Optimizing the Use of LIDAR in Wind Farms: Minimizing Life-Cycle Cost Impact of Yaw Error

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Abstract. Yaw error lowers the efficiency and reliability of wind turbines resulting in higher maintenance costs. LIDAR devices can correct the yaw error; however, they are expensive, which creates a trade-off between their costs and benefits. In this study, a stochastic discrete-event simulation model is developed that models the operation of a wind farm. We optimize the net present value (NPV) changes associated with using LIDAR devices in a wind farm to determine the optimum number of LIDAR devices and their associated turbine stay time as a function of number of turbines in the wind farm for specific turbine sizes.

1. Introduction

One of the contributors to the high cost of electricity production from wind farms is yaw error. Yaw error is the angle between the wind turbine’s central axis and the wind flow. Yaw error reduces the energy production while putting extra cyclic loads on the turbine’s components, which results in higher maintenance costs.

Inaccurate measurements of wind speed and direction result in formation of a bias in the yaw controller, which results in inaccurate measurements of yaw error known as static yaw error. Yaw error values observed in the field range from a few degrees to as much as 50°, with average values of approximately 7° [1], [2].

LIDAR devices can be used to measure the wind speed and direction ahead of the turbine by sending laser beams into the air ahead of the turbine. Particles carried by the free wind flow reflect the laser beam and by analysing the reflection, LIDAR can measure accurate wind speed and direction. The LIDAR data is then used to correct the yaw controller bias.

Although LIDAR technology has been around since the 1980s, the real breakthrough of using it in the wind industry did not happen until the past decade. As a result, it is still considered a niche technology with a large learning curve. Use of LIDAR in applications such as wind resource assessment and wind turbine performance improvements have given valuable experiences to the LIDAR manufacturers and farm operators. Continued improvements in optics, electro-optics, packaging and software have helped LIDAR technology meet the industry standards such as IEC, IEA, etc. However, there are still challenges to the widespread use of LIDAR on wind turbines for control applications. A large challenge for the future use of LIDAR is a lack of quantification of the trade-off between benefits and costs.

In this work, we develop a model that simulates the operation of a wind farm and calculates the cash flows associated with the wind farm. We then use net present value (NPV) as a metric and by
optimizing the difference in NPV for cases of with and without LIDAR, we determine how many LIDAR devices a wind farm requires and how often they need to be circulated in the wind farm in order to maximize the LIDAR’s value.

2. Modelling Approach

NPV is defined as sum of all cash flows through the life cycle of a project. In the case of a wind farm the expected commission of wind farm is 20 years. Cash flows can be positive (income) or negative (costs and investments). Equation 1 shows how NPV is calculated.

\[
NPV = \sum_{i=0}^{N} CF_i
\]

where:
\( CF \): discounted cash flows
\( N \): project period (e.g., number of time periods)

In order to evaluate the investment, two NPV cases are compared. The first case is a ‘no-LIDAR’ case where the operation of the wind farm through its lifetime is modelled without using LIDAR to correct the yaw error. The second case is a ‘LIDAR’ case where there are one or more LIDAR devices in the wind farm, circulating between turbines and correcting the yaw error. Two specific cash flows in wind farm operation are affected by yaw error, performance (revenue) and maintenance. The costs attributed to LIDAR are its procurement, the operation and maintenance of the LIDAR and its replacement. The LIDAR cash flow appears in the “LIDAR” case. The goal is to maximize the positive NPV change (\( \Delta NPV \)) between the LIDAR and no-LIDAR cases. Since we are calculating a difference between the NPV values, there is no need to calculate the wind farm cash flows that are not affected by LIDAR (i.e., they subtract out of the \( \Delta NPV \)).

2.1. Performance

Yaw error affects the wind speed on turbine blades by a \( \cos(\alpha) \) relation where \( \alpha \) is the yaw error value (Equation 2),

\[
V = V_{flow} \cos(\alpha)
\]

\[
P = \frac{1}{2} \rho AV^3
\]

where:
\( V \): wind speed on rotor
\( V_{flow} \): free wind flow speed
\( \alpha \): yaw error
\( P \): Power production
\( \rho \): air density
\( A \): rotor area

From a theoretical point of view, since the power production of a wind turbine relates to wind speed with a cube relation \( P \propto V^3 \), then the effects of yaw error on energy production should be translated as \( P \propto \cos^2(\alpha) \). Several studies examined this theoretical relation through experimental data or simulation [1]–[4]. Their work shows that the although \( \cos^2(\alpha) \) is a good estimate, for certain ranges of wind speeds \( \cos^2(\alpha) \) yields accurate results as well. In this work, in order to model the efficiency of wind turbines as a function of yaw error, we use the \( \cos^3(\alpha) \) relation. By doing so, we can calculate the performance related cash flows of a wind farm over its life-cycle operation period, which usually spans around 20 years. These are positive cash flows.

