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Model predictive control with finite control set for variable-speed wind turbines

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ABSTRACT

The existing model predictive control (MPC) algorithm for variable-speed wind turbines (WTs) is using continuous control set and solved by a quadratic programming method. Its main drawbacks are the heavily computational burden and the difficulty to implement. This paper introduces an alternative MPC method by using finite control set, which is used in controlling WTs at the first attempt. To do this, first of all, the WT's nonlinear model is linearized with information provided by a non-standard extended Kalman filter. Secondly, a discrete-time linear model of the system is used to predict the future value of the interested state variable for possible control sets. In view of the fact that control objectives are different within two operation zones partitioned by wind speed, two quality functions are predefined. One quality function evaluates the optimal generator speed tracking error together with the penalty of torque actuator action at below rated wind speed, while the other evaluates the rated generator speed tracking error and the penalty of pitch actuator action at above rated wind speed. Then, the corresponding control set which minimizes the quality function is selected. Finally, some simulation results are demonstrated to visualize the effectiveness and feasibility of the proposed method.

1. Introduction

To compete with other renewable energy, it is important to maximize the power output per unit investment in wind energy industry. The production cost per unit of power decreases with an increase of the size of the wind turbine (WT), therefore modern WTs is developed toward large size. However, a larger-size WT has always a more flexible structure that easily can suffer from fatigue loads. Thus, an important design goal for wind turbine controller is to improve power production and reduce fatigue loads on turbine components.

The classical Proportional-Integral-Derivative (PID) control method is widely used in wind energy industry [1,2]. Therein, a dichotomous, single-input single-output architecture is employed, where a torque control and a pitch control are decoupled along the operation trajectory defined by different scheduling parameters [3]. Meanwhile, to handle the nonlinear aerodynamics feature, gain scheduling technology has been proposed to predefine PID gains in terms of pitch angle value or rotor speed value. Through applying the gain scheduling technology, control performance of the WT is enhanced but not yet optimal. For example, over-speed problem under large turbulent wind and gust, may not be well solved by classical PID control [4]. Moreover, the relevant performance of the fatigue load is not well covered under the PID control structure.

To improve the performance of the WT, many researches have studied various advanced control solutions, such as fuzzy logic control [5,6], linear-quadratic-Gaussian (LQG) control [7], nonlinear control [8,9], $H\infty$ control [10], sliding mode control [11], and model predictive control (MPC) [12,13,15–20]. Most of these advanced control methods have common optimization principles. Compared with classical PID control, the main advantage of optimization-based strategies consists in their capability of multi-objective achievement. As proposed in Ref. [12], through putting weights on the load-relevant quantities, such as pitch actuator action, torque actuator action, and etc., fatigue loads of the corresponding components may be reduced.

Among these advanced control strategies, the MPC is chosen over others based on its key feature that it enables optimal solution of a control problem while honouring constraints imposed upon by WT's designer [13]. Besides, the MPC has another potential

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advantage that it is able to predict behaviour in future using a plant's model. The MPC applied can be classified into two main categories [14]: the MPC with continuous control set and the one with finite control set. The first group has been recently proposed for the control problem of the WT. The earliest studies can be referred to Henriksen's master thesis [15] and his Ph.D. thesis [16]. In their studies, three model predictive controllers have been presented based on different models including off-line linearized model, on-line linearized model and non-linear model. From their simulation results, the presented controllers showed good performance in reducing fatigue loads at the same time avoiding an increase of pitch motion. The results are inspiring but not realistic for that the results were obtained under perfect wind speed prediction. A more practical approach is to measure the wind speed with new sensing technologies, such as LIDAR. An accurate measurement of the wind profile over the entire rotor plane can enable predictive control more effective. The MPC using the knowledge of future wind condition has been proposed in the literature [17,18] and showed prominent effect on the performance of the WT. From above studies, it is evident that the MPC is beneficial for the WT's performance. However, these existing MPC studies use continuous control set and none of them addresses the computational burden faced by them. Practically, the main drawback of the MPC with continuous control set is the requirement to solve a quadratic programming problem on line [19,20]. This has restricted its applications. More importantly, the design procedure is a routine and the solution is implicitly solved from algebraic equations. Further optimized manipulation is hard to carry out for the MPC with continuous control set.

Motivated by the aforementioned studies, the alternative solution is to use the MPC with finite control set. Compared with its counterpart, one of the most attractive features is its intuitive and logical procedure to set out the control problem, which makes it easy to understand as a concept and simple to implement. The MPC with finite control set has been intensively studied in power electronics and drives [14,21,22]. The core ideal is behind that a discrete model is used to predict the behaviour of the system for every admissible control set sequence up to the prediction horizon. The control set that minimizes a predefined cost function is finally selected to be applied in the next sampling instant. This paper introduces this novel method in controlling WTs at the first attempt. In this paper, a detailed explanation of the method is presented including the models used for target state prediction and the quality function used for control set selection. For clarity, the conventional dichotomous, single-input single-output architecture is employed, where the torque control set and the pitch control set are respectively selected along the operation trajectory defined by an estimate wind speed. Finally, some simulation tests have been conducted to validate the proposed method and the obtained results illustrate the effectiveness of the proposed method.

The remainder of this work is organized as follows: First, the modeling of a commercialized wind turbine is described. Then, the control problem is described and formulated. Later, the proposed MPC method with finite control set is introduced and discussed. This is followed by validations, which are carried out via simulation tests. Finally, the conclusion is made.

2. The concerned WT and its modeling

2.1. The studied wind turbine

The studied WT is a 1.5 MW doubly-fed machine with 82 m rotor diameter manufactured by the China Ming Yang Wind Power (CMYWP). The WT's specifications are shown in Table 1.

Table 1
Specifications of the studied WT.

