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A Return on Investment Model for the Implementation of New Technologies on Wind Turbines

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***Abstract*— Renewable energy from wind and solar are considered to be the main alternatives to fossil fuels. The costs of renewable energy technologies are high and without tax credits they are not currently competitive with fossil fuels in many markets. Improvements in the performance or reduction in operational costs will have significant impacts on the price of renewable energy and ultimately impact their competitiveness. New technologies targeted at improving the efficiency of the current systems or reducing their life-cycle costs will help, however these technologies are expensive and detailed cost tradeoff and return on investment (ROI) analysis is required to make business cases for them. In this paper we formulate an ROI model and describe its implementation in a stochastic discrete-event simulator to calculate financial tradeoffs and enable business cases for technology insertion into wind farms. The new ROI model includes changes in revenue and operations costs (including changes in reliability due to the technology insertion) and introduces the concept of identical timeline conditions to guarantee a meaningful ROI calculation. A case study for using LIDAR to increase the efficiency and improve the reliability of wind turbines in a wind farm is provided.**

***Index Terms*—Wind Energy, Cost Modeling, Return on Investment, ROI, Monte Carlo Simulation, Discrete-Event Simulation, Economic Analysis, LIDAR, reliability**

I. INTRODUCTION

ISSUES with fossil fuels such as a climate change, market volatility, geopolitical concerns (energy security), and pollution have convinced many nations to look to alternative sources of energy. Wind energy is a sustainable source of energy that many countries are considering as a replacement for fossil fuels. The potential for wind energy production in the United States is 32,000 TWh for onshore and 17,000 TWh for offshore installations [1]. The American Wind Energy Association (AWEA), reported that in November 2015, United States surpassed 70 GW of wind power production [2]. Currently nearly all US wind energy production is onshore with several offshore projects under study or construction [3]. With a 5-year extension of the Production Tax Credits (PTC) in the US 2016 budget, it is expected that more onshore and offshore projects will come online in the near future. By 2050, 80% of US energy consumption could be generated from renewable sources [4-5].

The total life cycle of a wind farm can extend more than 30 years (this includes site exploration, commissioning, lease, construction, operation and decommissioning), however, the operation period of a wind farm is usually 20 years (also referred to as support time). Costs occurring in this period are called operation and maintenance (O&M) costs and are the second largest cost contributor (behind the capital costs) to the total life-cycle cost of a wind farm. For example, in offshore installations, O&M costs represent between 24 to 31% of the total life-cycle costs [6].

During the support time, the wind farm operation generates revenue, which is a positive cash flow. The O&M costs throughout the life cycle generate a negative cash flow. Turbine manufacturers and farm owners constantly look for ways to increase the revenue cash-ins and reduce the costs, i.e., cash-outs. This can be achieved by adopting new methodologies in O&M, spare parts inventory management, making design changes to reduce the material and manufacturing costs, adding new technologies that increase the revenue production, implementing systems that extend maintenance cycles, etc. All of these methods or technologies require an investment, and in order to evaluate their financial benefits, a return on investment (ROI) analysis is required.

An ROI model for evaluating new technologies for renewable energy sources has to include the effects of the technology on both revenue production increases and O&M cost avoidances. The ROI model covers the cash flows during the support time and is a useful tool for the wind farm owners and operators. In this paper, we are focusing on the implementation of technologies that are used to improve the existing installed or soon to be installed systems (the technologies we are interested in are not necessarily included in the system at the design stage, and they may be added later in the turbine's life-cycle). It is important to point out that this paper investigates the ROI of adding technologies to the renewable energy systems and not the general ROI of using renewable energy.

The ROI model described in this paper is stochastic, meaning it considers the probabilistic nature of model inputs such as

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wind speed and the failure distributions that describe a component's reliability. In the case of revenue generation, probability distributions for wind speeds will be used in conjunction with the turbine's power curve for the stochastic analysis as opposed to a deterministic approach, which usually uses the capacity factor to calculate an average of energy production over a period of time. The model is implemented in a discrete-event simulation (DES) where failures and their subsequent maintenance activities are the events that change the state of the system (a wind turbine). The definition of failure in this paper is an event that requires a maintenance activity. Occurrence of a failure may or may not result in a complete shut-down of the system and the subsequent maintenance event could be activities such as repair, replacement or just an inspection.

