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Model Predictive Control of Wind Turbines using Uncertain LIDAR Measurements

Mahmood Mirzaei, Mohsen Soltani, Niels K. Poulsen and Hans H. Niemann

***Abstract*— The problem of Model predictive control (MPC) of wind turbines using uncertain LIDAR (LIght Detection And Ranging) measurements is considered. A nonlinear dynamical model of the wind turbine is obtained. We linearize the obtained nonlinear model for different operating points, which are determined by the effective wind speed on the rotor disc. We take the wind speed as a scheduling variable. The wind speed is measurable ahead of the turbine using LIDARs, therefore, the scheduling variable is known for the entire prediction horizon. By taking the advantage of having future values of the scheduling variable, we simplify state prediction for the MPC. Consequently, the control problem of the nonlinear system is simplified into a quadratic programming. We consider uncertainty in the wind propagation time, which is the traveling time of wind from the LIDAR measurement point to the rotor. An algorithm based on wind speed estimation and measurements from the LIDAR is devised to find an estimate of the delay and compensate for it before it is used in the controller. Comparisons between the MPC with error compensation, the MPC without error compensation and an MPC with re-linearization at each sample point based on wind speed estimation are given. It is shown that with appropriate signal processing techniques, LIDAR measurements improve the performance of the wind turbine controller.**

I. INTRODUCTION

In recent decades, there has been increasing interest in green energies, of which wind energy is one of the most important. Horizontal axis wind turbines are the most common wind energy conversion systems (WECS) and are hoped to be able to compete with fossil fuel power plants on energy price in near future. However, this demands better technology to reduce the electricity production price. Control can play an essential part in this context. This is because, on the one hand improved control methods can decrease the cost of energy by keeping the turbine close to its maximum efficiency. On the other hand, they can reduce structural fatigue and increase the lifetime of the wind turbine. There are several methods of wind turbine control, ranging from classical control methods, which are the most commonly used methods in real applications [1], to advanced control methods, which have been the focus of research in the past few years [2]. Gain scheduling [3], adaptive control [4], MIMO methods [5], nonlinear control [6], robust control [7], model predictive control [8], μ-Synthesis design [9] and robust MPC [10] are just to mention a few. Advanced model-based control methods are thought to be the future of wind turbine control, as they can conveniently employ new generations of sensors on wind turbines (e.g. LIDAR [11]), new generation, of actuators (e.g. trailing edge flaps [12]) and they also treat the turbine as a MIMO system. Model predictive control (MPC) has proved to be an effective tool to deal with multivariable constrained control problems [13]. As wind turbines are MIMO systems [5] with constraints on inputs and outputs, using MPC is reasonable. MPC has been an active area of research and has been successfully applied on different applications in the last decades [14]. In this work, we extend the idea of linear MPC to formulate a tractable predictive control of the nonlinear system of wind turbines. To do so, we use future values of the effective wind speed that acts as a scheduling variable in the model. LIDAR measurements are used to calculate the effective wind speed ahead of wind turbines [11]. Several works have considered wind turbine control using LIDAR measurements [15], [16] and [17]. However, it is also important to take uncertainty in the measurements into account as small errors in the calculations of the wind propagation time can severely degrade performance of the controller.

The paper is organized as follows. In section II, modeling of the wind turbine is explained, the nonlinear model is derived and a linear model is given whose parameters vary as a function of effective wind speed. In section III, our proposed method for solving model predictive control of the system is presented. Then, the control design is explained, and control objectives are discussed. In section IV, uncertainty in the LIDAR measurements are explained, and a method is proposed to reduce the most severe source of uncertainty. Finally, in section V, simulation results are given.

II. WIND TURBINE MODELING

In this section the nonlinear model and important degrees of freedom are explained. Afterwards the linearization procedure is described and the linear parameter varying model is given.