Parameters	Value
Rotor diameters	82 m
Number of rotor blades	3
Rated electrical power	1500 kW
Rated wind speed	$10.8 ms^{-1}$
Nominal rotor speed	$1.824 rads^{-1}$
Optimal TSR	9.5
Rotor moment of inertia	$4.94 \times 10^6 kg\cdot m^2$
Generator moment of inertia	$92 kg\cdot m^2$
Gearbox ratio	100.48
Drive train stiffness coefficient	$1.38 \times 10^8 Nmrad^{-1}$
Drive train damping coefficient	$1.0 \times 10^4 Nmsrad^{-1}$

2.2. The WT modeling

In this paper, the WT model includes a drive train system and the blade rotor aerodynamics.

The drive train is described by two inertias interconnected by a spring and a damper. The external forces to this 2-DOF system are the aerodynamic torque on the slow speed shaft and the generator reaction torque on the high speed shaft. The governing motion equation of this model is given by

$$\begin{aligned} J_g\dot{\omega}_g &= T_{sh}/N - T_g \\ J_r\dot{\omega}_r &= T_a - T_{sh} \\ T_{sh} &= s_{dt}\gamma + d_{dt}\dot{\gamma} \end{aligned} \tag{1}$$

where $\gamma = (\theta_r - \theta_g/N)$; ω_r and ω_g are rotor and generator rotational speeds, respectively; θ_r and θ_g are rotor and generator rotational angles, respectively; s_{dt} and d_{dt} are stiffness and damping coefficients of drive train, respectively; J_r and J_g are inertias of blade rotor and generator, respectively; T_a and T_g are aerodynamic torque and generator torque, respectively, and N is gearbox ratio.

The model of the aerodynamic power P_a is expressed as

$$P_a = T_a\omega_r = \rho\pi R^2V^3C_p(\lambda,\beta)/2 = \rho\pi\omega_r R^3V^2C_q(\lambda,\beta)/2 \tag{2}$$

where ρ is air density, R is rotor radius, V is the effective wind speed, and $C_p(\lambda,\beta)$ is aerodynamic power coefficient which is a nonlinear function of the TSR $-\lambda$ and pitch angle $-\beta$. The λ is defined by

$$\lambda = \omega_r R/V \tag{3}$$

3. Problem formulation

3.1. Control objectives

For a variable speed WT, two operation zones are distinguishable: below and above the rated wind speed. Control objectives within these two operation zones are different:

- The control objective is to maximize wind power capture at below rated wind speed;
- The control objective is to control the output power as the rated one at above rated wind speed.

3.2. Problem formulation

Above-mentioned control objectives can be formulated as an optimal problem under certain constraints, which is governed by

$$\begin{aligned}&\min|P_g-P_g^{opt}|\\&s.t.\left\{\omega_g\in\left[0,\omega_g^{rated}\right],T_g\in\left[0,T_g^{rated}\right],\beta\in\left[\beta^{\min},\beta^{\max}\right]\right\}\end{aligned} \tag{4}$$

where P_g is output power from generator and P_g^{opt} denotes optimal power. When assuming that power loss of the WT is negligible, P_g^{opt} equates to P_a.

From Eq. (2), P_a is obviously maximized when C_p is optimal. Owe to the good design of modern blades, C_p has the following characteristics [4]:

- There is only one maximal C_p for each pitch angle, solved by tracking the TSR;
- There is a single optimal pitch angle β^{opt} matching the global maximal C_p;
- There is monotone decreasing of C_p with an increase of pitch angle.

Therefore, the formulation in Eq. (4) can be divided into two parts as follows

$$\begin{aligned}&\min|\omega_r-\omega_r^{opt}|\\&s.t.\left\{T_g\in\left[0,T_g^{rated}\right],\beta=\beta^{opt}\right\}\end{aligned} \tag{5}$$

and

$$\begin{aligned}&\min|\omega_r-\omega_r^{rated}|\\&s.t.\left\{T_g=T_g^{rated},\beta\in\left[\beta^{\min},\beta^{\max}\right]\right\}\end{aligned} \tag{6}$$

From Eqs. (5) and (6), it is obvious that the control objective is fulfilled by controlling rotor speed ω_r:

- The control objective is to track the optimal value ω_r^{opt} at below rated wind speed;
- The control objective is to maintain the rated value ω_r^{rated} at above rated wind speed.

4. Conventional control strategy

In current stage, most industrial WTs employ the conventional control strategy that is based on the widely used PI-based control method.

At below rated wind speed, the pitch angle is fixed at β^{opt}, and the optimal speed tracking is manipulated by a PI-based torque controller. The specific control algorithm has been discussed in our precious study [23] and only a short description is given as follows: before reaching the rated speed, the PI-based torque controller is saturated and maintained at value of $K^{opt}\omega_g^2$; otherwise, the output of the controller is activated to control the speed at rated value.

At above rated wind speed, the torque controller is fixed at its rated value, and the rated speed maintaining is manipulated by a PI-based pitch controller. Since the WT's aerodynamics varies with different operation points, the PI parameters of the controller are scheduled in terms of pitch angle value [24,25].

Control performance of the WT relies on the PI-based controllers parameters, which are chosen by a traditional approach to design of commonly used linear controllers [24]. Firstly, the nonlinear model of the WT in Eqs. (1) and (2) is linearized at some specified operating points. Then, certain ranges of parameter are determined to maintain system stability at each linearization points. After that, qualified gain values are chosen by observation of the system response to step inputs. For the studied WT, the parameters of the PI-based conventional torque controller (CTC) are chosen as $k_p = 88.0$ and $k_i = 33.0$. The parameters of the PI-based conventional pitch controller (CPC) are chosen as $k_p = 0.0051$ and $k_i = 0.0015$ at 0° pitch angle, whereas other parameters of CPC are scheduled by a gain of $k = 0.4$ in terms of pitch angle and calculated by Ref. [25].

$$\begin{cases}k_p=0.0051/(1+k\beta/35)\\k_i=0.0015/(1+k\beta/35)\end{cases}\qquad\beta\in[0,\ 35] \tag{7}$$

Besides, the optimal torque gain is calculated by

$$K^{opt}=(1/2)\rho\pi R^5C_p^{opt}/\left(\lambda^{opt}N\right)^3 \tag{8}$$

where C_p^{opt} and λ^{opt} are optimal C_p and optimal λ, respectively. For the studied WT, $K^{opt} = 0.1269$.

