

# Guaranteeing high availability of wind turbines

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**ABSTRACT:** Modern wind turbines are relatively “immature” in the sense that they have not been fielded for a sufficient amount of time to assess their long-term viability. Availability, the ability of a system to function when it is required, is a major concern for alternative energy systems. Profits and environmental benefits will be lost if the costs and energy required to maintain a system outweigh the benefits obtained. Prognostics and system health management (PHM) methods can have a significant impact on the wind energy community. PHM enables the manufacturers and operators of complex systems to move from traditional time- or cycle-based maintenance to condition-based maintenance, which can significantly improve availability. This paper discusses the challenges in guaranteeing the high availability of wind turbines, and the use of PHM as a methodology to guarantee the high availability. A new sensor system for the health monitoring of turbine blades is proposed and a return on investment analysis for its use is presented.

## 1 INTRODUCTION

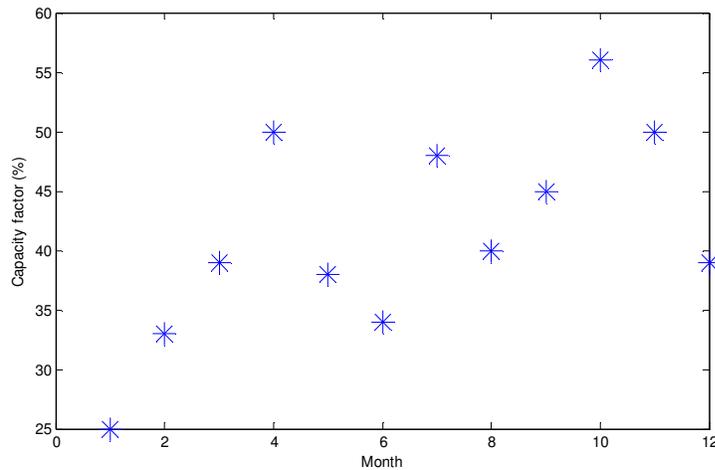
Alternative energy sources have increasingly gained the interest for governments, research institutes, academia, and industry in order to advance the penetration of sustainable energy to reduce the dependency on and environmental hazards posed by traditional energy sources such as coal and oil. Wind energy stands at the forefront of these energy sources; the United States Department of Energy (DoE) and the National Renewable Energy Lab (NREL) for instance, under the ‘20% Wind Energy by 2030’ plan, announced that the US could feasibly increase the wind energy’s contribution to 20% of the total electricity consumption in the United States by 2030 (U.S. DoE, 2008).

Wind energy sources face numerous challenges that obstruct them from competing with traditional sources, and capturing a significant market share. Wind energy has not been proven out over a sufficient amount of time to assess their long term viability. Furthermore, the reliability of wind turbines turned out to be different from what was originally predicted. Another major challenge with wind energy is intermittency, i.e., their energy generation is dependent on intermittent sources, as can be seen in Figure 1, which shows the wind capacity factor for Kansas wind farms from August 2007 to June 2008.

The figure shows the monthly capacity factor. Capacity factor is the ratio of the produced energy to the theoretical maximum capacity that can be produced.

The availability of wind turbines (and wind farms) will determine the energy impact they are able to have. In other words, if the system is unreliable and always unavailable because it is subjected to maintenance and repairs, then the potential profit from the source will drop drastically because the system is not able to produce the required energy. This can be even worse if the costs and energy associated with the maintenance of the system outweigh the profit obtained if the system is in operation.

In this paper, we present the major challenges of ensuring high availability of wind turbines. Prognostics and health management (PHM) is then proposed as a discipline of technologies and methods to ensure high availability. We present a new sensor system that can be used to ensure high availability of turbines.



**Figure 1. Capacity factor in a Kansas wind farm August 2007 to June 2008**  
(<http://kcc.ks.gov/energy/chart.htm>)

The work presented in this paper is structured as the following: Section 2 discusses the challenges for ensuring the availability of wind turbines. Section 3 introduces prognostics and health management as a method to ensure high availability of turbines. Section 4 discusses the state of health monitoring of wind turbines. Section 5 introduces a sensor system for the health management of blades and gearboxes, and includes a return on investment analysis, and Section 6 concludes the paper and provides directions for future research.