A. Nonlinear model

The dominant dynamics of the wind turbine come from its flexible structure. Several degrees of freedom could be considered to model the flexible structure, but for control

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design a few important degrees of freedom are considered. In this work we consider three degrees of freedom, namely the rotational degree of freedom (DOF), the drivetrain torsion and the tower fore-aft displacement. Nonlinearity of the wind turbine model mostly comes from its aerodynamics. Blade element momentum (BEM) theory is used to numerically calculate aerodynamic torque and thrust on the wind turbine [18]. Having aerodynamic torque and modeling the drivetrain and the tower fore-aft degrees of freedom with simple mass-spring-damper, the whole system equation with 3 degrees of freedom becomes:

$$J_r\dot{\Omega}_r = \mathcal{Q}_r - C_d(\Omega_r - \frac{\Omega_g}{N_g}) - K_d\psi \tag{1}$$

$$(N_gJ_g)\dot{\Omega}_g = C_d(\Omega_r - \frac{\Omega_g}{N_g}) + K_d\psi - N_g\mathcal{Q}_g \tag{2}$$

$$\dot{\psi} = \Omega_r - \frac{\Omega_g}{N_g} \tag{3}$$

$$M\ddot{x}_t = \mathcal{Q}_t - C_t\dot{x}_t - K_tx_t \tag{4}$$

$$\mathcal{P}_e = \mathcal{Q}_g\Omega_g \tag{5}$$

In which $\mathcal{Q}_r$ and $\mathcal{Q}_t$ are aerodynamic torque and thrust, J_r and J_g are rotor and generator moments of inertia, ψ is the drivetrain torsion, $\mathcal{Q}_g$ and Ω_g are the generator torque and rotational speed, N_g is the gearbox ration, C_d and K_d are the drivetrain damping and stiffness factors, respectively, lumped in the low speed side of the shaft. The tower mass, damping and stiffness factors are represented by M, C_t and K_t, respectively, and $\mathcal{P}_e$ and x_t are the generated electrical power and tower displacement, respectively. Values of the parameters can be found in [19].

B. Linearized model

To get a linear model of the system we need to linearize the model (1-5) around its operating points, which are determined by wind speed averaged on the rotor area. Wind speed changes along the blades and with the azimuth angle (angular position) of the rotor. This is because of wind shear, tower shadow and stochastic spatial distribution of the wind field. Therefore a single wind speed does not exist to be used and measured in order to find the operating point. We bypass this problem by defining a fictitious variable called effective wind speed ($\mathcal{V}_e$), which shows the effect of wind on the rotor disc of the wind turbine. Using the linearized aerodynamic torque and thrust, state space matrices for the 3 DOFs linearized model become:

$$\dot{\omega}_r = \frac{\alpha_1(v_e) - c}{J_r}\omega_r + \frac{c}{J_r}\omega_g - \frac{k}{J_r}\psi \tag{6}$$

$$+ \frac{\beta_{11}(v_e)}{J_r}\theta + \frac{\beta_{12}(v_e)}{J_r}(v_e - v_t) \tag{7}$$

$$\dot{\omega}_g = \frac{c}{N_gJ_g}\omega_r - \frac{c}{N_g^2J_g}\omega_g + \frac{k}{N_gJ_g}\psi - \frac{Q_g}{J_g} \tag{8}$$

$$\dot{\psi} = \omega_r - \frac{\omega_g}{N_g} \tag{9}$$

$$\dot{x}_t = v_t \tag{10}$$

$$\dot{v}_t = \frac{\alpha_2(v_e)}{M}\omega_r + \frac{\beta_{21}(v_e)}{M}\theta + \frac{\beta_{22}(v_e)}{M}(v_e - v_t) \tag{11}$$

$$- \frac{C_t}{M}v_t - \frac{K_t}{M}x_t \tag{12}$$

$$P_e = Q_{g_0}\omega_g + \omega_{g_0}Q_g \tag{13}$$

In which the lower-case variables are deviations away from steady state of the upper-case variables given in the equations (1-5). Consequently, the parameters of the linearized model are functions of wind speed, which in our approach acts as a scheduling variable. A detailed description of the model and linearization is given in [9].

