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Coordinated Optimization of Wind Turbine Mechanical Loads and Power with Model Predictive Strategy#

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ABSTRACT:

In desert, Gobi, and barren regions, while wind resources are abundant, the harsh environment presents challenges for the deployment of maintenance personnel and the safe operation of equipment. This significantly increases the maintenance costs of wind turbines(WTs). Therefore, a more effective control strategy is needed to reduce fatigue loads on critical components, thereby extending the lifespan of WTs and ensuring longer, safer operational periods. For WTs operating above rated wind speeds, wind shear, wake effects, and yaw movements can cause uneven mechanical loads on the turbine blades, resulting in power fluctuations. By adopting active load reduction technology, these uneven mechanical loads can be effectively minimized, thereby extending the turbine's lifespan. This paper establishes a linearized model of the WT system to achieve coordinated optimization of mechanical load and power. A coordinate transformation is performed to obtain an independent pitch prediction model suitable for model predictive control (MPC). A multi-input-multi-output independent pitch model predictive controller for the WT is then designed. Comparisons between the proposed strategy and traditional gain scheduling PI controllers demonstrate the effectiveness of the proposed method.

Keywords: renewable energy, wind turbines, mechanical loads, model predictive control, independent pitch control

NONMENCLATURE

Abbreviations	
WT	Wind Turbine
MPC	model predictive control

1. INTRODUCTION

The trend toward larger wind turbines (WTs) has become increasingly prominent in the wind energy industry. While this upscaling enhances power generation, it also leads to significantly greater structural loads. This issue is particularly acute in harsh environments such as deserts, Gobi, and wilderness areas, which are far removed from human settlements, making WT health monitoring and maintenance challenging. Consequently, large WTs must not only achieve stable power output but also reduce fatigue loads, thereby extending their service life and lowering the cost of electricity generation.

Reference [2] addresses the contradiction between power fluctuations and power generation efficiency for large inertia WTs operating below-rated wind speeds by proposing a flexible maximum power point tracking (MPPT) control strategy. However, this strategy does not consider the mechanical loads during system operation. Reference [3] establishes a simplified nonlinear model of the WT and proposes a nonlinear MPC pitch control strategy, which effectively mitigates wind speed disturbances. Nonetheless, designing a nonlinear MPC controller is complex, and solving the optimization problem requires considerable computational time, posing challenges for practical application. Reference [4] employs the Wiener model to design PI and MPC control strategies, achieving good pitch power regulation control effects, but this method does not consider load optimization. Thus, these methods fail to balance the reduction of mechanical loads with the coordination of power generation.

This study, based on the NREL 5MW WT, establishes a linearized model of the turbine and adopts an independent pitch control method based on MPC. This approach effectively reduces the fatigue load on the blade roots and tower base while maintaining stable power output in high wind speed regions above the rated wind speed.

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2. ESTABLISHMENT OF THE STATE-SPACE MODEL FOR WIND TURBINE INDIVIDUAL PITCH CONTROL

2.1 Establishment of the State-Space Model

For the design of WT control systems, parameters for the linearized state-space model are obtained through linearization using the WT dynamics simulation software OpenFAST[5]. The NREL 5MW model is utilized for the WT, with the selection of state variables determined by the model's accuracy and the requirements of the control algorithm. The modes chosen for this model include the first fore-aft mode of the tower, the first flapwise and edgewise modes of the three blades, and the flexible rotational mode of the drivetrain.

A typical large-scale three-blade horizontal-axis WT is a strongly nonlinear time-varying system. For the design of an individual pitch controller, it is necessary to consider the azimuth angle when linearizing the WT model to ensure that the control algorithm is applicable to both rotating and non-rotating structures. The model is as follows:

$$\begin{cases} \dot{x}(t) = A(\theta)x(t) + B(\theta)u(t) \\ y(t) = C(\theta)x(t) + D(\theta)u(t) \\ \dot{\theta}(t) = \omega(t) \end{cases} \tag{1}$$