5. Model predictive control with finite control set for the WT

5.1. The control strategy

The proposed predictive control strategy takes the method introduced in Ref. [21]. It is based on the fact that feasible control outputs can be categorized into finite control sets and models of the system can be used to predict the behaviour of the variables for each control set. For the appropriate control set to be applied, a selection criterion must be defined in this paper. This selection criterion is expressed as a quality function that will be evaluated for the predicted values of the variables to be controlled. Prediction of the future value of these variables is calculated for each possible control set. The control set that minimizes the quality function is selected.

When applied to the WT, the above control strategy can be summarized in the following steps:

- Define a quality function QF;
- Build a model of the WT and its possible control set;
- Build a model of the controlled variables for prediction;
- Evaluate the predicted value for each control set and select the one with minimal value for the quality function.

In this paper, the controlled variable is the rotor speed. Thus, the predictive model is needed to predict the behaviour of the rotor speed. To deal with the nonlinear and stochastic dynamics of the WT, a non-standard extended Kalman filter (EKF)-based estimator is employed to provide the predictive model with necessary information. A block diagram of the proposed predictive strategy is shown in Fig. 1. The control strategy is performed in the following steps:

(1) The reference rotor speed ω^* is obtained and determined by the estimated wind speed, and the actual rotor speed uses the value $\omega(k)$ estimated by the EKF-based estimator (block 1);
(2) The WT model (block 2) is used to predict the rotor speed $\omega(k+n)$ at time $k+n$ for each control set, $T_g^{set}(k)$ and $\beta^{set}(k)$.
(3) The quality function QF evaluates the quality of each control set at time $k+n$ and the control set that minimizes the quality function is selected and applied to the WT actuators (block 3).

5.2. Finite control set for torque and pitch actuator actions

For the WT, there are two control actuators, namely pitch actuator and torque actuator. Constrained by hardware limitation,

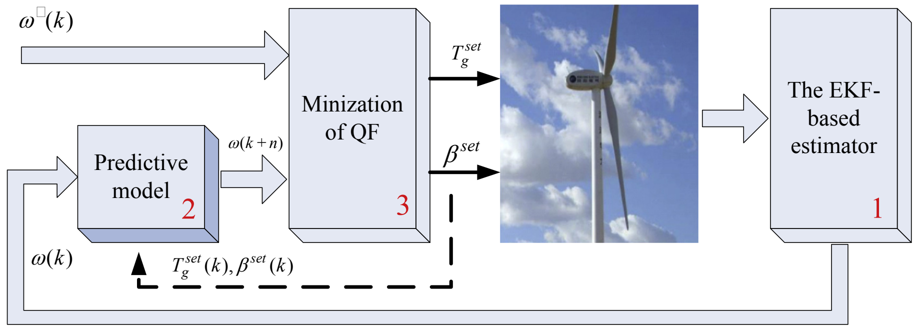

Fig. 1. Block diagram of the proposed predictive control strategy.

their permissible actions can be taken as finite sets. In this paper, control objective has been divided into two parts which are handled by torque actuator and pitch actuator, respectively. As shown in Eqs. (5) and (6), only one actuator is activated to fulfil a certain control objective. By doing so, the quantity of control set is greatly reduced and finite control set can be easily obtained.

In this paper, actuator actions are expressed in the form of motion rate. Regard to the fact that both pitch and torque rates have to meet the hardware limitation, the permissible ranges of their value can be expressed as follows:

$$\dot{T}_g \in \left[\dot{T}_g^{\min}, \dot{T}_g^{\max}\right] \tag{9}$$

and

$$\dot{\beta} \in \left[\dot{\beta}^{\min}, \dot{\beta}^{\max}\right] \tag{10}$$

When considering the minimal variation amplitudes of the torque rate and pitch rate being $\dot{T}_g^{amp}$ and $\dot{\beta}^{amp}$, the amounts of pitch and torque control sets are

$$n\left(\dot{T}_g\right) = \left(\dot{T}_g^{\max} - \dot{T}_g^{\min}\right) \Big/ \dot{T}_g^{amp} \tag{11}$$

and

$$n\left(\dot{\beta}\right) = \left(\dot{\beta}^{\max} - \dot{\beta}^{\min}\right) \Big/ \dot{\beta}^{amp} \tag{12}$$

5.3. Quality function

The quality function must be constructed according to the control objectives using the predicted variables from models and its references. The error between these variables is usually evaluated using a convex function such as absolute or quadratic values [22]. In this paper, quadratic quality functions are used. Meanwhile, the penalties on the motion of actuators are introduced. In this way, both performance of the speed tracking and actuator relevant fatigue load can be taken care through adjusting the corresponding weighting factors.

As aforementioned, the control problem is formulated into two parts, which are in the charge of different control actuators, respectively. Therefore, two quality functions are expressed as follows:

$$QF(1) = w_g^1 (\omega_r - \omega^*)^2 + w_g^2 \left(\dot{T}_g\right)^2 \tag{13}$$

and

$$QF(2) = w_\beta^1 (\omega_r - \omega^*)^2 + w_\beta^2 \left(\dot{\beta}\right)^2 \tag{14}$$

where w_g^1, w_g^2, w_β^1 and w_β^2 are the weighting factors to be adjusted.

5.4. Predictive model

Since the target objective is to control the rotor speed, the drive train model is necessary. For convenience, with $\omega_r = \omega_g / N$, the two-mass drive train model in Eq. (1) is simplified as

$$\left(J_r + N^2 J_g\right) \dot{\omega}_r = T_a - N T_g \tag{15}$$

Eq. (15) is further reformulated as

$$J_R \dot{\omega}_r = T_a - N T_g \tag{16}$$

where $J_R = J_r + N^2 J_g$.