C. Linear parameter varying model

According to the model given in the equations (6-13), matrices of the state space model become:

$$A(\gamma) = \begin{pmatrix} \frac{\alpha_1(\gamma)-c}{J_r} & \frac{c}{J_r} & -\frac{k}{J_r} & 0 & -\frac{\beta_{12}(\gamma)}{J_r} \\ \frac{c}{N_gJ_g} & -\frac{c}{N_g^2J_g} & \frac{k}{N_gJ_g} & 0 & 0 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ \frac{\alpha_2(\gamma)}{M_t} & 0 & 0 & -\frac{K_t}{M_t} & -\frac{C_t+\beta_{22}(\gamma)}{M_t} \end{pmatrix} \tag{14}$$

$$C(\gamma) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & Q_{g_0} & 0 & 0 & 0 \\ \frac{\alpha_2(\gamma)}{M_t} & 0 & 0 & -\frac{K_t}{M_t} & -\frac{C_t+\beta_{22}(\gamma)}{M_t} \end{pmatrix} \tag{15}$$

$$B(\gamma) = \begin{pmatrix} \frac{\beta_{11}(\gamma)}{J_r} & 0 \\ 0 & -\frac{1}{J_g} \\ 0 & 0 \\ 0 & 0 \\ \frac{\beta_{21}(\gamma)}{M_t} & 0 \end{pmatrix} \quad D(\gamma) = \begin{pmatrix} 0 & 0 \\ 0 & \omega_{g_0} \\ \frac{\beta_{21}(\gamma)}{M_t} & 0 \end{pmatrix} \tag{16}$$

in which $x = \begin{pmatrix}\omega_r & \omega_g & \psi & x_t & \dot{x}_t\end{pmatrix}^T$, $u = \begin{pmatrix}\theta & Q_g\end{pmatrix}^T$ and $y = \begin{pmatrix}\omega_r & P_e & \dot{v}_t\end{pmatrix}^T$ are states, inputs and outputs respectively.

III. Controller Design

Wind turbine control is a challenging problem as the dynamics of the system changes based on wind speed which has a stochastic nature. In this paper, we use the wind speed as the scheduling variable. With the advances in the LIDAR technology [11] it is possible to measure wind speed ahead of the turbine and this enables us to have the scheduling variable of the plant for the entire prediction horizon. As it was mentioned in section II, wind turbines are nonlinear dynamical systems and if we use the nonlinear model directly in the MPC formulation, the optimization problem associated with the MPC becomes non-convex. In general, non-convex optimization problems are very complicated to solve and there is no guarantee that we could achieve a global optimum. One way to avoid complex and non-convex optimization problems is to linearize the system around an equilibrium point and use the obtained linearized model as an approximation of the nonlinear model. However, for wind turbines, assumption of the approximate linear model does not hold for long prediction horizons. This is because the operating point of the system changes as a function of wind speed which, as mentioned, has a stochastic nature.

A. *Problem formulation*

The linear parameter varying (LPV) model of the nonlinear system is of the following form:

$$\tilde{x}_{k+1} = A(\gamma_k)\tilde{x}_k + B(\gamma_k)\tilde{u}_k \tag{17}$$

This model is formulated based on deviations from the operating point. However we need the model to be formulated in absolute values of inputs and states. Because in our problem the operating point changes as a function of the scheduling variable, we need to introduce a variable to capture its behavior. In order to rewrite the state space model in the absolute form we use $\tilde{x}_k = x_k - x_k^*, \tilde{u}_k = u_k - u_k^*$, where x_k^* and u_k^* are values of states and inputs at the operating point. Therefore, the LPV model becomes:

$$x_{k+1} = A(\gamma_k)(x_k - x_k^*) + B(\gamma_k)(u_k - u_k^*) + x_{k+1}^* \tag{18}$$

