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Repetitive Pitch Control for Vertical Axis Wind Turbine

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Abstract. Increasing demands in decentralized power plants have focused attention on Vertical Axis Wind Turbines (VAWTs). However, accessing high range of power from VAWTs is an impediment due to increased loads on the turbine blades. Here, we derive an optimal pitching action that reduces the periodic disturbance on turbine blades of VAWTs without affecting their power production. A control technique called Subspace Predictive Repetitive Control (SPRC) alongwith a LQ Tracker is used for recursive identification to estimate the parameters of VAWT model and further provide an optimal control law accordingly. Basis functions have been used to reduce the dimensionality of the control problem. Simulation results show a great potential of the data-driven SPRC approach coupled with LQ Tracker in reducing the turbine loads on VAWTs.

Keywords: Subspace Predictive Repetitive Control, LQ Tracker, VAWT, Basis Functions, Lifted Domain

1. Introduction

Over the past decade, the demand for wind energy has progressed significantly. However, the capital costs involved still pose a hindrance to its widespread. To overcome this limitation, various research groups have been working towards active control for reducing the blade root loads of a wind turbine. Bossanyi (2003) proposed an Individual Pitch Control (IPC) method to reduce the periodic loading of the wind turbine. Houtzager *et al.* (2013) used sinusoidal basis functions in Repetitive Control (RC) and showed promising results of reducing the blade root loads. Navalkar *et al.* (2014) designed Subspace Predictive Repetitive Control (SPRC) for online identification and adaptive RC law to enhance load reduction of Horizontal Axis Wind Turbine (HAWT).

Currently, most of the power production is done by the HAWTs due to their higher efficiency and increased reliability as compared to the Vertical Axis Wind Turbines (VAWTs). However, the upscaling, maintenance and installation of VAWTs are relatively easier. Also, the positioning of generator, gearbox and other heavy components at the ground level gives a higher structural stability to VAWTs, especially when positioned on a floating support structure. Further, the ability of VAWTs to face more gusty winds and their insensitivity to variations in wind direction motivates their usage even more (Beri *et al.* (2011)). Navalkar *et al.* (2014) used the constraint that summation of all pitch angles at a given instant should be zero to ensure that the power



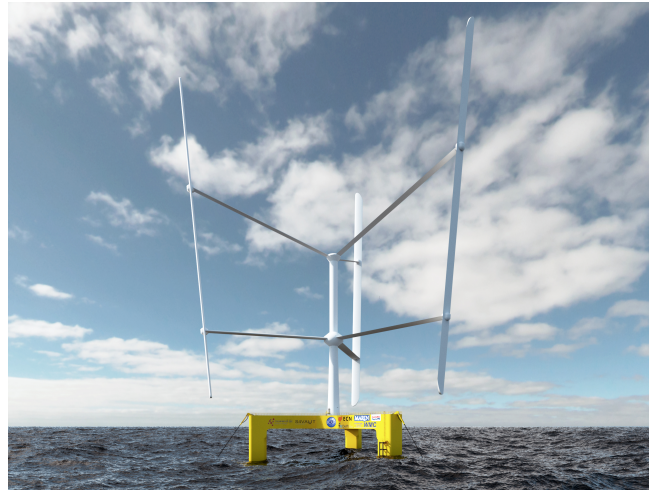


Figure 1. Floating VAWT with pitching blades (S4VAWT project), Huijs *et al.* (2018)

production of HAWTs is not affected with load reduction. However, due to cyclic variations in the angle of attack in the VAWTs, this approach does not work for VAWTs. This brings up the challenge of load mitigation in VAWTs while keeping their power production well within the acceptable limits. An offshore floating VAWT with pitching blades is shown in Figure 1.

The contribution of this paper includes a recursive least squares identification technique that estimates system parameters in the lifted domain. Basis functions are used in the identification and controller design to reduce the system dimensions. Further, it is followed by the formulation of RC law and implementation. Also, a novel algorithm of LQ tracker provides a freedom to the designer for balancing the blade load reduction with loss in power production. The algorithm gives complete flexibility in changing the weighting matrices on blade loads and power for VAWTs, thus making the implementation suitable for above rated wind speeds as well.