O&M cost modeling includes two steps. The first step is the reliability modeling of the components where the failure occurrence and their timings are modeled. In this step, reliability parameters for components are used to predict a failure time; these are the failure events in the DES. The second step is modeling the maintenance activities and their associated costs. Maintenance activities are based on the maintenance policy where farm operators perform maintenance actions that can be corrective (break-fix), preventive (scheduled routine maintenance) or predictive (condition-based maintenance). These are the maintenance events in the DES.

The ROI model described in this paper captures the changes that the insertion of a new technology will induce on the reliability of turbine components, independent of the maintenance strategy. In other words, the O&M cost variations solely due to changes in the timing of the failures will be accounted for even in cases where their subsequent maintenance actions stay the same.

A. Literature Review

There are many existing studies addressing O&M cost modeling of wind turbines and their optimization, these studies generally target finding the best maintenance policy, e.g., [7-12]. These works focus on calculating the maintenance costs of turbines (a single turbine or a group of turbines) through analytical methods [7–9] or simulation [10–12] over a specified period of time.

Many studies have investigated the financial benefits of implementing condition monitoring systems (CMS) on wind turbines, e.g., [13-21]. These studies investigate the changes in the O&M costs after implementing the CMS systems. The reference case in these studies is generally a maintenance policy without the CMS and then the technology insertion case is a new maintenance policy with CMS. The financial benefit is the difference in the O&M costs between the two cases. The focus of these studies is minimizing the cost of resolving (or avoiding) failures. As for generating failure times, some studies use failure rates [13-17] to generate a failure time while others consider the stochastic nature of the failure occurrences and use reliability distributions [18-20]. In [18–20], failure times were generated stochastically and the same values were used for the cases with CMS and without CMS.

Works that expressly calculate ROI are rare. May et al. [15] used a hidden Markov method to model O&M costs of a wind farm by generating failure times using components' failure rates. They use a preventive maintenance strategy as a reference case and CMS based predictive maintenance as the technology case. They discuss ROI qualitatively but did not calculate any values. Erguido et al. [21] investigated the effects of using CMS on maintenance through simulation. Although their work is primarily focused on maintenance modeling and cost calculations, they introduce an ROI formula that only includes revenue parameters and then use it to calculate a deterministic ROI associated with several scenarios.

While the existing models provide the tools needed to calculate the O&M costs and quantify the economic benefits of changing the maintenance policy of wind turbines, they are not generally capable of calculating the ROI for the cases where a new technology changes the reliability of turbine components.

In other (non-wind) fields such as electronic systems, stochastic ROI models for the implementation of condition monitoring systems have been developed [22-23], but these models also only focus on changes in the maintenance policy due to the implementation of CMS. They are not capable of incorporating revenue generation and do not accommodate the calculation of ROI if the reliability distributions are affected by technology insertion.

Although there are some O&M models that consider the stochastic nature of the parameters, an ROI calculation (see Section II) when the new technology affects the reliability of the components is considerably more complicated than simply running an O&M model with and without the technology insertion and comparing the results. For example, in works by Besnard et al. [18] and Van Horenbeek et al. [19], the reliability distributions remain unchanged and can be used for the two cases of with technology and without technology, but this is not a feasible approach in cases where the reliability distributions change. In order to make a viable comparison for the cases of with and without technology in a stochastic model, the two cases have to have identical conditions to make the analysis meaningful, and insuring identical conditions is non-trivial (see Section III).

In this study, we formulate an ROI model, explain its application in a stochastic model for cases where the new technology changes the reliability of the system and illustrate its implementation with a case study. In the case study the particular technology insertion of interest is light detection and ranging (LIDAR) systems on wind turbines, which impacts both the reliability of key subsystems and the efficiency of the turbine, subsequently effecting the turbine's revenue generation.

II. ROI Model Formulation

The common definition of ROI is the ratio of gain as a result of an investment to the investment,

$$\text{ROI}=\frac{\text{Return-Investment}}{\text{Investment}} \tag{1}$$

For the applications considered in this paper, investment cost is the cost of purchasing the technology, maintaining it, keeping an inventory of the spare parts needed to support the technology and any other costs directly associated with the technology.