which could be written as:

$$x_{k+1} = A(\gamma_k)x_k + B(\gamma_k)u_k + \lambda_k \tag{19}$$

with

$$\lambda_k = x_{k+1}^* - A(\gamma_k)x_k^* - B(\gamma_k)u_k^* \tag{20}$$

Now having the LPV model of the system we proceed to compute state predictions. In our method the predicted state is a function of the current state x_k, the control inputs u_n, as well as the scheduling variable $\Gamma_n = \left(\gamma_{k+1}, \gamma_{k+2}, \dots \gamma_{k+n}\right)^T$ for $n = 1, 2, \dots, N-1$ and we assume that the scheduling variable is known for the entire prediction. Therefore, the predicted state could be written as:

$$x_{k+1}(\gamma_k) = A(\gamma_k)x_k + B(\gamma_k)u_k + \lambda_k \tag{21}$$

and for $n \in \mathbb{Z}, n \geq 1$:

$$\begin{aligned} x_{k+n+1}(\Gamma_n) = &\left(\textstyle\prod_{i=0}^{n} A^T(\gamma_{k+i})x_k\right)^T \\ &+ \sum_{j=0}^{n-1} \left(\textstyle\prod_{i=1}^{n-j} A^T(\gamma_{k+i})\right)^T B(\gamma_{k+j})u_{k+j} \\ &+ \sum_{j=0}^{n-1} \left(\textstyle\prod_{i=0}^{n-j} A^T(\gamma_{k+i})\right)^T \lambda_{k+(n-1)-j} \\ &+ B(\gamma_{k+n})u_{k+n} + \lambda_{k+n} \end{aligned} \tag{22}$$

Using the above equations we can write down the stacked predicted state as:

$$X = \Phi(\Gamma)x_k + \mathcal{H}_u(\Gamma)U + \Phi_\lambda(\Gamma)\Lambda \tag{23}$$

After computing the state predictions as functions of control inputs, we can write down the optimization problem similar to a linear MPC problem as a quadratic program, more details can be found in [20].

B. *Control objectives*

The most basic control objective of a wind turbine is to maximize captured power during the life time of the wind turbine that is to to maximize captured power when wind speed is below its rated value. This is also called maximum power point tracking (MPPT). However when wind speed is above rated, control objective becomes regulation of the outputs around their rated values while trying to minimize dynamic loads on the structure. These objectives should be achieved against fluctuations in wind speed which acts as a disturbance to the system. In this work we have considered operation of the wind turbine in above rated (full load region). Therefore, we try to regulate rotational speed and generated power around their rated values and remove the effect of wind speed fluctuations.

IV. Uncertain LIDAR measurements

LIDAR measurements are used to have a preview of the wind speed [11], however these measurements are erroneous and uncertain. In this work, we have considered the uncertainties to be the measurement noise and uncertainty in the estimation of the wind propagation time. The propagation time is the time that the wind travels between the LIDAR measurement point to the rotor disc. The unknown delay is the most important uncertainty in the wind propagation time estimation. Lead or lag errors in the wind speed measurement, which is fed to the controller, severely reduce the performance of the controller. In order to bypass this problem, in this work, we have designed an Extended Kalman filter which estimates the effective wind speed on the rotor plane. Then this estimate is compared against the filtered information that comes from LIDAR measurements. Cross-covariance of the estimated wind speed and LIDAR measurements are used to get an estimate of the delay between the two signals. Subsequently, the estimated delay is compensated for in LIDAR measurements and the resulting wind speed information is fed to the controller.