To obtain an explicit relation among rotor speed, torque rate and pitch rate, the time derivative of Eq. (16) is deduced as

$$J_R \ddot{\omega}_r = (\partial T_a / \partial \omega_r) \dot{\omega}_r + (\partial T_a / \partial V) \dot{V} + (\partial T_a / \partial \beta) \dot{\beta} - N \dot{T}_g \tag{17}$$

Based on Eq. (17), a discrete-time form for a sampling time T_s can be used to predict the future dynamics of the rotor speed for each control set at the kth sampling instant.

Approximating the second derivative $\ddot{\omega}_r$ by

$$\ddot{\omega}_r = (\dot{\omega}_r(k+1) - \dot{\omega}_r(k)) / T_s \tag{18}$$

and replacing it in Eq. (17), the following expression is obtained for the future dynamics of rotor speed:

$$\begin{aligned} \dot{\omega}_r(k+1) = \Big(& (\partial T_a / \partial \omega_r) \dot{\omega}_r(k) + (\partial T_a / \partial V) \dot{V}(k) + (\partial T_a / \partial \beta) \dot{\beta}(k) \\ & - N \dot{T}_g(k) \Big) T_s / J_R + \dot{\omega}_r(k) \end{aligned} \tag{19}$$

Approximating the derivative $\dot{\omega}_r$ by

$$\dot{\omega}_r(k+1) = (\omega_r(k+1) - \omega_r(k)) / T_s \tag{20}$$

and replacing it in Eq. (19), the predicted rotor speed at the $k+1$ th sampling instant is obtained and calculated by:

$$\omega_r(k+1) = \Big((\partial T_a/\partial\omega_r)\dot{\omega}_r(k) + (\partial T_a/\partial V)\dot{V}(k) + (\partial T_a/\partial\beta)\dot{\beta}(k) - N\dot{T}_g(k)\Big)T_sT_s/J_R + \dot{\omega}_r(k))T_s + \omega_r(k) \quad (21)$$

Finally, in Eq. (21), the future value of the rotor speed can be predicted by the control sets $\dot{T}_g(k)$ and $\dot{\beta}(k)$, and other related state variables at time k.

As seen from Eq. (21), to predict the future rotor speed, related state variables are necessary to obtain, which includes nonlinear characteristics of the WT: $\partial T_a/\partial\omega_r$, $\partial T_a/\partial V$, and $\partial T_a/\partial\beta$, the derivatives of rotor speed and the wind speed: $\dot{\omega}_r$ and $\dot{V}$. These variables take their estimates provided by a non-standard EKF-based estimator in this paper.

5.5. The wind speed estimator

Since the standard EKF-based wind speed estimator is suffering from its utilization of imprecise measured wind speed [26,27], the non-standard EKF-based solution proposed in Ref. [28] is applied. It uses a virtual measurement that is derived from an inversion of a static aerodynamic model.

To design the EFK-based estimator, the concerned system model has to be modeled in the following nonlinear form [29,30]:

$$\begin{aligned} \dot{x} &= f(x,u) + w \\ y &= h(x,u) + v \end{aligned} \quad (22)$$

where x is the state, u is input, y is the measurement, w is the process noise and v is the measurement noise.

The WT model includes three parts: drive train, aerodynamic power, and the effective wind speed. Based on Eq. (1), the two-mass drive train model is reformulated as follows:

$$\begin{aligned} \dot{\omega}_r &= a_r + w_{\omega r} \\ \dot{a}_r &= [\dot{T}_a - s_{dt}(\omega_r - \omega_g/N) - d_{dt}(a_r - a_g/N)]/J_r + w_{ar} \\ \dot{\omega}_g &= a_g + w_{\omega g} \\ \dot{a}_g &= [s_{dt}(\omega_r - \omega_g/N)/N + d_{dt}(a_r - a_g/N)/N - \dot{T}_g]/J_g + w_{ag} \end{aligned} \quad (23)$$

where w_{ar} and w_{ag} are the process noises of a_r and a_g, respectively; a_r and a_g are acceleration speeds of rotor and generator, respectively.

Based on Eq. (2), the aerodynamic power model is reformulated as

$$\dot{P}_a = (\partial P_a/\partial\omega_r)\dot{\omega}_r + (\partial P_a/\partial V)\dot{V} + (\partial P_a/\partial\beta)\dot{\beta} \quad (24)$$

The effective wind speed (EWS) model is set up by taking the tower shadow effect into consideration and given by

$$\begin{aligned} \dot{V} &= V_1 + w_V \\ \dot{V}_1 &= V_2 + w_{V1} \\ \dot{V}_2 &= -N_b^2\omega_r^2V_1 - 2N_bd_v\omega_rV_2 + w_{V2} \end{aligned} \quad (25)$$

where V_1 and V_2 are the EWS′ derivative and the derivative of its derivative, respectively; w_V, w_{V1} and w_{V2} are the process noises of V, V_1 and V_2, respectively. The tower shadow effect is embodied as a function of the rotor speed and blade number N_b. Meanwhile, the tower shadow effect is damped by the factor d_V.

Besides the state model set, the measurement part is also required. For the non-standard EKF-based wind speed estimator, the virtual wind speed measurement is derived by

$$V^m = \Big(2P_a\Big/\Big(\rho\pi R^2C_p(\lambda,\beta)\Big)\Big)^{1/3} + v_V \quad (26)$$

The aerodynamic power can be calculated by

$$P_a^m = P_e^m + \Big(J_ra_r^m + NJ_ga_g^m\Big)\omega_r^m + v_{pa} \quad (27)$$

Besides V^m and P_a^m, the measurement parts include the state variables in Eq. (23). By using Eqs. (23)–(27), the whole model is in the same form as that in Eq. (22), where the state x, input u, and output y are given by

$$x = \begin{pmatrix} V & V_1 & V_2 & \omega_r & a_r & \omega_g & a_g & P_a \end{pmatrix}^T \quad (28)$$

$$u = \begin{pmatrix} T_g & \beta \end{pmatrix}^T \quad (29)$$

$$y = \begin{pmatrix} \omega_r^m & a_r^m & \omega_g^m & a_g^m & V^m & P_a^m \end{pmatrix}^T \quad (30)$$

Based on Eqs. (28)–(30), the standard EKF algorithm can be employed. From the estimator, besides the state variables' estimates can be obtained, and the nonlinear parts in Eq. (21) are also derived at the same time.