## 2 CHALLENGES IN AVAILABILITY OF WIND TURBINES

The Wind Energy Operations & Maintenance Report was recently published (Asmus and Seitzler, 2010) and included a discussion highlighting the challenges with wind energy systems. Some of the most notable conclusions are that the operation and maintenance (O&M) costs for wind power are double or triple the figures originally projected, they are particularly high in the United States. Another interesting fact is that many gearboxes, designed for a 20-year life, are failing after 6 to 8 years of operation.

These challenges indicate that reliability, maintainability, and availability stand among the key challenges to the economic viability of wind turbines and their ability to compete with traditional energy sources. This section summarizes these challenges.

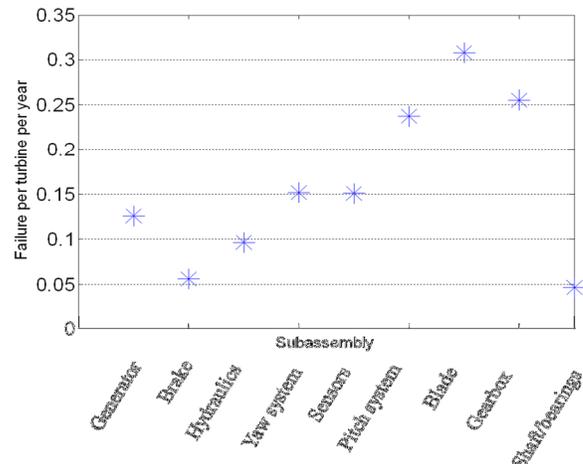
### 2.1 Reliability

Ideally, the turbines would behave in the field just as they perform under testing of stated conditions. However, most fielded turbines are relatively new and have not been subject to enough testing and qualification. This resulted in a dramatic difference

in the actual life of the system and the one stated on the specification sheet.

Simulating the actual conditions where the system will be implemented is challenging and may not be properly accounted for in the testing phase for wind turbines. However, reproducing the actual conditions may be challenging - reproducing the waves and the harsh weather conditions and the interaction with other environmental factors may be impossible to account for in a lab testing environment. Reliability testing similar to aeronautics can be used. The two fields share multiple criteria: stringent environment conditions and challenges reproducing these conditions. Highly accelerated life testing (HALT) and highly accelerated stress screening (HASS) are examples of environmental tests used in other disciplines.

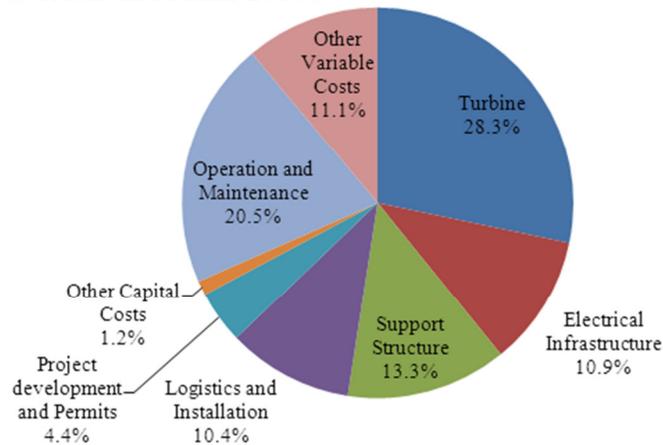
Figure 2 adopts the data from (Arabian-Hoseynabadi et al. (2010)) to show the reliability of wind turbines showing the failure rate of different sub-assemblies. The plot shows that multiple subassemblies have a significant yearly rate of failure.



**Figure 2. Reliability of wind turbines**

## 2.2 Maintainability

The maintainability of wind turbines emerged as a major challenge for their economic viability. For an offshore wind turbine for instance, the operation and maintenance accounts for the second largest share of the turbine's life-cycle cost as seen in Figure 3 (Musial and Ram, 2010).



**Figure 3. Projected life cycle cost breakdown for offshore wind turbines**

Figure 3 shows the projected cost for an offshore wind turbine in the United States. With the operations maintenance cost being as high as 20% of the total cost, if the turbine is not maintained as it is originally intended to be then the cost is going to rise even more and pose more challenges on the economic viability.