In this model, [x、y、u] represent the state variables, output variables, and input variables, respectively. The output variables are chosen as the blade root bending moments $[M_{y1}, M_{y2}, M_{y3}]^T$, and the input variables are selected as the pitch angles of the three blades $[\beta_1, \beta_2, \beta_3]^T$. θ is the rotor azimuth angle, ω is the rotor speed, and $A(\theta)$、$B(\theta)$、$C(\theta)$、$D(\theta)$ are the azimuth angle-dependent model matrices.

$$\begin{cases} A(\theta) = A_0 + A_{\cos}\cos(\theta) + A_{\sin}\sin(\theta) \\ B(\theta) = B_0 + B_{\cos}\cos(\theta) + B_{\sin}\sin(\theta) \\ C(\theta) = C_0 + C_{\cos}\cos(\theta) + C_{\sin}\sin(\theta) \\ D(\theta) = D_0 + D_{\cos}\cos(\theta) + D_{\sin}\sin(\theta) \end{cases} \tag{2}$$

The linear time-varying state-space model in the rotating coordinate system is obtained. The corresponding mathematical transformations must be performed to design the model predictive controller.

2.2 Coordinate Transformation of the State-Space Model

By applying a coordinate transformation to the model in the rotating coordinate system, a linear time-varying model in the dq coordinate system can be obtained. The blade coordinate transformation formula is given by:

$$T(\theta) = \frac{2}{3}\begin{bmatrix} \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \cos\theta & \cos(\theta + \frac{2\pi}{3}) & \cos(\theta + \frac{4\pi}{3}) \\ \sin\theta & \sin(\theta + \frac{2\pi}{3}) & \sin(\theta + \frac{2\pi}{3}) \end{bmatrix} \tag{3}$$

In the formula, θ represents the azimuth angle. First, we introduce a transformation of the state vector and construct an invertible diagonal matrix $T_x(\theta)$ to perform the dq-coordinate transformation on the rotational coordinate variables while keeping the variables in the non-rotational coordinate system unchanged. Similarly, diagonal matrices $T_y(\theta)$ and $T_u(\theta)$ are respectively constructed to perform coordinate transformations on the output and input vectors:

$$x_{dq} = T_x(\theta)x, u_{dq} = T_u(\theta)u, y_{dq} = T_y(\theta)y \tag{4}$$

By combining the state vector, input vector, and output vector transformation matrices, the state-space model of the WT in the dq-coordinate system is obtained as follows:

$$\begin{cases} \dot{x}_{dq}(t) = A_{dq}(\theta)x_{dq}(t) + B_{dq}(\theta)u_{dq}(t) \\ y_{dq}(t) = C_{dq}(\theta)x_{dq}(t) + D_{dq}(\theta)u_{dq}(t) \end{cases} \tag{5}$$

In which

$$\begin{cases} A_{dq} = (T_{x(\theta)}A + \dot{T}_{x(\theta)})T^{-1}_{x(\theta)} \\ B_{dq} = T_{x(\theta)}BT^{-1}_{u(\theta)} \\ C_{dq} = T_{x(\theta)}CT^{-1}_{x(\theta)} \\ D_{dq} = T_{y(\theta)}BT^{-1}_{u(\theta)} \end{cases} \tag{6}$$

The average period model method is applied to eliminate the dependency on the azimuth angle, resulting in a linear time-invariant state-space model that meets the precision requirements for pitch control design.

3. MODEL PREDICTIVE CONTROLLER DESIGN

3.1 Establishment of Prediction Equations

Model Predictive Control is a form of optimization control. At each sampling instant, based on the current measurement information, an open-loop optimization problem over a finite time horizon is solved online. The first element of the resulting control sequence is then applied to the controlled object. At the next sampling instant, this process is repeated: the optimization problem is updated with new measurement values and resolved.