6. Simulation results and discussion

The proposed control strategy is tested on the two-mass mathematical model created with Matlab/Simulink Tool Box [31]. Some parameters are taken from Table 1 and the blade data are obtained from the concerned WT. Simulation tests are carried out in a wide wind-speed region through the predefined wind speeds. For the concerned WT, the permissible $\dot{T}_g$ and $\dot{\beta}$ range in $[-5000Nms^{-1}, 5000Nms^{-1}]$ and $[-10\text{deg}s^{-1}, 10\text{deg}s^{-1}]$, respectively. In this paper, $\dot{T}_g^{amp}$ and $\dot{\beta}^{amp}$ are chosen as $\dot{T}_g^{amp} = 10Nms^{-1}$ and $\dot{\beta}^{amp} = 0.01\text{deg}s^{-1}$.

To achieve a satisfactory performance, the weighting factors in the quality functions have to be determined. Unfortunately, there is no systematic way to obtain those parameters in MPC [14]. In this paper, the weighting factors calculation is performed using trial and error procedures. In order to obtain qualified weighting factors in an efficient way, we fix the first weighting factor at 1, and increase the second factor from zero by step [32]. Control performance is evaluated at each step and the second factor with best performance is chosen. After running a quantity of simulations, the weighting factors in the $QF(1)$ are chosen as $w_g^1 = 1$ and $w_g^2 = 6e-7$, and the ones in the $QF(2)$ are chosen as $w_\beta^1 = 1$ and $w_\beta^2 = 7.1e-1$, respectively. Meanwhile, the length of the prediction horizon is also necessary to be decided. Long prediction horizons are chosen as $n = 6$ and $n = 5$ for the torque and pitch control strategies, respectively.

6.1. Simulation results

6.1.1. Simulation results for optimal speed tracking

To validate the optimal speed tracking capability of the proposed control strategy, the wind speed with step-up amplitude in the range of 3 m/s - 10 m/s is used. Meanwhile, the aforementioned PI-based CTC is developed and its performance is used to compare with the proposed one.

Comparison results of rotor speed, the TSR, output power, output torque and its derivative are illustrated in Fig. 2. One can see that the CTC and the proposed MPC work well in the entire wind region, while the CTC does not guarantee a good dynamic response. The rotor speed under the MPC tracks the optimal one much closer than the one under the CTC, therefore the resulted TSR is tightly held to the optimal value of 9.5. This result means that production performance of the WT could be greatly enhanced by the MPC. Meanwhile, it is also noticeable that the payback of the fast speed tracking is that there is an intensive torque action and quite long time to be stabilized.

6.1.2. Simulation results for rated speed maintaining

To validate capability for maintaining the rated speed of the proposed control strategy, the wind speed with step-up amplitude in the range of 11 m/s - 25 m/s is used. Meanwhile, the afore-mentioned PI-based CPC is developed and its performance is used to compare with the proposed one.

Comparison results of rotor speed, output power, pitch angle and its derivative are illustrated in Fig. 3. One can see that the CPC and the proposed MPC work well in the entire wind region, while the CPC does not offer good speed suppression function. The pitch actuator under the MPC gives a faster action than the one under the CPC, therefore the resulted rotor speed is well maintained to the rated value of $1.824 rads^{-1}$. This result shows that over-speed problem faced by the CPC is potentially alleviated by the MPC. Therefore, it is beneficial to the reduction of extreme load under large turbulent wind and gust. Similar as the consequence of the fast speed tracking, the paybacks of the speed suppression are an intensive pitch action and long stabilized time.

6.1.3. Simulation results for model error

Considering that the quality of the control strategy depends on the predictive model, the effect of model error is studied by simulations. In this simulation case, rotor aerodynamics is assumed with modeling error. The aerodynamic power coefficient uses parameters from an earlier version of the studied WT's blade. The $C_p(\lambda, \beta)$ surface and the error surface are shown in Fig. 4.

The simulation results for different wind regions are drawn in Fig. 5, which are compared with the ones under normal case without model error. From the results in Figs. (4) and (5), it can be seen that the model error is very small but has an obvious influence on the estimated wind speed. There are offset errors between estimated wind speeds and the real ones. However, the influence on optimal speed tracking and rated speed maintaining is not obvious, in fact, it can be neglected. To sum up, the stability of the proposed controllers is immune to the offset error of aerodynamic power coefficient. The reason is behind that the proposed control schemes utilize the estimated states' derivatives rather than themselves.

6.1.4. Simulation results for quality function sets with different weighting factors

To illustrate control performance by quality functions with different weighting factors (summarized in Table 2), simulation results with six quality function sets are shown in Fig. 6, where the wind speed is defined with same settings in Section 6.3. In this paper, there are two weighting factors in the defined quality functions. It is clear that, when the second factors in $QF(1)$ and $QF(2)$ are decreasing, both actuator actions are getting larger