'Return' are the changes that the investment makes to the life-cycle cost of the system. Return, in the context of this paper, is a combination of revenue increase due to additional energy generation and avoided cost due to reliability improvements. 'Return' is cumulative, which means that at any instant in time, the value of the 'return' is the accumulation of all 'returns' from time zero to that instant in time. The 'return' and 'investment' terms are calculated using a DES, and since the DES models a timeline, ROI is a function of time. At the beginning of time, the 'return' is zero so the ROI is -1. As the time progresses, depending on the financial effects of the investment, the ROI moves away from -1 in either direction. Depending on the expected life of the new technology (if it has a lifespan that is less than the system it is added to, it will have to be purchased again), the investment costs and the recurring maintenance costs become functions of time as well.

During the support time, a wind farm produces energy, which generates revenue and also requires maintenance that costs money. Any new technology that is implemented on a wind turbine, can affect either the revenue or maintenance costs or both. If the new technology lowers the O&M costs, this would be considered avoided costs.

The 'return' in (1) can be expanded to include the returns due to both O&M cost avoidances and the extra revenue generation (revenue gain),

$$\text{ROI}=\frac{(AC+RG)-I}{I} \tag{2}$$

where:

AC = avoided costs
RG = revenue gain
I = investment

In order to calculate the 'avoided costs' the total life-cycle cost (LCC) of the wind farm during the support time has to be considered. LCC includes all the maintenance costs ($C_{O\&M}$), inventory costs (C_{inv}), recurring leasing costs (C_L), insurance costs (C_I), administrative costs (C_A) and any other costs (C_{oth}).

$$LCC = C_{O\&M} + C_{inv} + C_L + C_I + C_A + C_{oth} \tag{3}$$

Avoided costs are the difference between the LCC for the cases with and without the technology insertion:

$$AC = LCC_{no\text{-}tech} - LCC_{tech} \tag{4}$$

Costs that are not affected by the insertion of the new technology will be the same with and without the new technology and are considered to be a zero net sum gain or loss. If, for example, the insertion of a new technology does not affect any of the cost contributions in (3) except the $C_{O\&M}$ (this is the situation in the case study discussed in Section IV), then (4) becomes a function of only the O&M costs:

$$AC = C_{O\&M_{no\text{-}tech}} - C_{O\&M_{tech}} \tag{5}$$

The 'revenue gain' calculations are straightforward. The 'revenue gain' is simply the difference between the revenues with and without the new technology insertion.

$$RG = R_{tech} - R_{no\text{-}tech} \tag{6}$$

By substituting (5) and (6) into (2), the relation for the ROI becomes:

$$\text{ROI} = \frac{(C_{O\&M_{no\text{-}tech}} - C_{O\&M_{tech}}) + (R_{tech} - R_{no\text{-}tech}) - I}{I} \tag{7}$$

It is important to pay attention to the meaning of the two 'returns', the O&M 'return' (AC) is less money spent for the maintenance of the wind turbines, while the revenue 'return' (RG) is extra money generated due to better performance (higher efficiency) of the turbines.

Although (7) is relatively simple, the real challenge is how to implement the solution so that "identical timeline conditions" (defined in Section III) are enforced when the costs and revenues in (7) are computed in a stochastic environment.

III. ROI Model Implementation

The ROI model in this paper has been implemented as a stochastic discrete-event simulation (DES) that models a timeline of events whose order is determined by sampling the reliability distributions of the components.[1] The timeline is then costed, and the process is repeated many times to construct appropriate statistics.

A. Identical Timeline Conditions Requirement

Calculation of the ROI is performed using a Monte Carlo analysis approach that requires dependent sampling of parallel life cycles for cases with and without technology insertion. The ROI calculation is the comparison of two cases consisting of a base or 'no-tech' situation, which is the operation of the system without the new technology and a new situation or 'tech' situation, which is the operation of the system after the insertion of the new technology. In order to make a viable comparison,

[1] An alternative solution would be to use renewal functions. While using renewal functions is more computationally efficient, it represents an analytical simplification of a sequence of events. The DES is an actual model of the real (sampled) sequence of events. A renewal function determines how many renewals occur during a chosen period of time, but does not determine the actual times when those renewals take place and a renewal function cannot provide the sequence of events when multiple different components are involved. In addition, renewal functions implicitly assume that the reliability distribution is the same before and after a maintenance event, which may not be the case. We have used DES because it allows more fidelity in the cost modeling process and the identical timeline conditions constraint imposed by the ROI calculation creates a dependency between the technology and no-technology cases, which is not straightforward to model with renewal functions.

the two cases have to be evaluated under 'identical timeline conditions', which means that the external conditions that contribute to the timing and/or costs of the events are the same, e.g., wind speeds and energy prices. The external conditions may be sampled from distributions but the same sequence of samples at the same times must be used. For example, a wind turbine without LIDAR is subjected to 15 m/s wind at 10:00 am on August 1, 2017 when the energy price is 0.2 $/kWh. The same turbine with LIDAR must also be subjected to 15 m/s wind at 10:00 am on August 1, 2017 when the energy price is 0.2 $/kWh. This example, demonstrates identical timeline conditions. In this simple example, the price paid for the energy generated is the same, but the revenue may be different because of the improved efficiency of the turbine. In this case, the requirement for identical timeline conditions for revenue is met by using identical wind speeds for both cases.