2.2. Reliability

Yaw error puts extra cyclic loads on some of turbine components such as blades, gearbox, yaw controller, etc. By reducing yaw error, these loads will be reduced, which delays the fatigue and
subsequence failure of these components. A model that calculates the reliability improvements of turbine components as a function of yaw error reduction was used to quantify the effects of yaw error on reliability improvements [5] (for example, a yaw error correction from 7° to 0° results in about 15% reliability improvement). In this work, it is assumed that the reliability values reported in [6]–[9] are for turbines with an average yaw error value of 7°, which is the reported observed average value by several studies [1], [2]. In this case study we use the 2-parameter Weibull reliability distribution information for the components failures from [6]. Table 1 shows the components and their reliability parameters.

| Component      | Scale Parameter (years) [6] | Shape Parameter [6] |
|----------------|-----------------------------|---------------------|
| Blade          | 10.32                       | 1.04                |
| Generator      | 27.43                       | 1.2                 |
| Gearbox        | 45.72                       | 1.83                |
| Pitch Control  | 4.72                        | 1.57                |

By using this model we will be able to calculate the failure time of various turbine components. The associated costs of maintenance that come with these failures make up the operation and maintenance cash flow of the wind farm during its commission period. These are negative cash flows.

2.3. LIDAR

An obstacle in widespread use of LIDAR is its cost. The costs of LIDAR have to be considered in conjunction with its potential benefits. The financial benefits of LIDAR will be reflected on improvements in levelized cost of electricity (LCOE). Reductions in costs of blades and tower will reduce the CAPEX. Reductions in structural loads of these components will improve their reliability and, as a result, the OPEX costs will reduce too, nevertheless improving in the efficiency of the turbine and increasing the average energy production.

Currently, there are various types of LIDAR devices in the market with a wide range of performance and costs. Sometimes, poor performance of the low-quality LIDAR devices damages the opinion of the decision-makers about the concept of using LIDAR in control applications. Overall, the benefits of using LDIAR and its associated costs have to be considered at the same time during the decision-making process. There exists a right balance between the performance and reliability improvements with the costs of LIDAR-assisted control solution that is a highly beneficial and profitable option for the OEMs and operators.

Using LIDAR adds an extra cash flow to the calculations, which is the cost of purchase (and repurchase) of LIDAR devices, their maintenance costs and the cost of circulating LIDAR devices between the turbines in the wind farm.

2.4. Model Implementation

The model is formulated in a discrete-event simulator where each wind turbine is considered as a system. The state of the system changes when an event occurs. Events could be a wind speed change, a failure event, a maintenance event, etc. Parameters that affect the events could be stochastic, for example, yaw error, reliability of the components and wind speed all have stochastic behaviour and follow probability distributions. A Monte Carlo methodology is used to perform the sampling.

In order to implement the model, two cases have to be considered. A no-LIDAR case, which simulates the operation of wind farm without LIDAR devices and under yawed conditions. The cash flows for this case only include performance and reliability cash flows.

The second case is the LIDAR case where there are one or more LIDAR devices circulating between turbines in the wind farm and correcting the yaw error on each turbine. This case has higher performance cash flows and lower maintenance cost cash flows. It also includes the LIDAR costs’ cash flow, which create a cost trade-off between benefits and costs of using LIDAR. By calculating
ANPV values, we can then optimize it to find the scenarios where the returns are optimum for the wind farm owner.

In order to compare the two LIDAR and no-LIDAR cases, there have to be dependencies between the two cases. These dependencies are referred to as identical timeline conditions, which means that the two cases have to share some external conditions in order to make the analysis meaningful. For example, at a certain time, the wind speed has to blow at the same speed for both the LIDAR and no-LIDAR cases. The only difference between the two cases would be the value of yaw error. Meeting the requirements of identical timeline conditions are more straightforward for the performance modelling than it is for reliability. Details of how to model this for the maintenance of turbines is thoroughly explained in [10].

3. Modelling Results

We consider a case study where there are one or more LIDAR devices that circulate between the wind turbines. Each LIDAR stays on a turbine for a period of time, which we call the “stay time”. During this period, LIDAR collects the necessary data for calibrating the wind turbine controller. The collected data is used to correct a bias that results in the yaw error formation. At the end of the stay time, the LIDAR is moved to another turbine that has large yaw error values\(^1\). Each calibrated yaw controller loses its calibration over time, and therefore requires subsequent LIDAR visits.