Furthermore, wind turbines require special workforce that is trained to maintain the particular system, and require non-traditional resources such as vessels and cranes.

Another major concern in the renewable energy sources is the maintenance paradigm that is usually chosen. If the system is run to failure and unscheduled maintenance occurs, it has a big effect on the cost of maintenance. Typically one would want to have predictive maintenance in order to minimize cost.

## 2.3 Availability

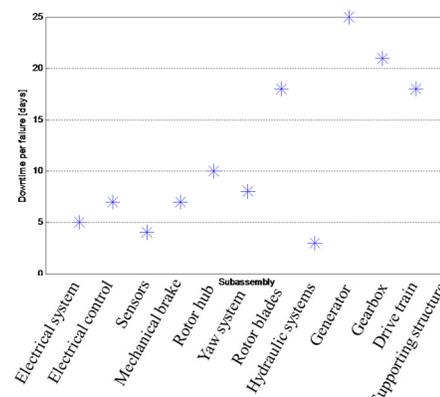
Availability, the ability of a system to function when it is required (Jazouli and Sandborn, 2010), is a function of its reliability and how efficiently it can be maintained. Hence the availability of turbines will actually determine the energy impact. In other words, if the system is unreliable and always unavailable because it is subject to maintenance and repairs, then the potential profit from the source will drop drastically because the system is not able to produce the required energy.

Specifications for wind turbines for instance state an availability of 98%, which accounts for few days of maintenance during the year and it is assumed

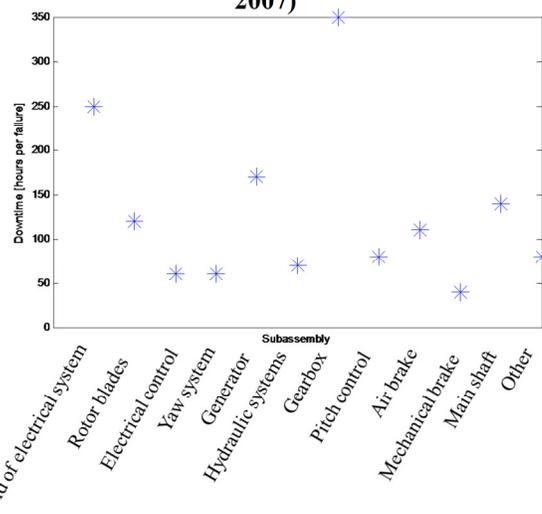
that the turbine will be operating during the rest of the year. Ideally we would want the renewable energy sources to produce energy whenever it can. This is unrealistic however, and there's a need to take into consideration the challenges and limitations as to when and how to perform maintenance.

Another aspect of availability is the need of nontraditional resources for maintenance. Offshore wind farms require vessels with cranes that can sometime go out only a couple times a year. If one turbine broke right after a maintenance action has been performed on it, then it will not be available until next time the vessel is out for maintenance.

Kuhn (2007) studied the failure rates of 235 small wind turbines and assessed the annual frequency rate and the corresponding downtime for different subassemblies. The results can be seen in figure 4. Similar analysis for large scale wind turbines were analyzed by (Wilkinson et al., 2009) and the results are seen in figure 5. The figure shows the downtime in hours for the turbine corresponding to different subassemblies. The failure rates for the same subassemblies are shown in Figure 2



**Figure 4. Downtime for wind turbines (Kühn, 2007)**



**Figure 5. Downtime per subassembly (Wilkinson et al. (2009))**

## 3 PROGNOSTICS AND HEALTH MANAGEMENT

Prognostics and health management (PHM) is a discipline consisting of technologies and methods to

assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk (Pecht, 2008 and Cheng et al., 2010). PHM is an enabling technology that allows the industry to transition from traditional maintenance to condition-based maintenance. It is also an enabler of performance-based contracts.

The main approaches for PHM are: 1) model-based approaches, which utilize knowledge of a product's life cycle loading conditions, geometry, material properties, and failure mechanisms to estimate its remaining useful life; 2) data-driven approaches, which look at current and historical data to estimate the remaining useful life of a product using machine learning and statistical methods; and 3) fusion approaches which incorporate the benefits from the first two methods.