Since MPC follows the principle of rolling horizon control, the current state information of the controlled object is used for prediction and control at the next time step. It is assumed in MPC that the current input $u_{(k)}$ does not affect the current output $y_{(k)}$, leading to the assumption $D_m = 0$. By performing discrete differentiation on equation(5) and applying augmentation transformations, a new predictive model is obtained:

$$\begin{bmatrix} \Delta x_{dq}(k+1) \\ y_{dq}(k+1) \end{bmatrix} = \begin{bmatrix} DT\cdot A+I & O \\ C & I \end{bmatrix}\begin{bmatrix} \Delta x_{dq}(k) \\ y_{dq}(k) \end{bmatrix} + \begin{bmatrix} DT\cdot B\cdot T_{mbc}(\theta_k) \\ D\cdot T_{mbc}(\theta_k) \end{bmatrix}\Delta u(k) + \begin{bmatrix} DT\cdot B_d \\ D_d \end{bmatrix}\Delta w(k)$$
$$y_{dq}(k) = \begin{bmatrix} O & I \end{bmatrix}\begin{bmatrix} \Delta x_{dq}(k) \\ y_{dq}(k) \end{bmatrix} \tag{7}$$

Assuming $\Delta u(k) = u(k) - u(k-1)$, restate the equation as:

$$\begin{aligned} x_m(k+1) &= A_m x_m(k) + B_{m,k}\Delta u(k) + B_{md}\Delta w(k) \\ y(k) &= C_m x_m(k) \end{aligned} \tag{8}$$

In which

$$x_m(k) = [\Delta x_{dq}(k) \ \ \mathrm{y}_{dq}(k)]^T,$$
$$A_m = \begin{bmatrix} DT\cdot A+I & O \\ C & I \end{bmatrix}, B_{m,k} = \begin{bmatrix} DT\cdot B\cdot T_{mbc}(\theta_k) \\ D\cdot T_{mbc}(\theta_k) \end{bmatrix}, \tag{9}$$
$$B_{md} = \begin{bmatrix} DT\cdot B_d \\ D_d \end{bmatrix}, C_m = \begin{bmatrix} O & I \end{bmatrix}$$

Based on the augmented matrix(8), the control input predicts the future state variables over a finite time horizon:

$$x_m(k_i+N_p \mid k_i) = A_m^{N_p} x_m(k_i) + \begin{bmatrix} A_m^{N_p-1}B_{m,k_i}\Delta u(k_i) + A_m^{N_p-2}B_{m,k_i+1}\Delta u(k_i+1) + \\ \cdots + A_m^{N_p-N_c}B_{m,k_i+N_c-1}\Delta u(k_i+N_c-1) \end{bmatrix} \tag{10}$$

Predict the output variables over a finite future time horizon：

$$\begin{aligned} y(k_i+N_p \mid k_i) = C_m A_m^{N_p} x_m(k_i) & \\ + &\begin{bmatrix} C_m A_m^{N_p-1}B_{m,k_i}\Delta u(k_i) + C_m A_m^{N_p-2}B_{m,k_i+1}\Delta u(k_i+1) + \\ \cdots + C_m A_m^{N_p-N_c}B_{m,k_i+N_c-1}\Delta u(k_i+N_c-1) \end{bmatrix} \\ + &\begin{bmatrix} C_m A_m^{N_p-1}B_{md}\Delta w(k_i) + C_m A_m^{N_p-2}B_{md}\Delta w(k_i+1) + \\ \cdots + C_m A_m^{N_p-N_c}B_{md}\Delta w(k_i+N_p-1) \end{bmatrix} \end{aligned} \tag{11}$$

where N_c and N_p represent the control horizon and prediction horizon respectively, with $N_c \le N_p$. Define the output and input vectors:

$$\begin{aligned} Y &= [y(k_i+1 \mid k_i), y(k_i+2 \mid k_i), \cdots, y(k_i+N_p \mid k_i)]^T \\ \Delta U &= [\Delta u(k_i), \Delta u(k_i+1), \cdots, \Delta u(k_i+N_c-1)]^T \\ \Delta W &= [\Delta w(k_i), \Delta w(k_i+1), \cdots, \Delta w(k_i+N_c-1)]^T \end{aligned} \tag{12}$$