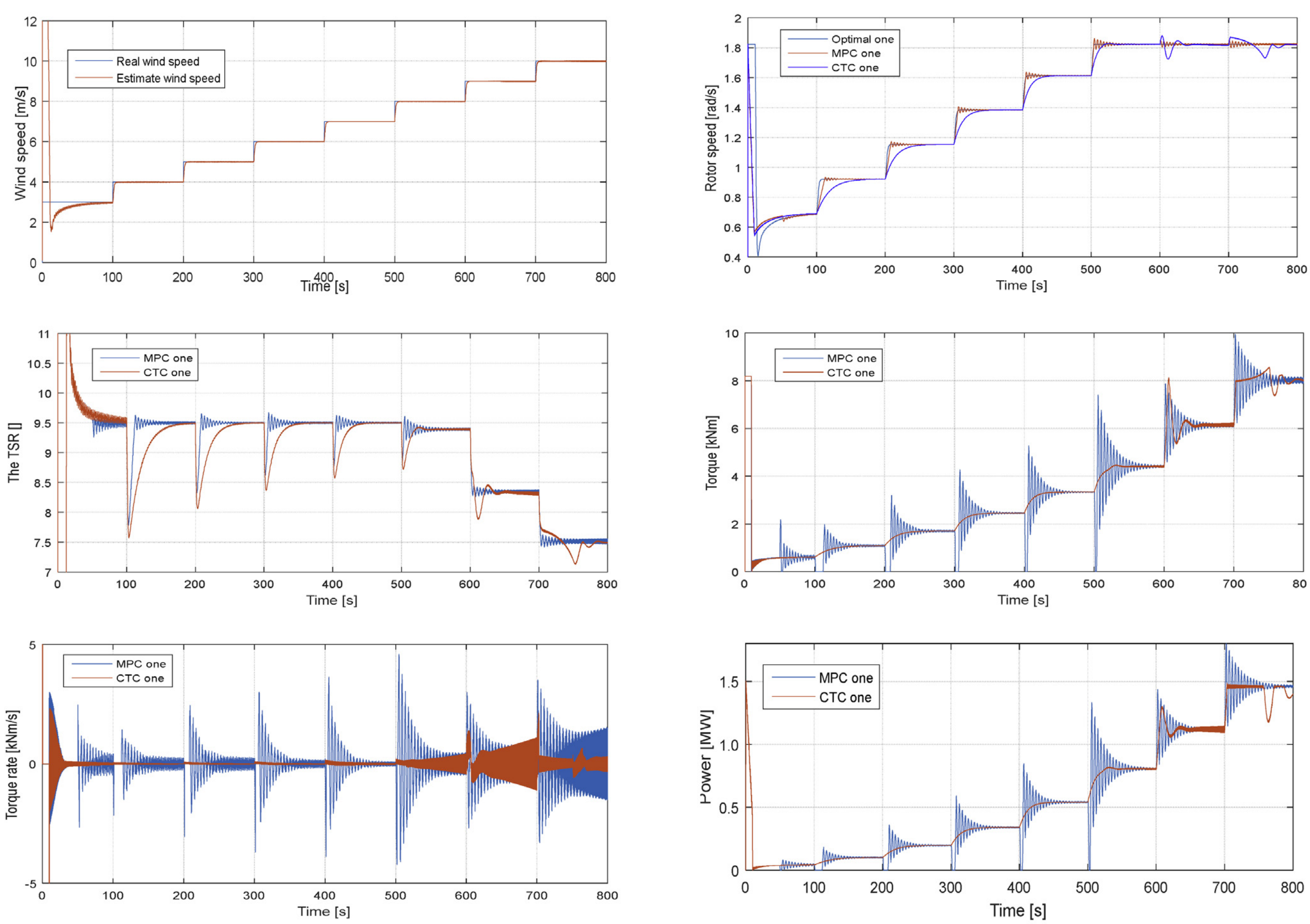

Fig. 2. Simulation results comparisons between the CTC and proposed torque control strategy.

