18, Generator speed, Torsional torque, Pitch angle and Generator power output is compared using all three controllers discussed above i.e. PI, IFLC and MPC controllers. We found MPC is the best among all except torsional torque. In particular generator output power depicted in Figure 18 is excellent.



(a)

(b)

(c)

(d)

Figure 13 Step wind (down) response for (a) Generator speed (b) Torsional torque (c) Pitch angle (d) Generator power.

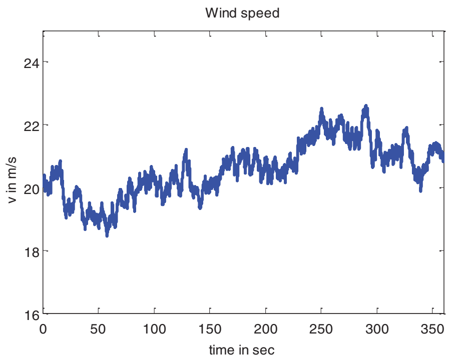


Figure 14 Simulated Wind speed (0-360s).

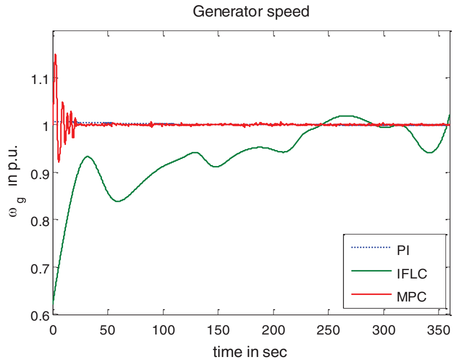


Figure 15 Comparison of generator speed.

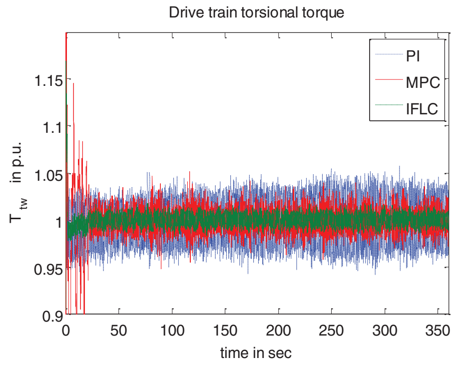


Figure 16 Comparison of drive train torsional torque.

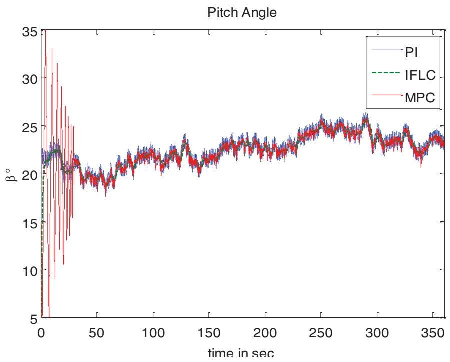


Figure 17 Comparison of blade pitch angle.

5. CONCLUSIONS

For model predictive control studies, controlling of speed, torsional torque, pitch angle and output power of a variable speed

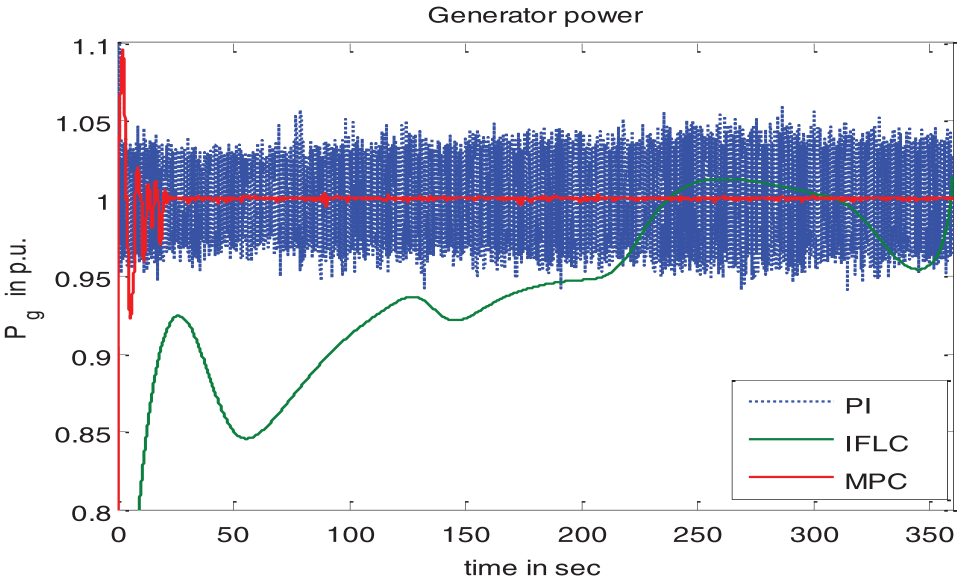


Figure 18 Comparison of generator output power response for above rated wind speed.

wind turbine above the rated wind speeds, the wind turbine model is represented by steady state model which is obtained by linearization of non linear mathematical model based on single operating point. The MPC and IFLC are observed to be suitable alternatives to classical PI controllers in handling uncertain variation of wind speeds with power generation. From the results obtained it is found that the proposed MPC based pitch angle controller is more robust to wind speed variation when compared to IFLC and PI controller. Hence MPC may be applied to other nonlinear systems.

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