In a PHM cycle, the health of the system is monitored continuously with sensor systems. Data is collected either in real-time (continuous monitoring), or stored and used off-board when analysis is not in the system. The first step in the analysis consists of preprocessing the collected data. When data is ready, it is used within a diagnostic algorithm; anomalies are reported when there is a change from a healthy state, then the root-cause of the anomaly is identified. A prognostic algorithm is then used to predict the remaining useful life (RUL) of the component/system. The RUL is used by the decision-maker to manage the health of the system and take the appropriate action prior to the failure.

Systems incorporate PHM for a number of reasons that include: failure avoidance, life cycle cost reduction, warranty verification, future system design improvements, and availability improvement. Benefits of PHM extend to the whole life cycle of the system to include the following stages: design and development, production and construction, operations, logistic support and maintenance, and phase-out and disposal.

### 3.1 *Benefits for the system design*

Large scale wind turbines are relatively immature and may have not been tested and qualified well enough, PHM can play a pivotal role in their success by addressing this shortcoming. PHM can be used to optimize the design and improve qualification of the system. PHM enables the collection of information throughout the life-cycle of the turbine. The information collected on the loads and environment that the turbines see during its life-cycle can be used in future testing to make sure that new designs are seeing the same profiles.

### 3.2 *Benefits during the operation of the system*

PHM can predict when a failure will happen which gives lead time to entities involved in the operation,

management, and maintenance of the system to take actions and ensure availability. This information can avoid catastrophic failure of systems. A knowledge about the end of life of the gearbox of a wind turbine can avoid the catastrophic damage of the gearbox which can cost up to 15% of the total cost of the turbine.

The information from PHM can be used in the control of the wind turbine. If a turbine is degrading, then the decision-maker can reduce the load on it by controlling the angle of the blades and make it run at a lower speed. This will ensure that the turbine is still available and operating until the next time maintenance resources are available.

PHM can potentially play a critical role in defining and enhancing warranty services for wind turbines and farms.

### 3.3 *Logistics and maintenance optimization*

PHM allows the move from traditional maintenance (scheduled or unscheduled) to the more cost effective condition-based maintenance (CBM). CBM can provide benefits including minimizing scheduled and unscheduled maintenance, extending maintenance cycles, improving maintenance effectiveness, and reducing maintenance costs.

The information from PHM can be further used to optimize logistic supply chain (Khalak and Tierno, 2006) which is critical for wind turbines. For example, the PHM information can be used to order a blade and have it shipped to the wind farm to minimize logistics leadtime in the case of a failing blade.

## 4 HEALTH MONITORING IN WIND TURBINES

PHM has been performed on wind turbines for: gearbox, bearings, oil, blades, electronics, and overall performance.

Gearboxes are the subassemblies with the most advanced PHM. A common approach is to monitor gearbox vibration using accelerometers and use vibration analysis approaches to detect faults (Huang et al., 2008).

Oil analysis is performed to safeguard the oil quality and the components involved. It is mostly executed off line, by taking samples. The oil is analyzed for wear debris. In wear debris analysis, the quantity, size distribution, morphology and color of wear debris is determined, which can provide information on the wear modes, wear sources, and wear phases present in the machine (Ebersbach, et al., 2006).

Blade failures are due to: core damage, disbonding, cracks, delamination, broken fibers. The analysis of the blades is typically done by examining

the physical conditions of materials, which are methods done offline to monitor crack growth.

Power electronics and electronic controls account for a small chunk of the cost but have a big effect on downtime as can be seen from figures 4 and 5. There have been several diagnostic approaches developed for power electronic devices especially IGBTs but these are done to detect faulty components rather than detection before they occur. Such methods include neural networks, wavelet analysis, Bond graph methods.

A comprehensive review of condition monitoring of wind turbines can be seen in Hameed et al. (2009)

## 5 LOCAL HEALTH MONITORING SOLUTION

This section presents a solution for real-time, on-board as well as low power and local solution for health monitoring of wind turbines.

### 5.1 NEEDS

The main failure modes and sites of wind turbines have been reviewed (Arabian et al. 2010) and (Yang et al., 2008) and the mechanical failures either on blades or gearboxes appeared in the top10 failure modes. Further, according to literature (Yang et al., 2009) and (Djurovic et al., 2009), in order to be able to develop health monitoring diagnosis (and the associated computation), the following sensors are necessary: temperature, pressure, vibration, acoustics, and strain. Moreover, voltage, current and signal (digital as well as analog) sensors are a useful complement (Yang et al., 2008 b). More detailed requested values are given hereby for vibration and strain sensors.