The case for failure times is not as straightforward as wind speeds. Component failures are a function of various parameters, material microstructures, environmental conditions, etc. The environmental conditions put loads on the components (here we only focus on cyclic loads and not overstress loads), which cause stresses. These stresses will eventually result in component failures. If new technologies can be adopted that decrease the loading on a component, a subsequent reliability improvement can be obtained. This will change the reliability distributions of the components.

It is challenging to compare the two cases under identical timeline conditions when the reliability inputs of the model are stochastic and a DES is used. In order to construct the timeline, probability distributions corresponding to the reliability of components are sampled to get failure times and their subsequent maintenance events, which then will be costed. If there was only one case in the analysis (e.g., *no-tech*), this could be done using straightforward Monte Carlo analysis. However, when there are two cases (such as those compared in the ROI calculations) with reliability distributions that change, the analysis becomes complicated due to stochastic nature of the inputs. Obviously when the reliability distributions change due to the implementation of a new technology, identical failure time samples cannot be used (unlike the wind speed samples that were used for both cases). On the other hand, running Monte Carlo twice (once for *tech* and once for *no-tech* case) independent of each other will not guarantee the identical timeline conditions. Even more important, once the reliability of the components are improved, the new failure times have to be later than the failure time for the *no-tech* case.

Details on how the identical timeline conditions are implemented are provided in the Appendix. The Appendix also discusses the specific implementation of the identical timeline conditions to systems where the technology insertion changes the reliability of the system.

IV. LIDAR Implementation Case Study

In this section, we implement the methodology for calculating the ROI for the use of LIDAR devices on wind turbines. LIDAR devices are mounted on the turbine nacelle and use laser beams to detect the wind speed and direction ahead of the turbine. The information can then be used for the minimization of yaw error. Yaw error is the angle between the wind flow direction and the rotor's central axis in the horizontal plane. The presence of yaw error reduces the energy production of the turbine (less revenue) and puts extra cyclic stresses on components, which results in earlier than expected failures and subsequent maintenances (greater O&M costs). Note that LIDAR has many other applications such as collective pitch control to reduce the structural loads on the turbine, power curve measurement, etc. In the example in this study, we only consider LIDAR's minimization of the yaw error and its effects on turbine efficiency and reliability.

The ROI model is implemented for a wind farm consisted of 50 turbines. The turbines have a power rating of 4.2 MW, hub height of 135 m and rotor diameter of 127 m is assumed with cut-in speed of 3 m/s, cut-out of 25 m/s and rated speed of 14 m/s. Figure 1 shows the turbine's assumed power curve.

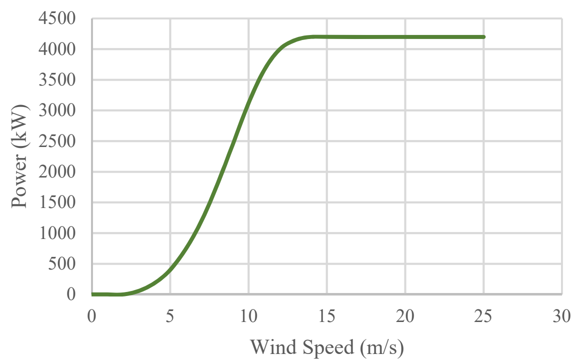

Figure 1- Power curve of a 4.2 MW wind turbine

The system is a single turbine where we assume that the failure of a single component results in the total shut down of the turbine. The turbine is assumed to have only two states, operational and stopped. There are 5 components modeled for the turbine: blades, gearbox, generator, pitch control and the electronics. There are various studies that investigated the reliability of turbine components, e.g., [24–27]; here we use the values from Spinato et al. [26], where failure is defined as the total loss of functionality for the component and each failure results in a component replacement. In this case study, only failure events that result in a component replacement are considered, i.e., no repairs are considered. The reliability modeling is stochastic and failures follow 2-paramter Weibull probability distributions. Failures and their subsequent maintenance events are modeled in a DES. Maintenance is predictive for the first four components and corrective for the electronics. It is assumed that upon receiving an alert from the monitoring system, a maintenance crew will be deployed to perform the required maintenance. The replacements are assumed to be as good as new. Each maintenance event leads to a downtime of the turbine. Maintenance costs consist of the replacement component costs, transportation, labor, installation, etc. The maintenance event costs are assumed to remain the same over the support life of the turbine. Table I shows the Weibull parameters that describe the failure of the