Equation (8) can be rewritten as：

$$Y = P x_m(k_i) + H\Delta U + H_d \Delta W \tag{13}$$

In which

$$P = [C_m A_m \quad C_m A_m^2 \quad C_m A_m^3 \quad \cdots \quad C_m A_m^{N_p}]^T$$
$$H = \begin{bmatrix} C_m B_{m,k_i} & 0 & 0 & \cdots & 0 \\ C_m A_m B_{m,k_i} & C_m B_{m,k_i+1} & 0 & \cdots & 0 \\ C_m A_m^2 B_{m,k_i} & C_m A_m B_{m,k_i+1} & C_m B_{m,k_i+2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_m A_m^{N_p-1} B_{m,k_i} & C_m A_m^{N_p-2} B_{m,k_i+1} & C_m A_m^{N_p-3} B_{m,k_i+3} & \cdots & C_m A_m^{N_p-N_c} B_{m,k_i+N_c-1} \end{bmatrix}$$
$$H_d = \begin{bmatrix} C_m B_{md} & 0 & 0 & \cdots & 0 \\ C_m A_m B_{md} & C_m B_{md} & 0 & \cdots & 0 \\ C_m A_m^2 B_{md} & C_m A_m B_{md} & C_m B_{md} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_m A_m^{N_p-1} B_{md} & C_m A_m^{N_p-2} B_{md} & C_m A_m^{N_p-3} B_{md} & \cdots & C_m A_m^{0} B_{md} \end{bmatrix} \tag{14}$$

3.2 Definition of Control Objectives and System Constraints

The objective function is defined as follows:

$$\begin{aligned} J &= (Y-R_s)^T Q (Y-R_s) + \Delta U^T R \Delta U \\ R_s &= \overbrace{\left[r(k_i), r(k_i), \cdots, r(k_i)\right]^T}^{N_p} \end{aligned} \tag{15}$$

Ignore the terms in the previous equation that are unrelated to the control variables, and set $E = H^T Q H + R$, $F = 2(Px(k_i) + H_d \Delta W - R_s)^T Q H$, yielding:

$$J = \Delta U^T E \Delta U + F \Delta U \tag{16}$$

The input constraints for the control are:

$$\begin{aligned} u_{\min} &\le u(k_i) \le u_{\max} \\ \Delta u_{\min} &\le u(k_i) - u(k-1) \le \Delta u_{\max} \end{aligned} \tag{17}$$

To reliably follow the set point, it is not sufficient to only follow the optimization objective. Therefore, output constraints are necessary, resulting in a quadratic optimization problem with linear constraints:

$$
\begin{aligned}
&J = \Delta U^T E \Delta U + F \Delta U \\
&A_{cons} \Delta U \le b
\end{aligned}
\tag{18}
$$

Find the optimal solution of the input constraint at time k, take the first set of results, and calculate the control input:

$$
\begin{aligned}
&\Delta u(k) = \begin{bmatrix} I_{3\times 3} & 0 & \cdots & 0 \end{bmatrix} \Delta U \\
&u(k) = u(k-1) + \Delta u(k)
\end{aligned}
\tag{19}
$$

MPC requires measuring the state variables of the current state model. The Kalman state observer can be used to estimate some unmeasurable state variables of the wind turbine, thereby enabling the rolling optimization computation of the MPC.

4. SIMULATION ANALYSIS OF WIND TURBINE LOAD CHARACTERISTICS

This paper uses the open-source software OpenFAST from the National Renewable Energy Laboratory (NREL) in conjunction with MATLAB/Simulink for controller design and simulation analysis. The Turbsim tool is utilized to generate the turbulent wind model with an average wind speed of 15 m/s. The WT has a rated power of 5 MW, a rated wind speed of 11.4 m/s, a cut-in wind speed of 3 m/s, and a cut-out wind speed of 25 m/s.

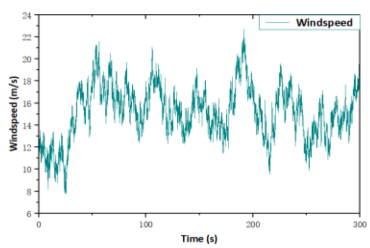

Fig. 1 Turbulent wind

This paper compares the simulation results of the MPC independent pitch control with the Baseline-PI unified pitch control method. The comparison reveals that the MPC independent pitch control strategy has a more significant advantage in reducing blade root moments and tower base moments. Specifically, within the range of 100s-200s, the average blade root moments of Blade 1, Blade 2, and Blade 3 under MPC independent pitch control are reduced by 1.9%, 2.3%, and 7%, respectively, compared to the Baseline.