Frequencies of interest depend on the defects to be characterized (Yang et al., 2009) and (Djurovic et al., 2009),

- 100-550 Hz DFIG (doubly-fed induction generators)
- 100±1 Hz Generator stator and grid imbalance faults
- 50±1 Hz Faults occurring in the whole wind turbine drive train
- 25~32.5 Hz Mechanical faults caused by or unbalanced blades and shaft
- 5~30 Hz Electrical faults caused by a generator rotor winding fault or rotor eccentricity

Strain gauges should be able to measure up to 4 500  $\mu\epsilon$  (or 0.45 %) with a resolution of 1  $\mu\epsilon$ . The storage capacity should be greater than 2 MB.

CALCE presented a sensor system for prognostics and health management Cheng et al. (2010). The sensors are used to monitor environmental, operational, and performance-related characteristics. Pecht (2008) also presents a number of guidelines for sensor selection for PHM application. A list of sensors with their respective

properties is presented. Guidelines for sensor selection are also discussed.

### 5.2 TRIADE

TRIADE is a technology that has been developed for aeronautic applications. The architecture encompasses temperature, pressure, vibration, strain and acoustic sensors that can be used to monitor the health of a turbine (see table 1). Figure 6 describes the organization with remote as well as on-board sensors and figure 7 shows the realization of the actual solution. The small dimension of this solution is a definite advantage to implement it in places where space and weight are at a premium.

Table 1. Description of the sensors of TRIADE

Sensors	Reference	Numbers
Temperature	SHT21	1
	SOI sensor	1
Pressure	MS5534C	1
Vibrations	832M1	1 (3D)
Strain gauge	1-LY4x-6/1000	6
	SOI sensors	1
Acoustic	AE transducers	3 channels of 8 sensors each

One main advantage of the TRIADE solution is that it has been designed to be implemented on and within composite structures on-board helicopters in moving parts. Mechanical simulations have been made to ensure that the architecture is strong enough to withstand these harsh conditions. Environmental and functional tests will be led as well. Hence, an implementation directly on a blade is possible.

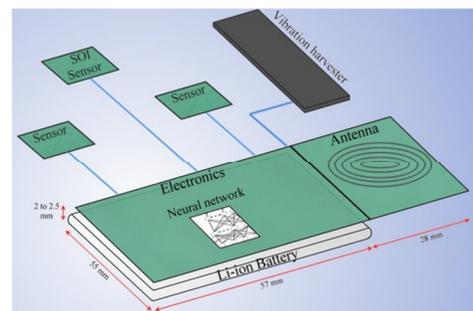


Figure 6. Architecture of the TRIADE solution

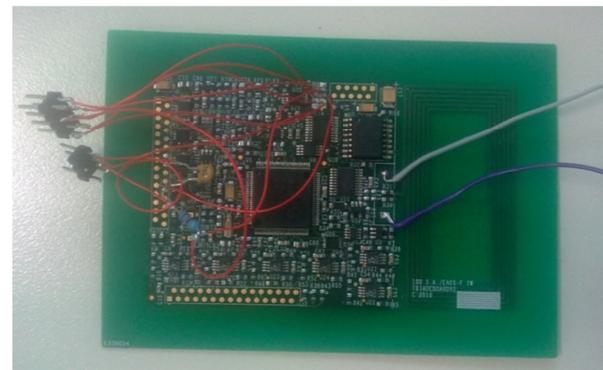


Figure 7. Photograph of the TRIADE solution

The main characteristics of the sensors fulfill the needs for wind turbine health monitoring as shown in table 2.

Table 2. Characteristics of the sensors

sensors	Range	
temperature	-40/+125°C	< 0.04°C/yr drift
pressure	10/1100 mbar	-1 mbar/yr drift
vibrations	2-1000 Hz	Max sampling rate 12 kHz
strain	± 5 000 µε	Self-compensated
acoustic	Impact detection	

The TRIADE solution is designed to be autonomous. The on-board microcontroller that has been selected for the Smart Tag belongs to the MSP430 family from Texas Instruments. It is specifically designed for ultra-low-power applications, having flexible clocking system, multiple low-power modes, instant wake-up and intelligent autonomous peripherals, features that enable true ultra-low-power optimization and dramatically extend battery life.