TABLE I
MAINTENANCE INPUT PARAMETERS FOR THIS CASE STUDY

Component	Scale Parameter (years) [26]	Shape Parameter [26]	Average Downtime (days) [28]	Average Maintenance Cost ($) [13]
Blade	10.323	1.042	7	200,000
Gearbox	45.72	1.835	5	300,000
Generator	27.43	1.2	3	150,000
Pitch Control	4.72	1.57	2	50,000
Electronics	1.471	0.87	3	10,000

components [26], maintenance costs [13] and the downtimes associated with each failure [28].

All cash flows are discounted to year 0 using a discount rate of 7%/year. The terms used in the ROI calculation in (7) at a particular point in time are the present value of all cash flows from the beginning of support time to that point in time.

Yaw error affects the reliability of the first 4 components in Table I. It is assumed that the reliability parameters in Table I represent cases where there is an average of 7˚ yaw error. This is the average value observed in the field [29]. It is assumed that the LIDAR can reduce the yaw error values to as low as 0˚. We assume that this will result in a 20% improvement in the reliability. The calculations for reliability improvement come from an earlier study [30] where results from an aero-elastic analysis [31] were used in a Basquin model to calculate the relation between reliability and stresses. It is important to point out the uncertainties associated with aero-elastic models, where the output of the model can have significant uncertainties (for further discussion on this topic see [32–35] and Section IV.B of this paper). In the Weibull distribution, the scale parameter represent 63% unreliability (63% of the samples have failed by the scale parameter time), therefore, a 20% improvement in reliability, translates into a 20% improvement in the scale parameter.

The assumed mechanism of yaw error correction using LIDAR is as follows. There is a single LIDAR device for the whole farm. The LIDAR will be installed on the turbine's nacelle for a period of time, collects data that will be used to correct the yaw error on that turbine. After two weeks, the LIDAR will be taken down and moved to the next turbine in the farm. With 50 turbines in a farm and a single LIDAR, each turbine gets the LIDAR once every two years. After the LIDAR is removed from the turbine, the yaw error remains minimized for a period of time and then regresses back to an uncorrected value (7˚ in this example) as shown in Figure 2.

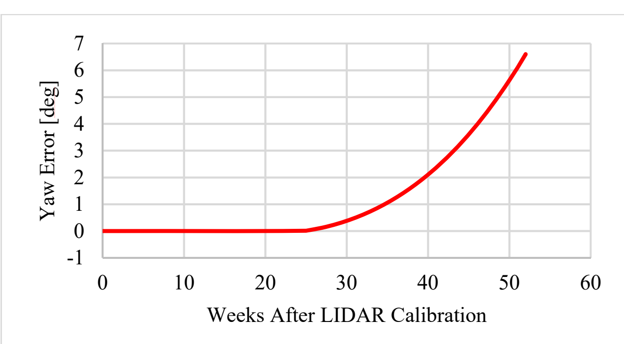

Figure 2- Yaw regression over time after LIDAR correction

Yaw error affects the speed of the wind flow as shown in (8). This means that the presence of yaw error lowers the wind speed on the blades.

$$V_{yawed} = V_{flow} \cos^3(\alpha) \tag{8}$$

where:
V = wind speed
α = yaw error

In order to calculate the power production, wind speeds are sampled from the corresponding distribution, effects of yaw included, then the corresponding power based on the turbine power curve shown in Figure 1 is calculated. The same wind speeds are used for both cases of LIDAR and no-LIDAR as described in Section III, however the yaw error for the two cases are different. The no-LIDAR case has a high yaw error (e.g., 7˚), while the LIDAR case has a lower yaw error determined from Figure 2.

