Systems Engineering for Lidar-Assisted Control: A Sequential Approach

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Abstract. This work presents a sequential approach to explore and optimize the benefits of lidar-assisted control for wind turbines. The optimization is divided in three steps: lidar hardware, lidar data processing, and feedback controller optimization. Appropriate optimization criteria and computational efficient models are used for the intermediate steps and energy production is optimized in the last step with a full aero-elastic model to provide an estimation of lidar-assisted control without the need of a detailed cost model. The case study shows that lidar-assisted control together with an adjustment of the power level are promising to extend the life-time of wind turbines and finally increase the energy capture.

1. Introduction
Lidar-Assisted control (LAC) is a promising technology to improve the control performance of wind turbines [1]. For the industrial use, the benefits in control performance need to be translated into economic benefits. This is a complex task due to the multi-disciplinary character of the problem involving meteorology, remote sensing technology, signal processing, controls and mechanics. In general, there are two scenarios for the application of LAC. First, the retrofit scenario, where a lidar system is installed on an already designed and installed turbine. Second, the integrated design scenario, where a lidar system is fully integrated into the systems’ design process of a wind turbine. In both scenarios, there are a large number of parameters impacting the economics. Here, the systems engineering initiative [2] provides methods and tools. Systems engineering has been already successfully applied to wind turbines [3] and wind farms [4]. Basically, the design process is considered to be a large optimization problem: the free parameters are used as optimization variables, constraints are defined in mathematical expressions, and economic considerations are translated into a cost function. The optimization problem is then solved automated by appropriate algorithms to find the best set of parameters. The crucial point here is to define appropriate interfaces for tools and to set up the optimization problem such that the algorithms are able to find the solution computationally efficiently.

This paper presents an initial application of systems engineering for lidar-assisted control to the retrofit scenario. It outlines how different tools can be combined to divide the process into three sub-problems which can be solved sequentially. In Section 2 the approach is detailed and in Section 3 the simulation scenario is described. Section 4 presents the results and Section 5 the conclusions.
2. A Sequential Approach to Systems Engineering for Lidar-Assisted Control

There are several parameter which impact the benefit of LAC in a systems engineering study. They can be clustered in parameters specific for the site, turbine, feedback and feedforward control, lidar data processing, and lidar data hardware. The most important ones are listed in Figure 1. The free parameters in this study are written in green. Eventually, the main goal of LAC is the maximization of the economic benefit within all possible constraints (mostly turbine and lidar hardware). In a monolithic approach for systems engineering, the optimal set of the free parameters can be determined by solving a very large constrained optimization problem maximizing the economic benefit, see Figure 2 (left). The advantage of such an approach is that all possible interdependencies of parameters are considered. However, a monolithic approach is computationally expensive and since it is a complex problem, special care is necessary to avoid the optimization algorithm to end up in a local minimum.

In this work, a sequential approach is presented, Figure 2 (right): In a first step, the lidar hardware is optimized to provide the best measurement coherence for the rotor-effective wind speed \([5, 6, 7]\). This decoupling is reasonable, since a lidar hardware providing the best correlated rotor-effective wind speed is optimal for all LAC setups rejecting this disturbance. Here, the measurement coherence bandwidth, the wavenumber \(k_{0.5}\) at which the coherence drops to 0.5 is maximized. When assuming isotropy, \(k_{0.5}\) can be considered to be inverse proportional to the "smallest detectable eddy size" \(d_{\text{eddy,min}}\), see Figure 3:

\[
d_{\text{eddy,min}} = \frac{2\pi}{k_{0.5}}. \tag{1}
\]

In this case, \(d_{\text{eddy,min}}\) is the size of the eddies which can be still detected with a 50\% level of the coherence. Normalizing \(d_{\text{eddy,min}}\) with the rotor size allows to have a measure independent of the rotor size. Detecting smaller structures than \(1D\) is not important for the proposed feedforward control, since collective blade pitch and generator torque impact the whole rotor at once. Usually a value of \(d_{\text{eddy,min}}\) close to \(1D\) indicates a very good lidar for fatigue load reduction. Improvements above this point are still possible, since in this case structures of \(1D\) size are captured by 50\% only.
In a second step, the lidar data processing is optimized to make best use of the information content within the signal. Again, this decoupling is reasonable, since all LAC setups using the rotor-effective wind speed will benefit from an optimal lidar data processing. Minimum lifetime weighted tower loads are used as a criterion. The lidar data processing consists of an adaptive filter used in several field testing campaigns, which aims to filter the rotor-effective wind speed estimate based on current correlation changing with the mean wind speed and to provide the signal with a fixed preview time to the controller. Simulation can be performed with a reduced simulation model to have less computational effort, since an accuracy of the load reduction is less important for this step.