This paper is structured as follows: Section 2 presents the simulation environment of the turbine used. Section 3 explains the theoretical concepts of SPRC and the LQ Tracker. Section 4 presents the simulation results and conclusions and future work are discussed in Section 5.

2. Turbine Model

In VAWTs, the main rotor shaft is set transverse to the direction of the incoming wind. Generally, two types of VAWTs are considered: Savonius Turbine and Darrieus Turbine. The Darrieus type wind turbine is considered for this work due to its higher efficiency. Blade Element Momentum (BEM) theory predicts the power output of VAWTs with a high accuracy (for lower tip speed ratios). These streamtube models are used to calculate the thrust force acting on the streamtube by using the conservation equations of mass, momentum and energy. The mass, momentum and energy conservation equations in the integral form are written as (Equations 1, 2 and 3) :

$$\frac{d}{dt} \int_{\Omega} \rho dV + \oint_{\partial\Omega} \rho \mathbf{u} \cdot \mathbf{n} dS = 0, \quad (1)$$

$$\frac{d}{dt} \int_{\Omega} \rho \mathbf{u} dV + \oint_{\partial\Omega} \rho \mathbf{u} (\mathbf{u} \cdot \mathbf{n}) dS = \sum F_{ext}, \quad (2)$$

and

$$\frac{d}{dt} \int_{\Omega} \rho u^2 dV + \oint_{\partial\Omega} \frac{1}{2} \rho u^2 (\mathbf{u} \cdot \mathbf{n}) dS = -P \quad (3)$$

where Ω represents the domain where the above equations can be applied with \mathbf{n} being a unit vector normal to $\partial\Omega$ pointing outwards, $\sum F$ is the summation of the forces received by the flow and P is the power output of the part of the turbine within the specified domain. Double Multiple Streamtube Model (DMST) is considered for the present work because it allows to compute the energy losses of the flow separately for front and rear part of the VAWT (Vallverdu (2014)).

Further, dynamic stall has a relevant role in the dynamics of VAWTs. It refers to the phenomenon when the lift force starts to decrease with very high angles of attack. Gormont (1973) proposed to consider dynamic stall in helicopter blades for VAWTs. The effect of the turbulent wakes generated by the front half of the turbine and received on the rear half is known as wake interaction (Vallverdu *et al.* (2016)). Gormont model of dynamic stall and wake interaction has been included in the model of the VAWT.

The dynamic loading of blades occurs at the fundamental frequency (1Z or rotor speed) and its harmonics. These blade loadings are reduced with the help of a SPRC controller which is discussed in the next section.

3. Theoretical Framework

An ideal controller design should be able to meet these objectives:

- Reduce the blade loadings
- Produce smooth pitching actions
- Does not affect the power production

The first two objectives are met by the SPRC technique (Navalkar *et al.* (2014)). The identification of parameters has been done in lifted domain. The basis functions helped in reducing the dimensions and hence the computational complexity of the algorithm. In this paper, a novel implementation of LQ Tracker helped in achieving the third objective. The steps involved in implementing SPRC with LQ Tracker have been explained in the following subsections:

3.1. Predictor

The dynamics of the wind turbine system (modelled as discrete time) in the predictor form can be given as :

$$x_{k+1} = Ax_k + Bu_k + Ed_k + Ke_k \quad (4)$$

$$y_k = Cx_k + Du_k + Fd_k + e_k \quad (5)$$

where x_k is the state vector ($x_k \in \mathbb{R}^n$ where n is the number of states), u_k is the input vector representing the pitch angles of the blades ($u_k \in \mathbb{R}^{nu}$), d_k is the periodic disturbance due to the loading on the blades of the turbine ($d_k \in \mathbb{R}^{nd}$) with period Z , e_k represents the process noise of the system (i.e. wind disturbance) and K is the Kalman gain (Navalkar *et al.* (2014)). The stacking of the output vector (whose length is same as the period Z) gives:

$$Y_k = \begin{bmatrix} y_k \\ y_{k+1} \\ \cdot \\ \cdot \\ y_{k+Z-1} \end{bmatrix} \quad (6)$$