The LIDAR purchase price is assumed to be $120,000. The life span of a LIDAR is 5 years and a new LIDAR has to be purchased after this period is over. The LIDAR maintenance costs are $12,000 every 2 years. The costs of LIDAR, which are the 'investment' costs in the ROI formulation, are discounted using a 7%/year discount rate like the other cash flows. In this case study, the costs associated with circulating the LIDAR between turbines are not included.

A. Case Study Results

The model using the methodology explained in Sections II and III, was used to generate the progression of ROI values for the entire wind farm over time. At one-year time increments, the costs for the particular year were calculated, discounted and used in the (7) to calculate the corresponding ROI for that year.

Figure 3 shows the results of running a Monte Carlo analysis for 10,000 timelines of the entire wind farm. The white line in Figure 3 is the progression of ROI over time for a single example timeline. As it can be seen, ROI is a function of time. The drops in ROI are attributed to LIDAR maintenance costs or the purchase of a new LIDAR device. A positive ROI is

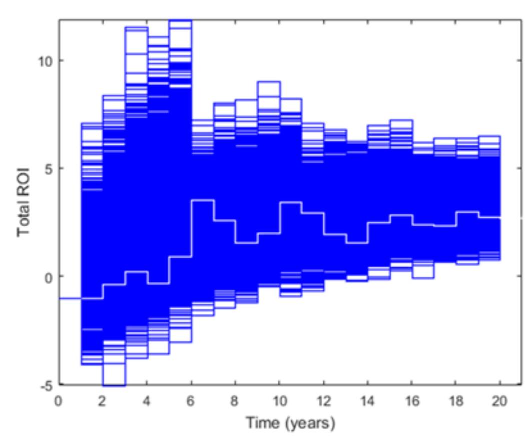

Figure 3-10,000 timelines of Monte Carlo analysis for ROI with their progression over time for the entire wind farm. The white line shows one example timeline

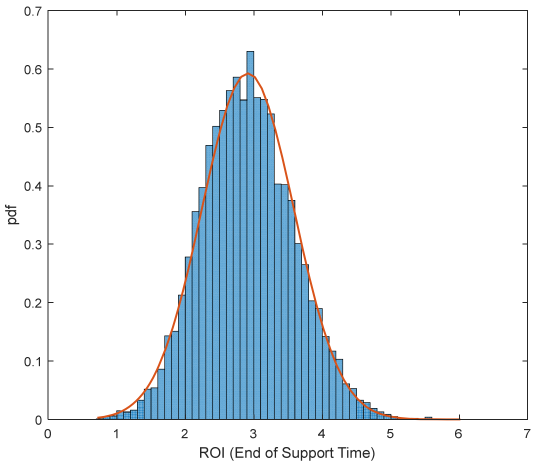

Figure 4- Histogram of possible ROI outcomes at the end of support time (20 years) for 10,000 timelines for the entire wind farm

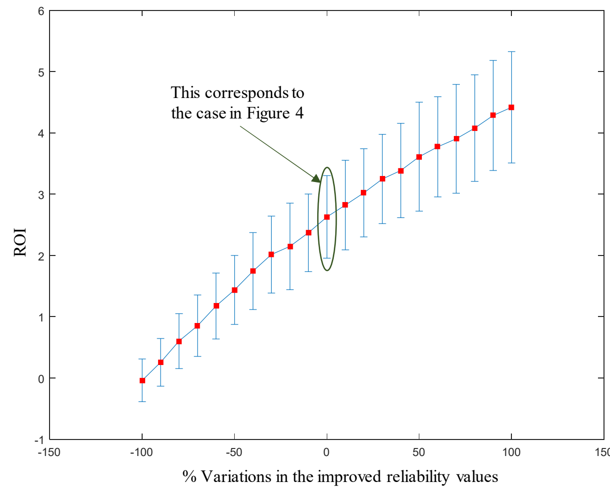

Figure 6- ROI Sensitivity to variations of improved reliability percentage

considered to be a successful investment from a financial viewpoint. Figure 4 shows the distribution of ROI values at the 20th year (the end of support time). The standard error for 10,000 timelines is less than 1%.

B. Case Study Sensitivity Analysis

A sensitivity analysis on the reliability improvement values for the components due to yaw error correction was performed to investigate the effects of uncertainties that are associated with the aero-elastic analysis. Different yaw error corrections result in different reliability improvements. The middle line in Figure 5 are the values used to generate Figure 4. In the uncertainty analysis, we incrementally change the reliability improvement values. The results of the sensitivity analysis are shown in Figure 6 with the middle point (0 on the horizontal axis) representing the results of Figure 4. In Figure 6, 100% drop (-100 on the horizontal axis of Figure 6) in the assumed reliability improvement percentage means that there is no reliability improvement due to the yaw error correction. A 100% increase in the default reliability improvement percentage values means all the values of the middle line in Figure 5 will double.