The data are retrieved through an RFID link. The passive RFID technology (@13.56 MHz) has been chosen for the RF communication link. Thus, the TRIADE Smart Tag acts like a passive RFID tag during communications. The tags of passive RFID systems do not need power supply and this is why they are called passive. Passive tags (the TRIADE Smart Tag included) are powered (during the communication phase) from the electromagnetic field generated by the RFID reader antenna. Thus, the RF link of the TRIADE platform consumes no power from the battery at all.

The RF energy harvester is used to scavenge energy from radio waves, convert the waves into DC power and replenish the battery. The operation of the harvester is accomplished by receiving radio waves with an antenna, converting the signal and conditioning the output power.

All these characteristics mean that it may be implemented in places which are not readily accessible, e.g. to monitor gearboxes. Data could be transferred on a regular basis, should an RF transceiver be installed in the wind turbine.

As a summary, TRIADE is able to send relevant data on blades and gearboxes in all relevant field of sensing.

### 5.3 Diagnostics and Prognostics

CALCE has developed other sensor solutions for remote monitoring and PHM. Examples include a sensor tag deployed on autonomous systems.

After data is collected, it is critical to use the information with diagnostic and prognostic algorithms in order to make strategic decisions and

harvest the benefits of PHM. For this purpose CALCE has developed a set of software tools and algorithms that help in data pre-processing, data mining, anomaly detection, diagnostics, and prognostics. Examples of these can be found in Cheng et al. (2010) Sotiris et al. (2010) and Kumar et al. (2010).

### 5.4 Return on Investment

Return on Investment (ROI) is a key means of gauging the economic merits of adopting PHM. The determination of the ROI allows managers to include quantitative, readily interpretable results in their decision-making. ROI analysis may be used to select between different PHM approaches, to optimize the use of a particular PHM approach, or to determine whether to adopt PHM versus more traditional maintenance approaches (Feldman et al., 2009). ROI is typically defined by:

$$ROI = \frac{\text{Return} - \text{Investment}}{\text{Investment}} \quad (1)$$

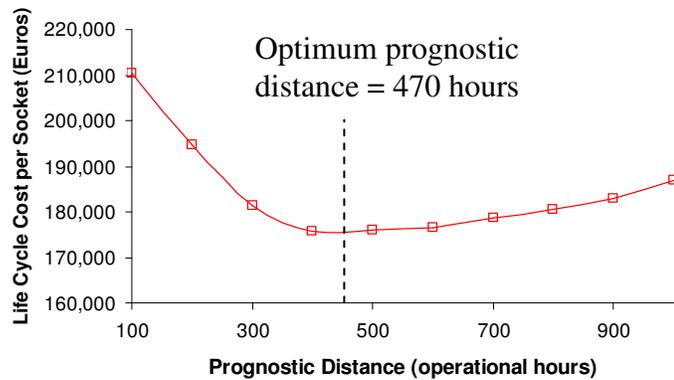
ROI calculations are application specific since the cost avoidance and investment can be different from one application to another. The data used in this example to represent turbines in an offshore wind farm was adopted from Andrawus et al. (2006) and Arabian-Hoseynabadi et al. (2010), Table 3. The ROI analysis was performed using CALCE's PHM ROI tool, Sandborn and Wilkinson (2007).

To enable the calculation of ROI, the analysis first determines the optimal prognostic distance when using a data-driven PHM approach (see Figure 8). Due to uncertainties in the RUL predicted by the PHM approach, waiting for the whole predicted RUL before taking maintenance action will result in significant unscheduled failures.