The stacked vectors for input, disturbance and error are defined in a similar way and represented by U_k , D_k and E_k . The disturbance vector (D_k) is constant for every period and

will be represented by \bar{D} . The lifted domain representation (iteration domain) of the system is formulated in equations 4 and 5 (Navalkar *et al.* (2014)) :

$$x_{j+1} = A^Z x_j + K_u U_j + K_d \bar{D} + K_y Y_j \quad (7)$$

$$Y_j = \Gamma x_j + H U_j + J \bar{D} + E_j \quad (8)$$

Here, j is the iteration index and formed by replacing the time index k with iteration index j such that $(k, k + Z, k + 2Z, \dots) \rightarrow (j, j + 1, j + 2, \dots)$. K_u is the extended controllability matrix and Γ is the extended observability matrix. K_d and K_y are defined similarly as K_u , replacing B by F and K respectively whereas H and J are called Toeplitz matrices (Navalkar *et al.* (2014)).

For sufficiently high value of Z , an assumption $A^Z \approx 0$ is made (as A is stable). This allows equation 8 to be re-written as:

$$Y_j = [\Gamma K_u \quad \Gamma K_y \quad H \quad (\Gamma K_d + J) \bar{D}] \begin{bmatrix} U_{j-1} \\ Y_{j-1} \\ U_j \\ 1 \end{bmatrix} + E_j \quad (9)$$

The noise vector E_j has no correlation with the present input-output data. Thus, in the lifted domain, E_j is an uncorrelated zero mean white noise sequence. The system parameters can be obtained from equation (9), provided the system is persistently excited. However, the identification problem is a high-dimensional one, as the input-output data is stacked over the period Z .

3.2. Basis Functions

This step addresses the problem of increased complexity by translating a large dimensional problem to a reduced domain, i.e. by projecting the input-output data into a basis function subspace. The input basis vectors (corresponding to the pitch angles) are used to shape the control input while the output basis vectors (corresponding to the blade loads and the total power production in a period) describe the output in the limited space. The output (Y) consist of blade loads (Y_l) and total power production in a period (Y_P). The identification of the blade loads and the total power is carried out differently. This part of the subsection focuses on identifying the blade loads. Considering ϕ_u and ϕ_y as the projection matrices, the reduced input and output matrices are given as:

$$U_r = \phi_u U_j, \quad Y_{l,r} = \phi_y Y_j \quad (10)$$

It has to be noted that ϕ_y contains the basis functions for the blade loads. As the input can have an effect on sinusoids in the output of the same frequency, the same basis functions are used to project the stacked input-output data (Navalkar *et al.* (2014)).

Projecting equation 9 into the projected subspace gives the blade loads in reduced domain for j th period :

$$Y_{l,r,j} = \begin{bmatrix} \phi_y \Gamma K_u \phi_u^\dagger & \phi_y \Gamma K_y \phi_y^\dagger & \phi_y H \phi_u^\dagger & \phi_y (\Gamma K_d + J) \bar{D} \end{bmatrix} \begin{bmatrix} U_{r,j-1} \\ Y_{r,j-1} \\ U_{r,j} \\ 1 \end{bmatrix} + \phi_y E_j \quad (11)$$

To obtain the total power in a period, a constant basis function (ϕ) of unity is taken:

$$Y_{p,r,j} = [1 \quad 1 \quad \cdots 1_{(1,Z)}] \begin{bmatrix} P_{j1} \\ P_{j2} \\ \vdots \\ P_{jZ} \end{bmatrix}, \quad \phi = [1 \quad 1 \quad \cdots 1_{(1,Z)}] \quad (12)$$

Here P_{ji} (where $i=1,2,\dots, Z$) represents the power of i th sample for j th rotation of wind turbine.