The costs of components are calculated using a cost model developed by [11]. Other maintenance costs such as costs of personnel, transportation, etc., are taken from [12], see Table 2. The maintenance strategy is assumed to be a combination of corrective and predictive maintenance similar to what explained in [13], [14].

| Model Input                        | Value  | Unit            |
|-----------------------------------|--------|-----------------|
| Discount Rate                     | 7%     | per year        |
| Energy Price                      | 0.144  | $/kWh           |
| LIDAR Price                       | 120,000| $/unit          |
| LIDAR Maintenance                 | 12,000 | $/unit-event    |
| Turbine Downtime Due to LIDAR Circulation | 1      | day (Installation/Uninstallation) |
| Transportation Cost               | 2000-5000 | $/day       |
| Number of Personnel Required      | 2-10   | per event       |
| Number of Hours                   | 6-12   | per day-personnel |
| Number of Days                    | 1-4    | per event       |
| Hourly Wages                      | 100    | $/hour          |
| Yaw Error Regression Profile      | 2      | years           |

In order to calculate the energy production of each wind turbine, the wind speed distribution of an offshore site in Delaware is used to calculate wind speeds. 10-minute wind speeds are used in conjunction with power curves of a 4MW wind turbine to calculate the power generation. An energy sale price of 0.144/kWh was used to calculate the revenue generation of turbines. The LIDAR devices used in this study cost $120,000 each and have a 10-year life and require maintenance every 2 years that costs $12,000/device.

An example result for a case with and without LIDAR is shown in Figure 1. By varying the stay time of LIDAR devices on the turbines for a 50-turbine farm with 5 LIDAR devices we determined

\(^1\) Supervisory Control and Data Acquisition System (SCADA) continuously monitors many parameters associated with each wind turbine. One of these parameters is the power production. If a turbine is producing much less power than it is expected to, this will be contributed to presence of large yaw error values.
that an 8 week stay time was optimum and resulted in the distribution of ΔNPV shown in Figure 1. Since the ΔNPV value is positive, this is considered as a good investment.

![Graph showing distribution of ΔNPV values](image1)

**Figure 1** - Distributions of ΔNPV values for 50 turbines with 5 LIDAR devices and 8 weeks stay time

Figure 2 shows an example result for the 50-turbine wind farm where ΔNPV is maximized in each case. With less circulation, the costs of circulating the LIDARs decrease. There is a downtime associated with each installation/uninstallation of a LIDAR device on a turbine, therefore less circulation is better. However, less frequent circulation may result in turbines that operate at large values of yaw error. When there are more LIDAR devices in the farm, the chances of having more turbines with large yaw error values decreases.

![Graph showing ΔNPV values](image2)

**Figure 2** - ΔNPV values for 50 turbines with 5 LIDAR devices and variable stay times

In the next step, we produce similar results to Figure 2 for different number of LIDAR devices in the wind farm to see which scenario results in the best returns for the case of 50 turbines in a wind farm. The results are shown in Figure 3.

![Graph showing results for different LIDAR devices](image3)

**Figure 3** - ΔNPV values for different number of LIDAR devices in the wind farm

From Figure 3, we can see that ΔNPV values fall after 17 LIDARs, which means that the costs of LIDAR begin to outweigh its benefits. Another observation from Figure 3 is the presence of several optimal cases. For example, 13, 16 and 17 LIDAR devices all have the same returns. This shows that
the optimum case is not unique and with different circulation policies, i.e., a fewer number of LIDAR devices but faster circulation, the farm owners could potentially get the same high returns.2

Lastly, we can repeat the same process and generate a plot that shows the optimum number of LIDAR devices for a wind farm for various numbers of turbines. This is shown in Figure 4. These are the values for cases with the fewest number of LIDAR devices that maximized the returns.

4. Conclusions

In this work, we developed a stochastic cost model, which is able to calculate the optimum number of LIDAR devices and their associated stay time on wind turbines as a function of turbine size and the number of turbines in a wind farm. The results show that as the number of turbines in the farm

2 The three optima shown in Figure 3 are only approximately the same as the results are only plotted to the nearest $100K. The results in Figure 3 for the ΔNPV are also the means for probability distributions of the ΔNPV. For practical purposes, the three results (13, 16 and 17 LIDAR) are the same.
increases, the optimum number of LIDAR increases (this is intuitive), but the results also show that there is no single optimum scenario for a specific wind farm. Optimum scenarios with fewer LIDAR devices that have a faster circulation time are approximately equivalent to scenarios with more LIDAR devices that have a shorter circulation time. More extensive modelling and results are included in [15].

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