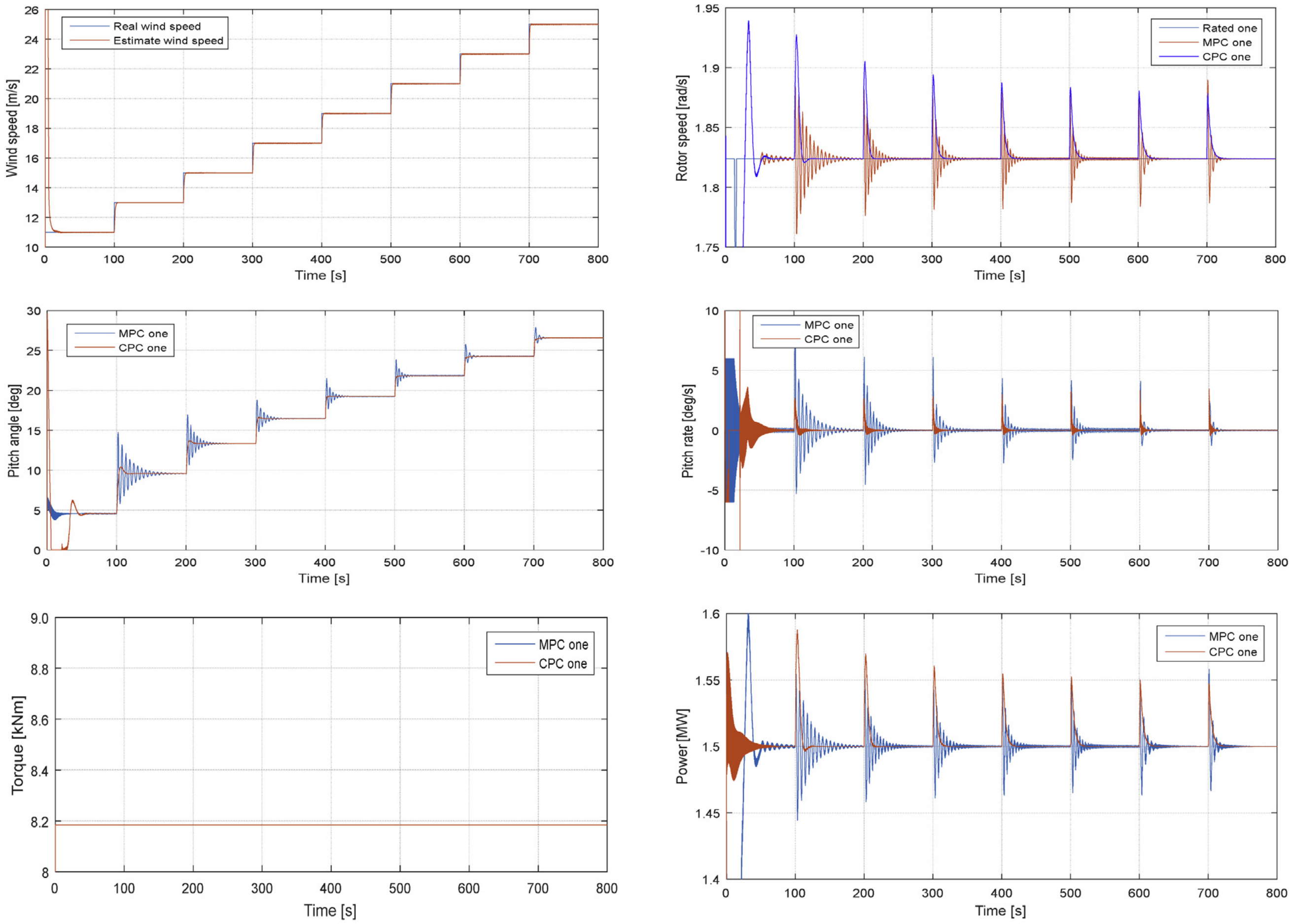

Fig. 3. Simulation results comparisons between the CPC and proposed pitch control strategy.

whereas both rotor speed tracking errors are getting smaller. However, smaller second factors easily result in actuators' over-action and consequently affect controller's stability, which can be observed from the results of quality function Set 1 and Set 4. These results justify the importance of the weighting factors in achieving qualified performance of MPC.

6.2. Result discussion

At the first attempt, the proposed control strategy is developed to control the WT with MPC using finite control set. Results obtained reveal that: (a) the MPC using finite control set is effective to control WTs in terms of optimal speed tracking and rated speed maintaining; (b) the MPC using finite control set results in a fast dynamic response, thus it has the advantage of fast speed tracking and over-speed suppression; (c) the MPC using finite control set is immune to offset modeling error; (d) overall performance in terms of control objective achievement and actuator usage can be optimized by adjusting weighting factors of quality functions. However, the proposed method also has much space for further improvement. The transition issue can be further tackled. When there is a large wind disturbance, the predict model employed could not provide precise future behaviour of the WT for the absence of wind speed prediction. In this case, a feasible way is to reschedule adjustable parameters, such as the prediction horizon length and weighting factors. In this study, we selected proper parameters that provided acceptable performance. However, to design a more robust and high-performance MPC-based control system, other adaptive techniques have to be investigated in future works.

7. Conclusions

In this paper, the MPC strategy with finite control set has been proposed for the variable-speed WT. The main contribution consists in showing that the nonlinear control problem of the WT can be transformed into two optimal control formulations which are solved by selecting the qualified control sets. Compared with the conventional MPC with continuous control set, the proposed MPC strategy consists in two advantages. On one hand, the solution for the algorithm is directly selected from available control sets, and consequently reduces computational burden. On the other hand, the intuitive and logical design procedure to set out the control problem makes it easy to understand as a concept and simple to implement. The effectiveness and feasibility of the proposed method have been demonstrated by simulation results.

When compared with conventional PI-based control method, the proposed method shows a faster dynamic response and multi-objective achievement. Our future work will be toward the optimization technique of improving its performance.

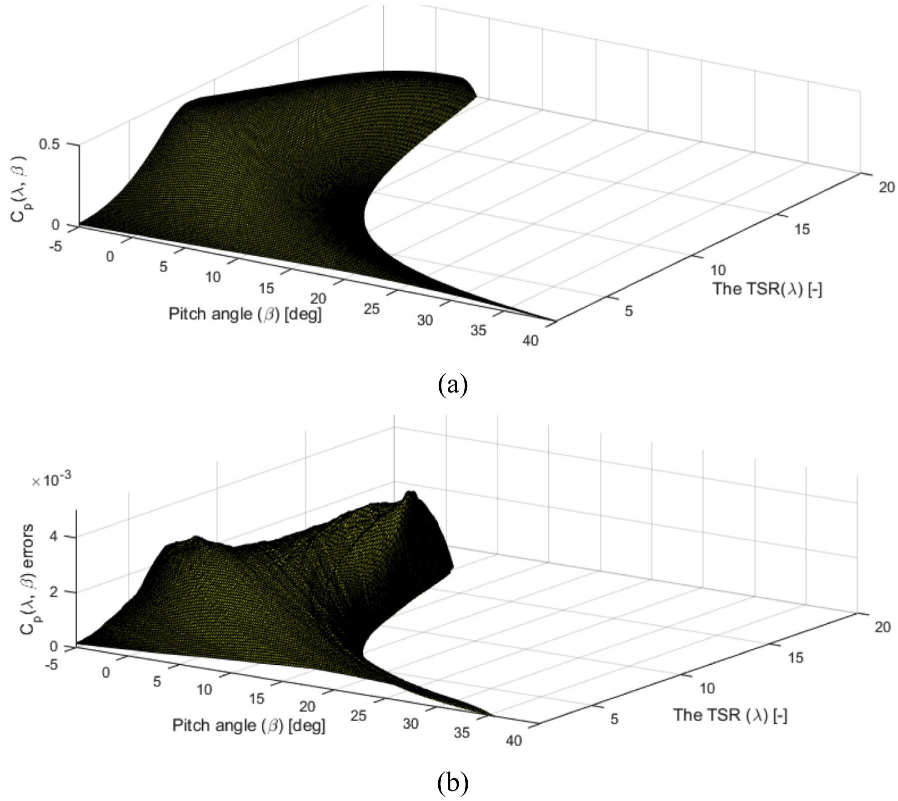

Fig. 4. The aerodynamic power coefficient $C_p(\lambda, \beta)$ surface for: (a) original one; (b) model error.