3.3. Identification

Equation 11 represents the output of system in the reduced domain. Now, the system identification step can be performed. Markov parameters (Ξ_r) can be obtained from equation 11 as:

$$\Xi_r = \begin{bmatrix} \phi_y \Gamma K_u \phi_u^\dagger & \phi_y \Gamma K_y \phi_y^\dagger & \phi_y H \phi_u^\dagger & \phi_y (\Gamma K_d + J) \bar{D} \end{bmatrix} \quad (13)$$

Recursive least squares approach has been taken to recursively estimate Ξ_r . A forgetting factor is used to make the identified parameters adaptive to the changing wind speed (Navalkar *et al.* (2014)). Markov parameters ($\hat{\Xi}_{r,j}$) for every iteration period (j) can be written as:

$$\hat{\Xi}_{r,j} = \begin{bmatrix} \widehat{\phi_y \Gamma K_u \phi_u^\dagger} & \widehat{\phi_y \Gamma K_y \phi_y^\dagger} & \widehat{\phi_y H \phi_u^\dagger} & \widehat{\phi_y (\Gamma K_d + J) \bar{D}} \end{bmatrix}_j \quad (14)$$

The output predictor can now be given as:

$$Y_{l,r,j} = \begin{bmatrix} \widehat{(\phi_y \Gamma K_u \phi_u^\dagger)}_j & \widehat{(\phi_y \Gamma K_y \phi_y^\dagger)}_j & \widehat{(\phi_y (\Gamma K_d + J) \bar{D})}_j \end{bmatrix} \begin{bmatrix} U_{r,j-1} \\ Y_{l,r,j-1} \\ 1 \end{bmatrix} + \widehat{(\phi_y H \phi_u^\dagger)}_j U_{r,j} \quad (15)$$

A similar step of system identification is repeated for the total power in a period. An estimate of the projected Markov parameters ($\hat{\Xi}_{P,r,j}$) for an iteration period (j) can be obtained as:

$$\hat{\Xi}_{P,r,j} = \begin{bmatrix} \widehat{\phi \Gamma_P K_{uP} \phi^\dagger} & \widehat{\phi \Gamma_P K_{yP} \phi^\dagger} & \widehat{\phi H_P \phi^\dagger} & \widehat{\phi (\Gamma_P K_{dP} + J_P) \bar{D}} \end{bmatrix}_j \quad (16)$$

3.4. Repetitive Control

The estimated parameters are used to design the Repetitive Controller that rejects the periodic disturbances. As in Navalkar *et al.* (2014), a difference operator δ can be used to eliminate the effect of the constant disturbance :

$$\delta Y_{r,j} = Y_{r,j} - Y_{r,j-1}, \quad \delta U_{r,j} = U_{r,j} - U_{r,j-1}, \quad \delta(1) = 0 \quad (17)$$

$Y_{r,j}$ represents the combined output of blade loads ($Y_{l,r,j}$) and total power production ($Y_{p,r,j}$) in a period. Equations 15, 16 and 17 can be combined to form:

$$xp_{j+1} = A_p xp_j + B_p up_j \quad (18)$$

$$yp_j = C_p xp_j + D_p up_j \quad (19)$$

where,

$$x_{pj} = \begin{bmatrix} Y1_{l,r,j-1} \\ \delta U1_{r,j-1} \\ \delta Y1_{l,r,j-1} \\ Y2_{l,r,j-1} \\ \delta U2_{r,j-1} \\ \delta Y2_{l,r,j-1} \\ Y3_{l,r,j-1} \\ \delta U3_{r,j-1} \\ \delta Y3_{l,r,j-1} \\ Y_{P,r,j-1} \\ \delta Y_{P,r,j-1} \end{bmatrix}, \quad y_{pj} = \begin{bmatrix} Y1_{l,r,j} \\ Y2_{l,r,j} \\ Y3_{l,r,j} \\ Y_{P,r,j} \end{bmatrix}, \quad u_{pj} = \begin{bmatrix} \delta U1_{r,j} \\ \delta U2_{r,j} \\ \delta U3_{r,j} \end{bmatrix} \quad (20)$$

$Yi_{l,r,j-1}$, $Y_{P,r,j-1}$ and $Ui_{r,j-1}$ with $i=1,2$ and 3 represent the loads (all three blades), total power produced and pitch inputs (all three blades) projected in reduced domain (in previous iteration) respectively. The matrices A_p , B_p , C_p and D_p with appropriate dimensions are defined in Kumar (2017). Equations 18 and 19 represent an extension to the problem formulation by Navalkar *et al.* (2014), as these equations allows the designer to optimize the power production and load reduction together.