It can be seen that for the left end (-100) of the sensitivity analysis in Figure 6 the average values of ROI drop to values

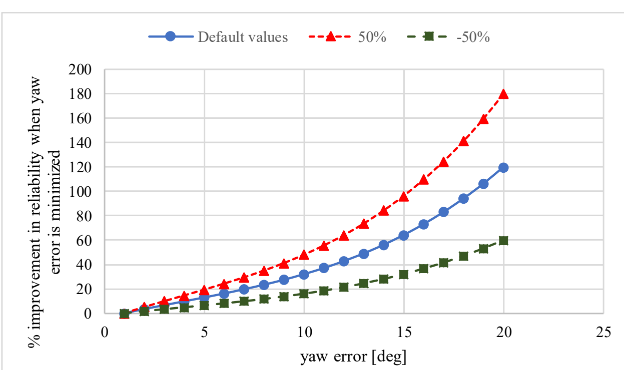

Figure 5- % improvement in reliability as a function of the yaw error that is minimized (determined from the model in [30]). ±50% variations from the default value of improved reliability are shown (these correspond to 50 and -50 in Figure 6)

close to zero. Based on Equation 7 and Figure 3, ROI starts at -1, so if there is no reliability improvement due to LIDAR, the energy production improvement still has a positive contribution to the overall ROI. The sensitivity analysis also indicates that the ROI could be 4 or greater; however there is a diminishing return and uncertainties are larger as the reliability improvement increases.

V. Discussion and Conclusion

In the ROI formula (7), the technology and no technology terms (for both revenue and O&M) are not independent of each other. For calculating these terms a dependency between *tech* and *no-tech* scenarios has to be considered in order to make the analyses meaningful. The calculations have to satisfy the requirement of having identical timeline conditions between the two cases so the conditions that affect the system behavior stay identical for both cases of *tech* and *no-tech*. If the insertion of a technology improves the reliability of the system, the time-to-failures for the technology case are longer than the no technology case, as a result, there has to be a dependency between the sampling of the time-to-failure times between technology and no technology cases.

The methodology explained in this paper focuses on the technologies that affect the reliability of components, meaning the insertion of the technology changes the failure time. This methodology is independent of the maintenance policy applied to the wind turbines. In cases where the maintenance actions change because of the new technology, the ROI model developed here is also applicable. Regardless of what the new maintenance policy is, the requirement of identical timeline conditions must apply to the generation of stochastic parameters in the modeling.

Equation (7) can be broken into its components to calculate ROI only considering revenue generation or only considering the O&M costs. This is applicable to situations where one cash flow contribution dominates the others. However, it is important to note that the total ROI in (7) is not the sum of revenue ROI and O&M ROI.

In the case study in this paper, we looked into the application of LIDAR for yaw error correction. Although the case study in this paper assumes a single LIDAR for the whole wind farm, the ROI analysis could be used to find an optimum number of LIDAR devices for a wind farm that yields the maximum ROI. It is important to point out the uncertainties in several inputs in this model. For example, as discussed in the case study, the reliability improvement of the components due to yaw error correction, comes from an aero-elastic study that may have significant uncertainties. Improving the aero-elastic models may be necessary to obtain more accurate results.

Future work will focus on the ability to have more than one LIDAR circulating in a farm, variable LIDAR stay time on a turbine and the determination of the optimum number of LIDARs for a farm with a known total power capacity and number of turbines. A more detailed LIDAR application and optimization will allow a more thorough sensitivity analysis to be performed to understand how ROI is affected by each input parameter.

Appendix - Creating Identical Timeline Conditions

As mentioned in Section III, the timeline for O&M is built by sampling reliability distributions. Each sample has a *value* that is generated from a probability distribution function (PDF) while the cumulative distribution function (CDF) gives the *probability* of occurrence of this particular sample at or earlier than its *value*. This process creates a group of samples that will eventually form the *failure times* for all the components of a turbine. We refer to this group as the failure time set, which has a corresponding probability set. The sequence of numbers in these sets is important, a change in the failure times sequence will change the sequence in the probabilities set as well.