A. *Wind speed estimation*

Wind speed estimation is essential in our control algorithm. A one DOF model of the wind turbine, including only rotor rotational degree of freedom is used for wind speed estimation. This model is augmented with a linear model of the effective wind speed. The effective wind speed can be modeled as a complicated nonlinear stochastic process. However, for practical control purposes, it could be approximated by a linear model [21]. In this model, the wind has two elements, mean value term (v_m) and turbulent term (v_t). The mean wind speed varies relatively slowly and could be considered constant during one simulation. The turbulent term could be modeled by the following transfer function:

$$v_t = \frac{k}{(p_1 s + 1)(p_2 s + 1)} e; \quad e \in N(0, 1) \tag{24}$$

The parameters p_1, p_2 and k which depend on the mean wind speed v_m could be found by second order approximation of the wind power spectrum [21]. This state space model

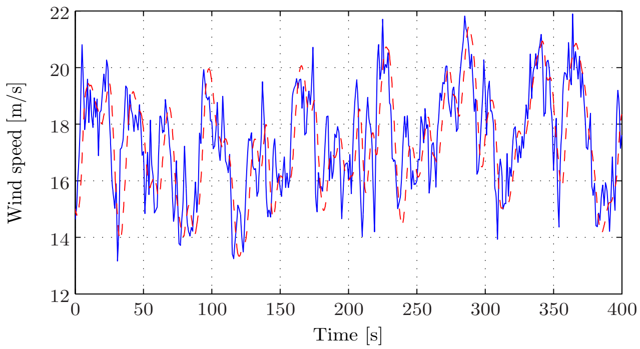

Fig. 1: Wind speed estimation (red-dashed line is the estimated wind speed and solid-blue line is the effective wind speed)

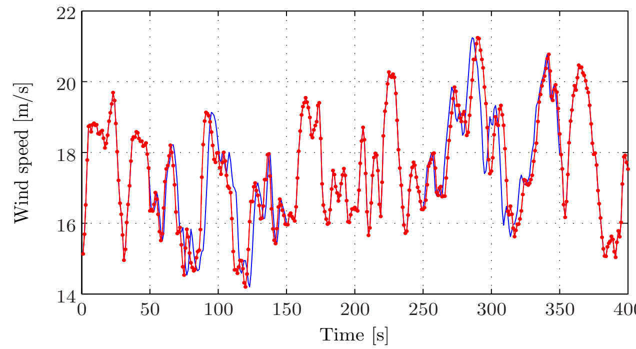

Fig. 2: Effective wind speed and LIDAR measurement with lead-lag errors (solid-blue is the effective wind speed, dotted-red is the LIDAR measurement)

is augmented with the following model to be used in the extended Kalman filter:

$$\dot{\Omega} = \frac{1}{J_r}\mathcal{Q}_r(\Omega, \Theta, \mathcal{V}_e) - \frac{1}{J_r}\mathcal{Q}_g \quad (25)$$

$$y = \begin{pmatrix}\Omega & \mathcal{P}_e\end{pmatrix}^T \quad (26)$$

Figure 1 shows wind speed and its estimate.

B. Lead-lag error estimation and compensation

For lead-lag error estimation, cross covariance of the estimated wind speed and measurements from the LIDAR for a window of size m-seconds is found. The result is a sequence which has $(2m-1)$ elements. By finding the maximum of the cross covariance, an estimate of the lead-lag error can be found. The window size is important as it should be long enough to avoid erroneous results. The errors especially emerge when the window of effective wind speed signal has big autocorrelation values. By choosing a window with sufficiently large size this problem could be avoided. However, choosing a too big window size will result in slow delay detection which reduces performance of the controller. Cross covariance of the estimated wind speed and LIDAR measurements, can be found using the following formula:

$$\phi_{\hat{v}v}(t) = E\{(\hat{v}_{n+t} - \mu_{\hat{v}})(v_n - \mu_v)^T\} \quad (27)$$

in which $\hat{v}$ is the estimated wind speed and v is the LIDAR measurements. Having the sequence of $\phi_{\hat{v}v}(t)$, one can calculate lead-lag error by the following formula:

$$t_e = \arg\max_t \phi_{\hat{v}v}(t) \quad (28)$$

in which $t_e = t_{\text{measurment}} - t_{\text{actual wind speed}}$. t_e is then passed through a low pass filter to remove fluctuations due to numerical errors and possible autocorrelations. Then it is used to shift LIDAR measurements. Afterwards the shifted signal is used in the controller. Figure 2 shows a comparison of the effective wind speed and the wind speed measured by LIDAR. There is a 4 seconds lead error at time $100s$ (in which the measurement is lead) and then at time $300s$ the same amount of lag error. Figure 3 shows a comparison between the introduced delay in the measurements and its estimation. The lead-lag error estimation is delayed, however it follows the shape of the actual delay. In the worst cases, when the LIDAR measurements does not give a good correlation with the wind speed estimation on the turbine, the measurements could be discarded and the turbine can operate without LIDAR measurements.

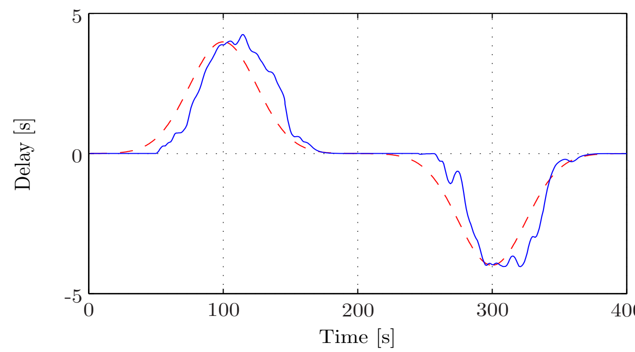

Fig. 3: Comparison of introduced delay and its estimation (solid-blue is the estimated delay, dashed-red is the introduced delay)

V. Simulations

In this section, simulation results for the obtained controllers are presented. The controllers are implemented in MATLAB and tested on a high fidelity wind turbine simulation software FAST [22] using the model of the reference wind turbine [19]. The results of the proposed approach with lead-lag error estimation are compared against two controllers with the same tunings. An MPC with the same LIDAR measurements but without error compensation and an MPC with re-linearization at each sample point based on estimated wind speed. Simulations are done using turbulent wind speed, with Kaimal model [23]. And TurbSim [24] is used to generate the wind profile. In order to stay in the full load region, a realization of turbulent wind speed is used from category C of the turbulence categories of the IEC 61400-1 [23] with the mean wind speed of $18m/s$. Control inputs are collective pitch of the blades θ and generator reaction torque Q_g. System outputs are rotor rotational speed ω_r, electrical power P_e and tower fore-aft acceleration $\ddot{x}_t$

TABLE I: Performance comparison (SD stands for standard deviation)

Parameters	MPC+LIDAR+ Compensation	MPC+ LIDAR	Linear MPC
SD of ω_r (RPM)	0.198	0.264	0.431
SD of P_e (M Watts)	0.108	0.123	0.179
Pitch travel (degrees)	554.8	606.5	842.9
SD of shaft moment (k N.M.)	0.702	0.812	1.159
SD of tower fore-aft acc.(m/s^2)	0.233	0.240	0.311

that are plotted in figures 4-8. Table I shows a comparison of the results between the proposed approach with lead-lag error estimation, the linear MPC based on estimated wind speed, the linear MPC with LIDAR measurements and without compensation. For comparisons, we have used pitch travel to take into account an approximation of the damage on the pitch actuator. Standard deviations (SD) of the rotational speed and generated power are also compared. As it in the table I and figures 4-8, the proposed approach gives better regulation on rotational speed and generated power (smaller standard deviations) while maintaining a smaller pitch activity and less deviations on tower fore-aft acceleration and drivetrain torsion.