3.5. LQ Tracker

The aim of the controller is to optimize the pitching action in such a way that blade loads and the loss of power in a period are minimized. Kumar (2017) provided a reference of zero loads (for asymptotic rejection of periodic loads) and the total power to be maintained in a period. In order to track the reference, the cost function (J_j) has to be minimized:

$$J_j = \frac{1}{2}(y_{pNc} - r'_{Nc})^T M (y_{pNc} - r'_{Nc}) + \frac{1}{2} \sum_{j=i}^{Nc-1} [(y_{pj} - r'_j)^T Q (y_{pj} - r'_j) + u_{pj}^T R u_{pj}] \quad (21)$$

Here r' represents the reference trajectory provided with Nc being the control horizon. M , Q and R are semi positive definite matrices and represent the weights on the final state, the current state and the current input of the system respectively. An augmented Lagrangian multiplier approach can be used to minimize the cost function yielding the update law (Kumar (2017)):

$$S_j = A_1^T [S_{j+1} - S_{j+1} B_p (B_p^T S_{j+1} B_p + \bar{R})^{-1} B_p^T S_{j+1}] A_1 + C_p^T Q C_p - N \bar{R}^{-1} N^T \quad (22)$$

$$v_j = A_1^T [S_{j+1} - S_{j+1} B_p (B_p^T S_{j+1} B_p + \bar{R})^{-1} B_p^T S_{j+1}] [-B_p \bar{R}^{-1} (B_p^T v_{j+1} + D_p^T Q r'_j)] + A_1 v_{j+1} + C_p^T Q r'_j - N \bar{R}^{-1} D_p^T Q r'_j \quad (23)$$

where

$$A_1 = (A_p - B_p \bar{R}^{-1} N^T), \quad \bar{R} = R + D_p^T Q D_p, \quad \text{and} \quad N = C_p^T Q D_p \quad (24)$$

With Nc being the control horizon, the boundary conditions are given by (Kumar (2017)):

$$S_{Nc} = C_p^T M C_p, \quad v_{Nc} = C_p^T M r'_Z \quad (25)$$

Minimizing the cost function (21) yields an optimal control law as (Kumar (2017)):

$$u_{pj}^{*optimal} = -K_j x_{pj} + K_j^v v_{j+1} + K_j^{vd} r'_j \quad (26)$$

K_j represents the feedback term, K_j^v is the feedforward term and a special term K_j^{vd} is introduced due to the feed-through term in equation 19. These terms are mathematically defined as:

$$K_j = (\bar{R} + B_p^T S_{j+1} B_p)^{-1} (N^T + B_p^T S_{j+1} A_p) \quad (27)$$

$$K_j^v = (\bar{R} + B_p^T S_{j+1} B_p)^{-1} B_p^T, \quad K_j^{vd} = (\bar{R} + B_p^T S_{j+1} B_p)^{-1} D_p^T Q \quad (28)$$

The Q matrix which represents the weighting on the current states of the system can be decomposed into two parts (one for the blade loads and other for the total power in a rotation)

$$Q = \begin{bmatrix} Q_l & 0 \\ 0 & Q_P \end{bmatrix} \quad (29)$$

Q_l represents the weighting on the blade loads whereas Q_P is the weighting on the total power. In below rated wind speeds, where the focus is to extract maximum power from the wind turbine, higher weighting on the total power can be assigned. In above rated wind speeds, higher weighting on the blade loads can be assigned to prevent ultimate loads. The optimal control law (equation 26) actually represents the difference between the current and past control action in reduced domain (equations 18 and 19). The optimal pitch angles are given by (Kumar (2017)):

$$U_{j,Z} = U_{j-1,Z} + \phi_u^\dagger \delta u_{pj}^{*optimal} \quad (30)$$

Thus Repetitive Control alongwith LQ Tracker has been formulated. The results obtained are discussed in the next section.