In a third and final step, the feedback control parameters are optimized to maximize the economic benefit. In the considered retrofit scenario, LAC is used for life-time-extension. In this study we focus on balancing the load reduction over tower, blades and low-speed shaft. With detailed information of the load envelopes and a detailed cost model of all components, the structure could be also optimized in this step, but is out of the scope of this work. Since an accurate estimate of the load reduction is important in this step, a full aero-elastic simulation model is used.

In the following section, the simulation scenario is detailed.
3. Description of Simulation Scenario

In this section, the simulation scenario is briefly described.

3.1. Wind Turbine Model

In this simulation study, the NREL 5 MW reference onshore wind turbine with a rotor diameter of $D = 126$ m implemented in FAST [8] and SLOW [9] is used. The FAST sFunction is integrated in MATLAB Simulink and is extended by a collective pitch actuator implemented as linear second order model with a damping factor of 0.7 and a undamped natural frequency of 1 Hz. No further changes have been done to the FAST model. The advantage of the SLOW model compared to the FAST model is that simulations are much faster (up to $1000\times$).

3.2. Wind Disturbance and Lidar Simulator

For this study, a 4-beam pulsed nacelle lidar is simulated, see Figure 4. The opening angle is fixed to $\arctan(0.5/2.5) = 11.3$ deg, such that the lidar can be additionally used for power performance testing (at 2.5 rotor diameter, the measurements are on a circle of the size of the rotor). The minimum distance is limited to 40 m and the measurement rate is fixed to 4 Hz. For this study, 10 measurement distances and a Gaussian volume weighting function are considered.

In this study we focus on normal operations and thus a Design Load Case (DLC) 1.2 following current standard [10] is carried out, using eleven one-hour turbulent wind fields from 4 m/s to 24 m/s based on class IA, see Appendix C.3 of [9].

Further, a tool-independent lidar simulator is used [11]. In a first step, the tool calculates the auto-spectra and cross-spectra of the rotor-effective wind speed and its lidar-estimate based on [12]. The following effects are considered: the limitation to line-of-sight wind speeds, the spatial averaging of the range weighting function, the discrete scanning, wind evolution (using a longitudinal decay of $\alpha = 0.1$ for an exponential wind evolution model [13]), and wind field reconstruction (all line-of-sight wind fields are condensed to one estimate of the rotor-effective wind speed using a dynamic wind field reconstruction method [9]). In a second step, the wind fields are reduced to the rotor-effective wind speed. Further, the corresponding lidar-estimate of the rotor-effective wind speed is calculated with the auto-spectra and cross-spectra. The preview of the calculated signal corresponds to the measurement distances and the mean wind speed. The advantage of this method is that it can be combined with the trajectory optimization, which already calculates the auto-spectra and cross-spectra of the first step, and with both simulation tools.
3.3. Baseline Feedback, Feedforward Controller and Lidar Data Processing

For the baseline controller, a modified version of the NREL 5 MW reference controller [8] is used. The modifications are:

- The reference torque controller is replaced by a PI torque controller. In region 1.5 the rotor speed set-point is 8 rpm. In region 2, the limits of the PI torque controller are adjusted such that it follows the reference torque controller. In region 2.5 the rotor speed set-point is rated rotor speed. In region 3, the upper limit aims for constant power.

- The set-point of the pitch controller in region 2.5 and of the torque controller in region 3 is adjusted by a set-point fading based on [14] providing a smooth transition.

The advantage for this study is that the sowento FB controller is much closer to industrial standards, allows straight-forward adjustment of the rated power, and enables less loads (see Figure 5): the life-time-weighted Damage Equivalent Loads (DEL) at the tower base are reduced by 12.5%, at the blade root by 5.0%, and at the low-speed-shaft by 2.5%, while the maximum over-speed is at a comparable level (15% over all wind speeds).

For the LAC, the collective pitch feedforward controller combined with an adaptive filter [9] is used. The adaptive filter is a first order low pass filter which changes the cut-of-frequency $f_{\text{cutoff}}$ with the mean wind speed $\bar{u}$ depending on the maximum coherent wave number $k_{\text{max}}$. Further, the filtered signal is buffered such that it is provided to the feedforward controller with a fixed prediction time $\tau$ for all wind speeds.
Figure 6: Optimization of lidar hardware based on coherence model: left points (in black circles) are minimum distances, other points are last distances. The other 8 distances are equally distributed, respectively. Optimum in red circle.