A. Generating Number Sets for Identical Timeline Conditions

The O&M costs of a particular turbine over the 20 years of support time is in part the result of failures that occur during this period. Assuming a simple case where the wind turbine has only one component whose failure times follow a probability distribution, for one particular timeline, the first failure time is the value of the first sample from the distribution. The second failure time is the value of second sample plus the failure time for the first sample and so on (this simple illustration assumes that the system is instantaneously restored upon failure). This is expressed in (A1).

$$FT_n = \sum_{i=1}^{n} (S_V)_i \tag{A1}$$

where:

FT_n = failure time of the nth failure measured from the start of the simulation

S_V = value sampled from the failure distribution

Three sets can be defined, a set of values $\{S_V\}$, a set of probabilities $\{S_{Pr}\}$ and a set of failure times $\{S_{FT}\}$. This is shown in Figure A1, where *Pr* is the probability of a sample taking on the value of *S* or less.

A path is one possible outcome of the O&M cost after the calculations of costs for each failure. The sequence of the

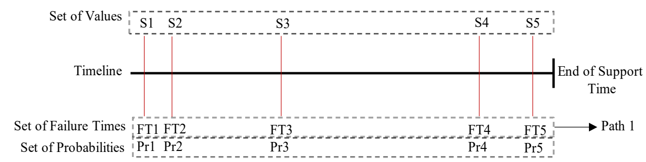

Figure A1- Illustration of different number sets

samples in every set is important, if the sequence changes, the path will change. Since there are infinite possible combinations of the $\{S_{FT}\}$ set, there are an infinite number of possible paths.

For a turbine that has multiple components, each with stochastic failure times, the process of sampling and calculating the failure time for each component is the same. However, the problem becomes a two-dimensional matrix, with one dimension (rows) representing the components of the turbine and one dimension (columns) representing the failure events. Three matrices can be defined for value, probability and failure time. Each row in a matrix is a subset. The union of all subsets in a matrix after reordering the elements considering the sequence of events becomes a set.

Since the turbine is a system comprised of several components, the set of failure times is the failure times of components as they occur over time on the timeline. This set of failure times is a new path for the O&M cost. The set of probabilities have the same sequence as the set of failure times.

B. Reliability Sampling for Identical Timeline Conditions

In order to create the identical timeline conditions, the same set of numbers has to be used. But the question remains, which set and how. When components have a new reliability distribution after the implementation of the new technology, the same failure times cannot be used for the two cases, hence using the identical set of failure times for the samples of the two cases becomes meaningless. However, it is still possible to use the identical 'set of probabilities'. Figure A2 shows how the probabilities of two samples can remain the same while the value of samples change. The probability values represent the randomness and thus they have to stay identical for the two cases. For example, the microstructure of the blade material of a particular turbine and its properties are identical for the two cases although the loading changes when the technology is used

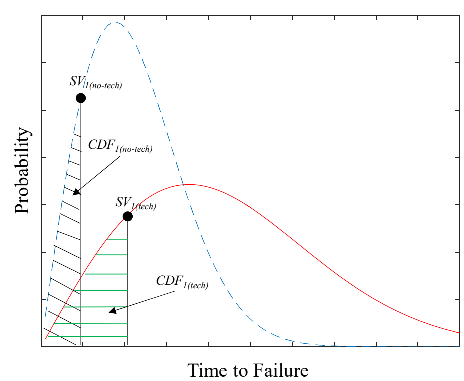

Figure A2- Schematic of sampling the reliability distributions for a particular failure in cases of technology and no technology. In this case *CDF*(*no-tech*) = *CDF*(*tech*), but *SV*(*no-tech*) ≠ *SV*(*tech*) thus the stresses and subsequent failure times will vary.

A turbine consists of many components and the reliability of multiple components change when the technology is used. In this case, the probabilities (CDF values) remain the same for each component, e.g., for component one, failures 1 through 5 have the same CDF values with *tech* and *no-tech*, but the value of the sample (which comes from the PDF) changes since the distribution has changed. In order to create identical timeline conditions, we use the same sequence of probabilities for the failures of 'each component', then generate their corresponding failure times and finally build the new timeline for the tech case based on the sequence of occurrence of the failures. The subsequent actions after the failure events are the maintenance events, which are dependent on the maintenance strategy. Taking this approach will automatically guarantee that when the technology improves the reliability, the new failures times are later than the failure times for the *no-tech* case.

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