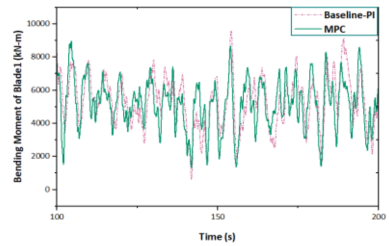

Fig. 2 Root Bending Moment of Blade 1

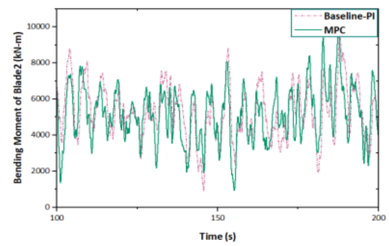

Fig. 3 Root Bending Moment of Blade 2

Under the MPC independent pitch control, the average

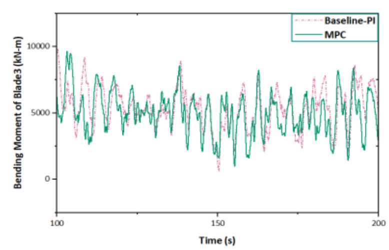

Fig. 4 Root Bending Moment of Blade 3

tower base moment is reduced by 3.9% compared to the Baseline, and the standard deviation is reduced by 27.8%.

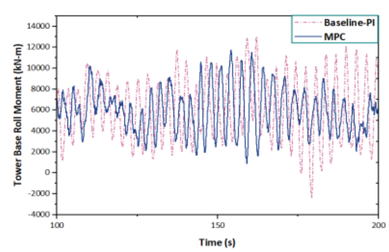

Fig. 5 Tower Base Roll Moment

In terms of the dynamic operating characteristics of the WT, the MPC independent pitch control method can achieve stable power tracking under high wind speed and turbulent wind conditions. Figures 6 and 7 show the pitch angle and pitch speed of the wind turbine during the 100-

200s time interval， both of which remain within the the two controllers. The power standard deviation under MPC independent pitch control is 16.7, which is about 52% less compared to 34.8 under the PI controller. This demonstrates better control performance in disturbance rejection.

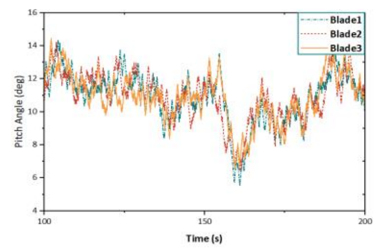

Fig. 6 Pitch Angle

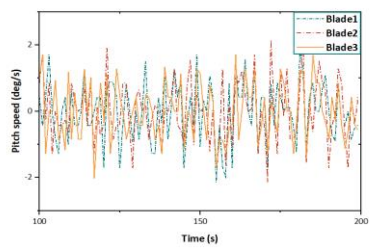

Fig. 7 Pitch Speed

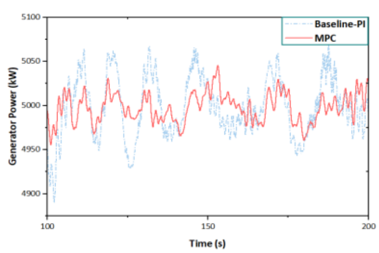

Fig. 8 Generator Power

5. CONCLUSIONS

This study establishes an OpenFAST-MATLAB/Simulink co-simulation model for wind turbine load control and compares the effects of model predictive independent pitch control with PI-based collective pitch control. The results show that the proposed multi-input-multi-output model predictive independent pitch control strategy reduces structural fatigue loads more effectively than constraint limits. Figure 8 shows the power curves under traditional methods, without causing power fluctuations. This indicates that the model predictive independent pitch controller has significant implications for extending the lifespan of wind turbines and reducing operation and maintenance costs in desert and Gobi environments.

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