4. Results
For simplicity, better illustration and to avoid local minima, brute force optimization is used for all optimization steps described in the following subsections.

4.1. Optimization of Lidar Hardware
In a first step, the lidar scan configuration is optimized using a frequency based correlation model [12]. Here, the measurement coherence bandwidth is calculated for several scan configurations and the one with the highest value is considered to be optimal. Several parameters can in theory be changed. Here we focus on the location of the 10 measurement ranges, where the first one is fixed to 40 m, the last one is the free parameter of the optimization, and the rest of the measurement distances is equally distributed between the first and the last one.

Figure 6 illustrates the results: For this turbine, site, and lidar constraints, the best scan from 40 m to 280 m reaches a $k_{0.5} = 0.0316 \text{ rad/m}$, corresponding to a smallest detectable eddy size of $d_{\text{eddy,min}} = 1.58D$. At a certain distance, no further improvement can be gained, since the effect of the wind evolution is increasing with distance and after $2.5D=315$ m the measurement will be outside of the rotor disc and thus less representative.

In this case combining multiple distances (here 10) with dynamic wind field reconstruction leads to better results compared to using a single distance alone. This cannot be generalized. An individual investigation for each lidar system is necessary. However, multiple distances have additional advantages, for example for extreme event detection, since large changes can be detected earlier by distances further away, and for differentiation of wind shears and wind direction.

Additional parameters such as the scan angles, the number of beams, scan rate, measurement volume etc. can be added to the optimization, but this is out of the scope of this work. More details about optimizing lidar systems for wind turbine control applications can be found in [7].
4.2. Optimization of Lidar Data Processing

In a second step, the optimal lidar hardware is used and the lidar data processing is optimized using DLC 1.2 simulations with the combined feedback-feedforward controller. Here, the SLOW model is used, since a full DLC 1.2 can be run in 10 s on a common PC. The free parameter are the feedforward prediction time and the maximum coherent wave number. The optimization criterion is the life-time weighted DEL of the tower base fore-aft bending moment \( M_yT \). The results are displayed in Figure 7. The optimal values are in this case a prediction time \( \tau \) of 1.6 s and maximum coherent wave number \( k_{\text{max}} \) of 0.028 rad/m.

4.3. Optimization of Combined Feedback-Feedforward Controller

Finally, the combined feedback-feedforward controller is optimized. Here, the FAST model, the optimal lidar scan configuration, and the optimal lidar data processing are used. LAC reduces significantly the tower and blade loads [9] but usually does not affect much the shaft loads. Increasing the rated power is not feasible in the retrofit scenario, if the margins of these loads or the power limit are already reached. However, LAC can be combined with de-rating the turbine for life-time-extension (LTE). The main optimization goal of this step is to increase the energy production by balancing the loss by de-rating and the gain by LAC.

The LTE potential for each component \( i \) based on the load reduction of the LAC compared to the baseline controller (FB) can be calculated by [15, 16]:

\[
\text{LTE}(i) = \left( \frac{\text{DEL}(i)_{\text{LAC}}}{\text{DEL}(i)_{\text{FB}}} \right)^{-m},
\]

where \( m = 4 \) is the Wöhler exponent for steel components (tower and shaft) and \( m = 10 \) for composite components (blades). Here, the tower base fore-aft bending moment \( M_yT \), the blade root out-of-plane bending moment \( M_{oop1} \) of blade 1, and the low-speed shaft torque \( M_{LSS} \) are considered. The overall LTE potential is then given by

\[
\text{LTE} = \min \{ \text{LTE}(M_yT), \text{LTE}(M_{oop1}), \text{LTE}(M_{LSS}) \}. 
\]

Finally, the increase in energy production \( \Delta \text{EP} \) can be calculated by

\[
\Delta \text{EP} = \text{AEP}_{\text{LAC}} \times \text{LTE} - \text{AEP}_{\text{FB}},
\]

where \( \text{AEP}_{\text{FB}} \) and \( \text{AEP}_{\text{LAC}} \) are the Annual Energy Production of the feedback controller and the LAC, respectively.
Figure 8: Optimization of de-rated feedback controller with LAC for different integration times $T_i$ and de-rating levels: Criterion is increase of energy production. Each point is based on a full DLC 1.2. Optimum is in red circle.