4. Simulations

The VAWT model to be used for simulations has already been described in Section 2. This model is simulated with rotor speed of 6 RPM, power output of 6 MW and wind speed of 10 m/s alongwith an additional integrated white noise (representing turbulence of around 3%). It is found that the energy of blade loads is distributed in 1Z, 2Z, 3Z, 4Z and 5Z (Figure 2). Apart from these frequencies, contribution of zero frequency part (i.e. constant) to the blade loads is also observed (Figure 2). Figure 3 shows that the fundamental frequency for power is 3P. To achieve an optimal control, second harmonic of power (i.e. 6Z) is also taken. Thus, a unity constant and frequencies from 1-6Z are used for defining the basis functions for blade loads. With the sample time of 0.02 s, the total number of samples for each blade in a rotation are 500. The basis functions reduce these samples to 13. Recursive Least Squares approach (with forgetting factor of 0.99) is used for system identification in reduced domain. 50 rotations are used for the identification step. These identified parameters are fed to the control algorithm. A control horizon of 5 periods is used. To produce smooth control signals, a higher weight on R matrix for basis functions from 4-6Z is used. Higher weight on Q_P is kept to prevent power loss while reducing blade loads. The response of controller (SPRC coupled with LQ Tracker) is visualized in Figures 4 and 5. Further, the pitch trajectories are symmetrically displaced by 120° and have almost same shape and amplitude (Figure 4), as expected.

Figure 5 shows blade load reduction of 22% in upstream and 11% in downstream side of wind turbine. A decrease of 3.5% in total power in a period is observed. The behaviour of the power curve (with and without control) is visualized in Figure 3. It shows that the main decrease in power is caused by the 3Z component, which has a positive side effect of reducing the power ripple. A higher weight on the basis functions for 4-6Z ensured smooth pitching actions (Figure

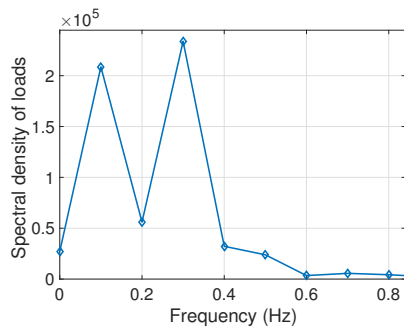


Figure 2. Frequency spectrum of the blade loads with no control technique.

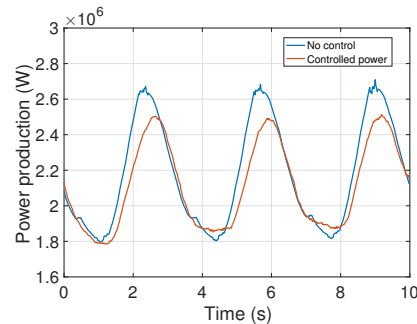


Figure 3. Comparing the response of the wind turbine model with and without control.

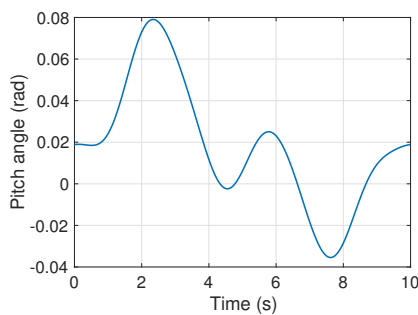


Figure 4. Optimum control action through SPRC (and LQ Tracker) technique for a rotation.