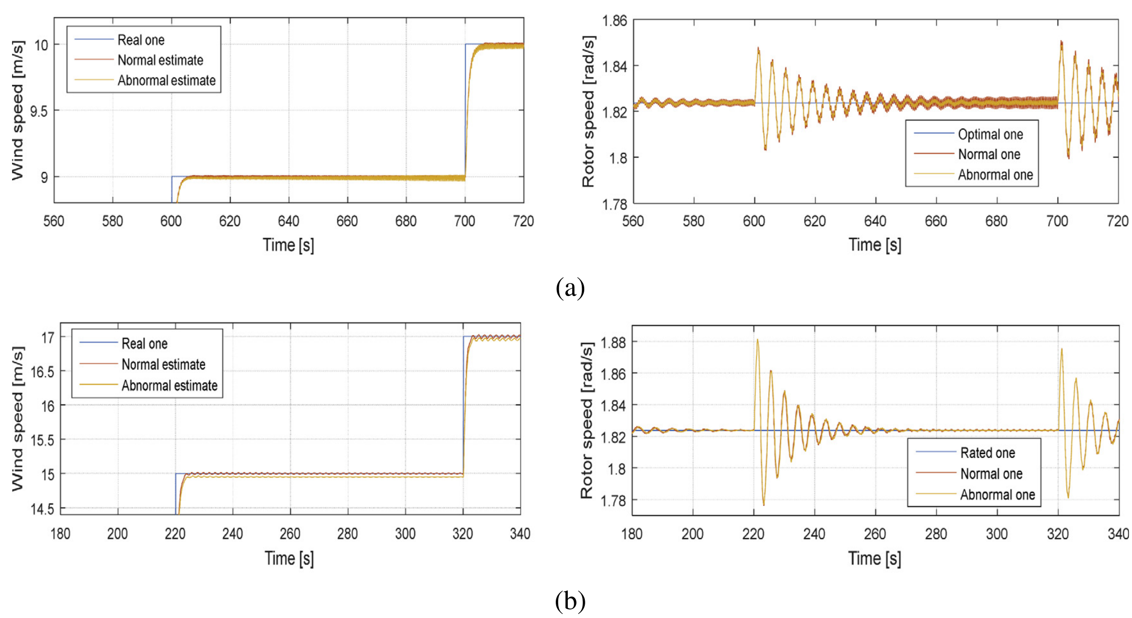

Fig. 5. Simulation results comparisons between normal case and abnormal case with model error under: (a) torque control strategy; (b) pitch control strategy.

Table 2
Quality function settings with different weighting factor.

Quality function	w_g^1	w_g^2	w_β^1	w_β^2
Set 1	1	$3e-7$	1	$7.1e-1$
Set 2	1	$6e-7$	1	$7.1e-1$
Set 3	1	$12e-7$	1	$7.1e-1$
Set 4	1	$6e-7$	1	$3.55e-1$
Set 5	1	$6e-7$	1	$7.1e-1$
Set 6	1	$6e-7$	1	$14.2e-1$

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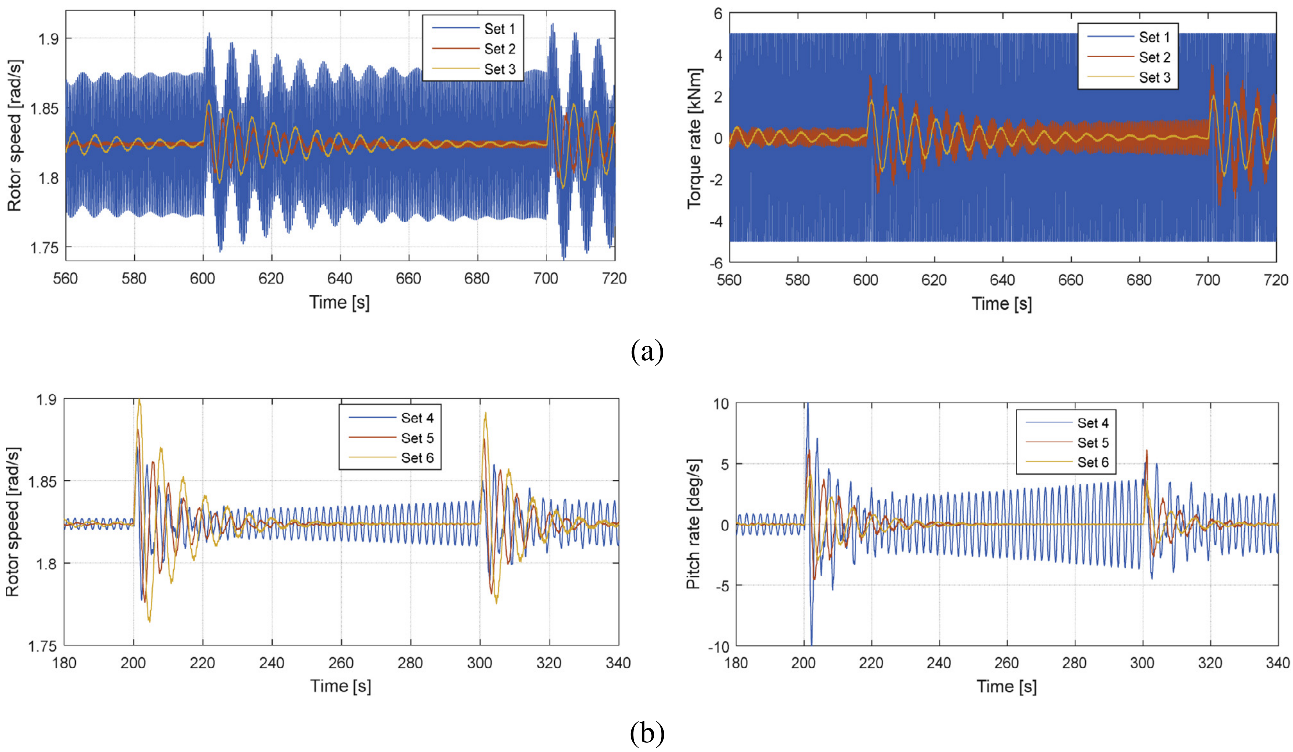

Fig. 6. Simulation results comparisons with different weighting factors under: (a) torque control strategy; (b) pitch control strategy.

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