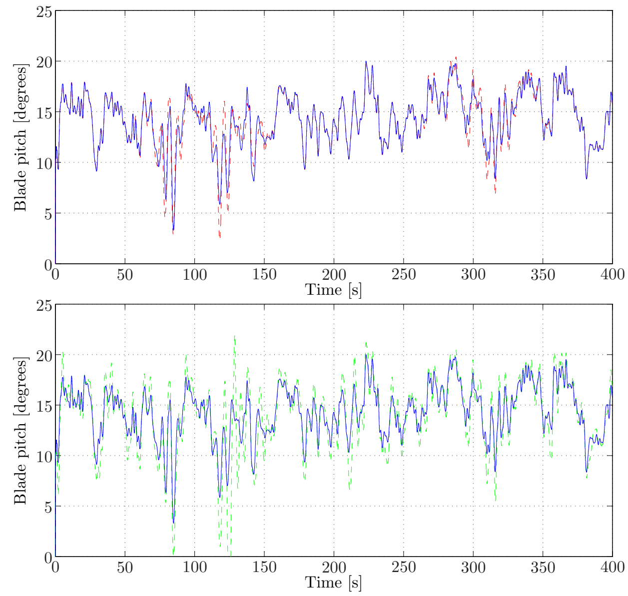

Fig. 4: Blade-pitch (degrees, solid-blue line is MPC with LIDAR and delay compensation, top figure: dashed-red line is MPC with LIDAR, without delay compensation and bottom figure: dashed-green line is linear MPC using estimated effective wind speed)

VI. Conclusions

LIDAR measurements are improve performance of wind turbines. However, errors in the calculation of the wind propagation time severely degrade the performance of the controller. In this work, we have shown that using appropriate signal processing techniques, these errors can be removed form the measurements and even in the worst cases, when LIDAR measurements are not reliable, the turbine can operate without using the data from the LIDAR.

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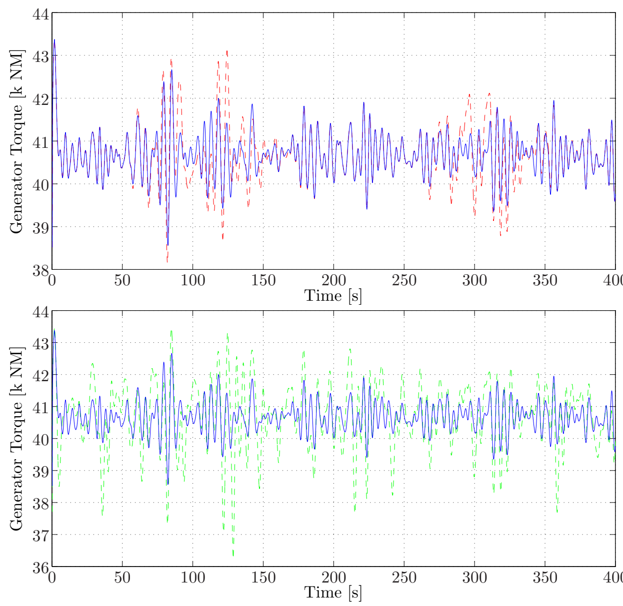

Fig. 5: Generator-torque (k NM, solid-blue line is MPC with LIDAR and delay compensation, top figure: dashed-red line is MPC with LIDAR, without delay compensation and bottom figure: dashed-green line is linear MPC using estimated effective wind speed)