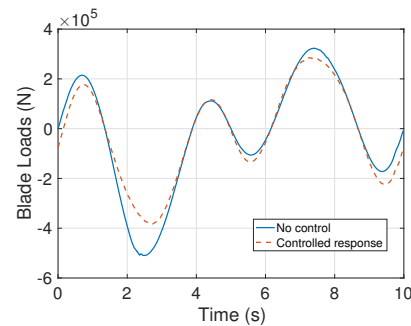


Figure 5. Reduction of blade loads through SPRC and LQ Tracker technique for a rotation.

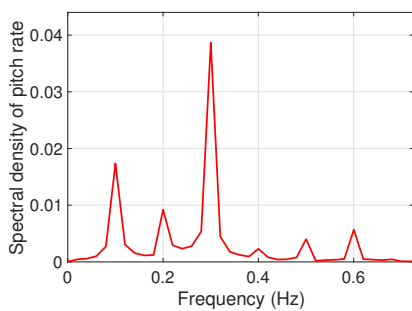


Figure 6. Pitch rate required by blades to achieve optimum control action

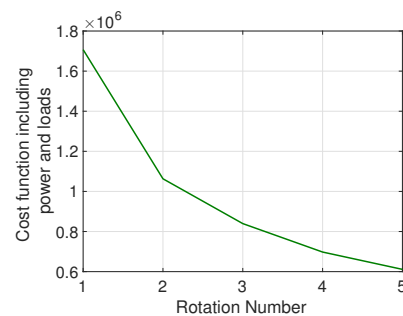


Figure 7. Cost function of LQ Tracker with higher weight on power.

6). The variation of the cost function over the control horizon is shown in Figure 7. It confirms the convergence of LQ Tracker.

Further, the VAWT model is also simulated with a high weight on blade loads. Figure 8 shows a huge reduction of blade loads by 22 % in upstream and 35 % in the downstream part. Consequently, the power in the whole period dropped by 18.7%. The pitching action required for this setting is shown in Figure 9.

The VAWT model was simulated for various wind speeds and the results are summarized in

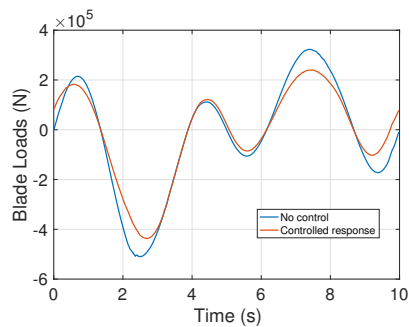


Figure 8. Implementing the controller with high weight on blade loads.

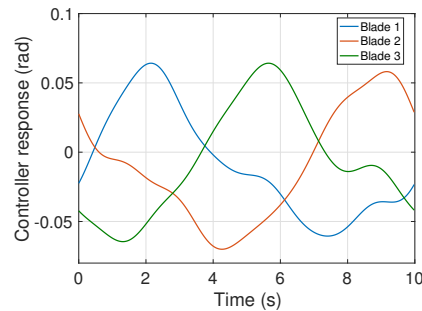


Figure 9. Optimum pitch trajectory for high weighting on blade loads.

Table 1. It has to be noted that the simulations are carried out by keeping a high weight on power production.

Table 1. Performance of VAWT model.

Performance	Wind speed (7 m/s)	Wind speed (10 m/s)	Wind speed (11.5 m/s)
Peak load reduction in upstream part	26.5 %	22.4 %	21.5 %
Peak load reduction in downstream part	No effect	11.6 %	25.2 %
Reduction in power in a rotation	1.8 %	3.6 %	2.6 %

5. Conclusions & Future Work

The SPRC has shown promising potential in achieving blade pitch control of VAWT. The wind turbine parameters can be identified recursively. The use of basis functions significantly reduces the control effort at high frequencies. LQ Tracker helped in decoupling the power production of the wind turbine from load control.

The work prepared here lays a foundation for further exploration of the possibilities of pitch controlled VAWTs. For instance, a varying rotor speed can be accounted for by changing the basis functions online and thus identifying the parameters online. It would be useful to extend the analysis to the situation in a wind farm and study the effectiveness of the controller in optimizing the wind farm.

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