The optimization of $\Delta EP$ is done by changing two parameters: the integration time $T_i$ of the de-rated feedback controller (original value $2.33\, s$) and the percentage of de-rating. The gain scheduling parameter $\theta_k = 6.3\, \text{deg}$ and the proportional gain $k_p = 0.0188\, \text{rad/(rad/s)}$ are kept constant in this study for simplicity. Having the same proportional gain for feedback only operation and feedback with LAC operation is advantageous in a real application, since it allows to switch to the re-tuned controller without a step in the demanded pitch angle.

The results are displayed in Figure 8. The optimum is found for a de-rating level of $85\%$ and an integration time of $7\, s$, where the life-time weighted DEL of the tower fore-aft bending moment and the low-speed shaft torque are reduced by $11.8\%$ and $11.5\%$, respectively (see Figure 9 and 10). The maximum over-speed can be kept below the $12\%$ of the baseline controller. The life-time weighted DEL for the blade root bending moment are reduced by $6.4\%$ (not displayed).

With Equation (2), the life-time can be increased for the tower by $65.1\%$, for the blades by $93.7\%$, and for the low-speed shaft by $63.1\%$. An overall increase in life-time of $63.1\%$ (LTE = 1.631) for the entire wind turbine can be assumed with Equation 3: Instead of one year of feedback only control, the turbine can be operated $1.631$ years with additional LAC. Due to the de-rating of $85\%$, the AEP is first reduced from $\text{AEP}_{FB} = 25.8\, \text{GWh}$ to $\text{AEP}_{LAC} = 24.3\, \text{GWh}$ (-$9.17\%$). Due to the longer operation time based on the load reduction however, the increase in energy production $\Delta EP$ is $12.4\, \text{GWh}$ using Equation (4).

Assuming roughly $40\, \text{EUR}$ to be reasonable gain per MWh (income minus additional operation and maintenance cost), the economic benefit is $496,000\, \text{EUR}$ minus the investment of a lidar and additional costs for the certification and control adjustments. If the LAC is used for several years, the benefits will increase with the same investment.

Since in Equation (4) several assumption are made, this number should be considered as an indication. Further, the following effects have not been included in the simulations and will impact the results in a real application:

- Data availability: If the lidar signal is not available, the benefits are not accessible. However, the effect of data availability on the benefits can be assumed to be linear, if the loss of the signal is detected and the baseline control activated.
- Interactions of blade blockage: Since nacelle-based lidar system are mounted behind the rotor, some measurements are blocked by the blades. The effect is usually small, if the measurement rate is high enough.
- Terrain complexity: In this study, no specific terrain or inflow angle has been considered.
- The fatigue loads during normal operation are often not the design driver. Reducing the fatigue loads only might not necessarily lead to a life-time extension.
Figure 9: Details of optimization of de-rated feedback controller: Over-speed (top), reduction in shaft loads (center) and tower loads (bottom) by feedback with LAC compared to feedback only. Each point is a based on a full DLC 1.2. Optimum is in red circle and detailed in Figure 10.

Figure 10: Comparison of life-time weighted results from FAST simulations. Over-speed (top), shaft loads (center), tower loads (bottom). Feedback only (blue) and de-rated feedback with LAC (red, optimal case of Figure 9). Each point is based on a one-hour simulation.
5. Conclusions
This paper presents a sequential approach to determine the optimal setup for lidar-assisted control (LAC) for wind turbines and to assess the benefit by using this technology. Brute force optimization is done for better illustration and simplicity. In a first step the lidar hardware is optimized with a frequency based correlation model to provide a signal with the highest information content. In a second step, the lidar data processing is optimized with a reduced simulation model to best extract the information. In a third step, a feedback controller combined with LAC is optimized for a de-rated wind turbine with a full aero-elastic model to equally distribute the load reduction on tower, blades and shaft. For a fatigue-designed wind turbine, this would yield a life-time extension of roughly 7.6 months for each year, in which the turbine is operated with LAC, resulting in an increase of 48% in energy production.

Although the study is based on several assumptions, the results indicate that LAC with the current technology can provide an attractive return of investments. A more detailed study is planed in the scope of the IEA Wind Task 32 on lidar\textsuperscript{1} and Task 37 on systems engineering\textsuperscript{2}.

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\textsuperscript{1} www.ieawindtask32.org
\textsuperscript{2} www.windbench.net/iea37