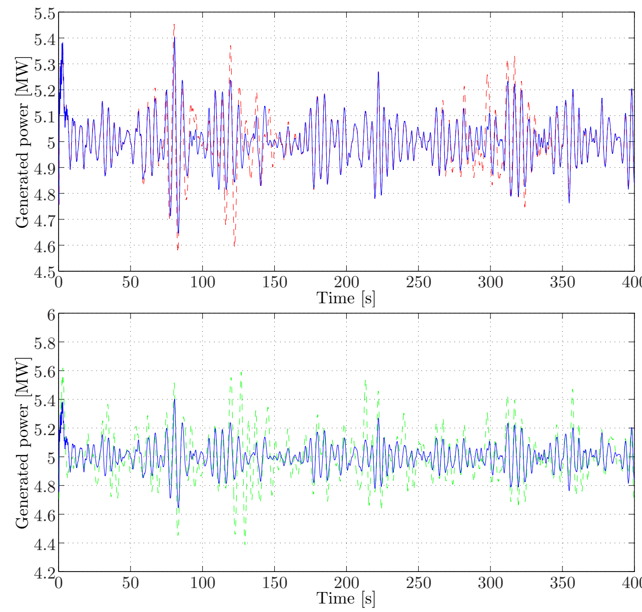

Fig. 7: Electrical power (M Watts, solid-blue line is MPC with LIDAR and delay compensation, top figure: dashed-red line is MPC with LIDAR, without delay compensation and bottom figure: dashed-green line is linear MPC using estimated effective wind speed)

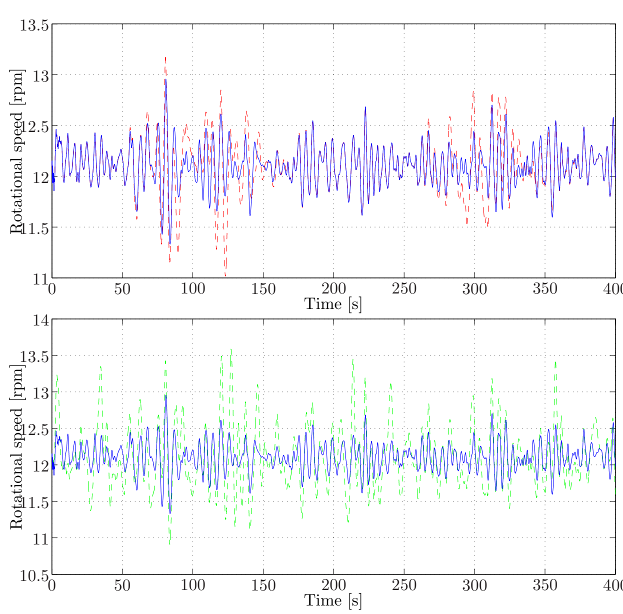

Fig. 6: Rotor rotational speed (RPM, solid-blue line is MPC with LIDAR and delay compensation, top figure: dashed-red line is MPC with LIDAR, without delay compensation and bottom figure: dashed-green line is linear MPC using estimated effective wind speed)

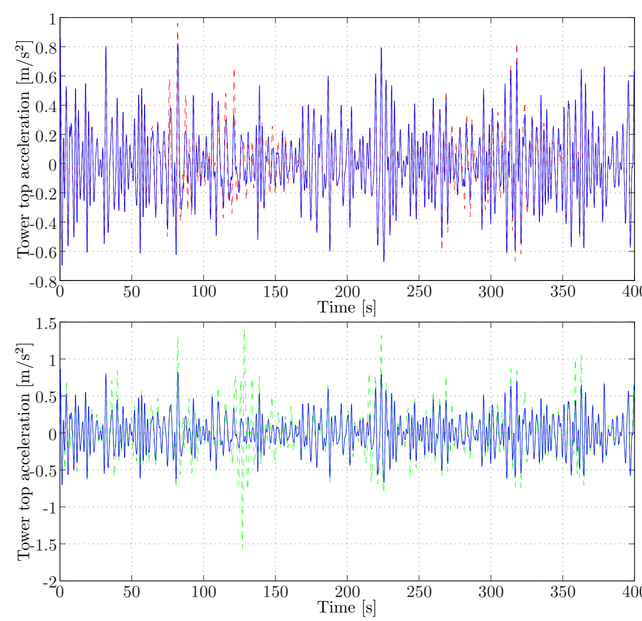

Fig. 8: Tower top velocity (m/s^2, solid-blue line is MPC with LIDAR and delay compensation, top figure: dashed-red line is MPC with LIDAR, without delay compensation and bottom figure: dashed-green line is linear MPC using estimated effective wind speed)