Table 3- Inputs to ROI model

Inputs	Values
Failure rate per year	0.308
Scale parameter	9,386
PHM acquisition cost (Euros)	300
Operational time per blade per year (hours)	2,891
Support life (years)	20
PHM annual infrastructure costs (Euros) per blade	1,282
PHM recurring costs per blade (Euros)	1,820
Blade base cost (Euros)	37,736
PHM non-recurring costs per fleet (Euros)	4,520
Number of blades per fleet	78
PHM non-recurring costs per blade (Euros)	57.95
Time to replace for scheduled maintenance (calendar hours)	168
Fraction of maintenance events requiring replacement (%)	100
Materials/Logistics cost per maintenance (replacement) event	1,606
Labor cost per maintenance (replacement) event	2,753
Total materials and labor	4,359
Value added tax (%)	0.175
Discount rate / cost of money (%)	0.082
Cost per hour out of service (Euros)	11
Time to replace for scheduled maintenance (calendar days)	7
Time to replace for unscheduled maintenance (calendar hours)	(Variable)
Number of turbines	26
Number of blades per turbine	3

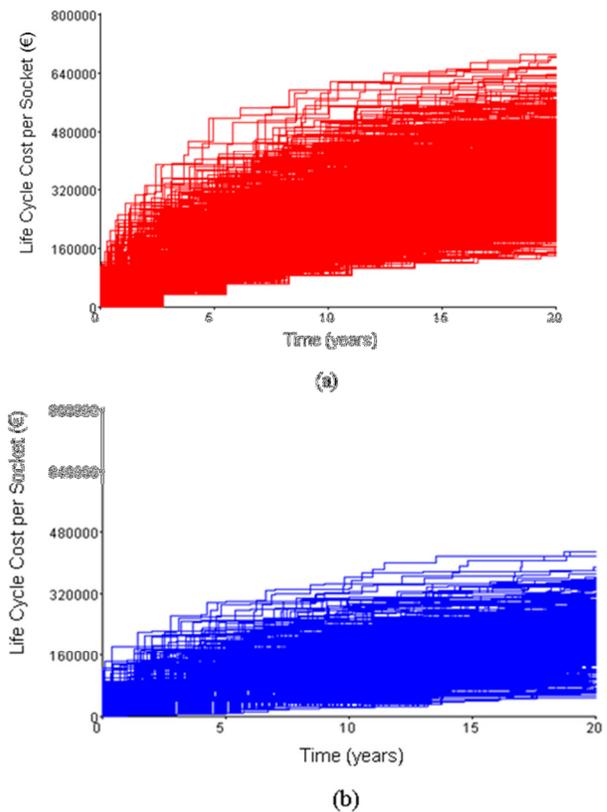
Prognostic distance is the amount of time before the forecasted failure (end of the RUL) that maintenance action should be taken. Small prognostics distances cause PHM to miss failures, while large distances are overly conservative and throw away lots of life. For the combination of PHM approach, implementation costs, reliability information, and operational profile assumed in this example, a prognostic distance of 470 hours yielded the minimum life cycle cost over the support life of the turbine. Similar analysis was conducted to determine the optimum fixed-interval scheduled maintenance interval. A fixed maintenance interval of 8,000 hours yielded the minimum life cycle cost over the support life. Again, small fixed maintenance intervals miss failures, while large intervals are overly conservative.



**Figure 8. Variation of mean life cycle cost with a fixed maintenance interval (1000-socket population).**

Figure 9 represents the accumulation of the life cycle cost per socket for both data-driven PHM and fixed-interval scheduled maintenance case. A socket is a location in a system (in the wind turbine) where a single instance of the item being maintained (a blade) is installed. The socket may be occupied by one or more items during the lifetime of the system. The time history of costs for each of 1000 sockets is shown in Figure 9. The data-driven PHM case resulted in an overall lower life cycle cost (mean = €173,213) compared to the best fixed-interval scheduled maintenance case (mean = €356,999). The data-driven PHM case requires fewer spares throughout the support life of the system. This is primarily due to maximizing the useful life of the blades, i.e., early warning of failures in the data-driven PHM case provided an opportunity to schedule and perform maintenance events closer to the actual failures, thus, avoid failures while maximizing the useful life. Alternatively, the fixed-interval scheduled maintenance case resulted in either throwing-away more useful-life (early intervention). In both cases, some unscheduled maintenance events (intervention that is too late) occurred. Intuitively the advantage of PHM over

fixed-interval maintenance for this case is shown in Figure 8 where the life cycle cost was minimized in the PHM case when the prognostics distance was 470 operational hours versus 8000 operational hours in the fixed-interval case.

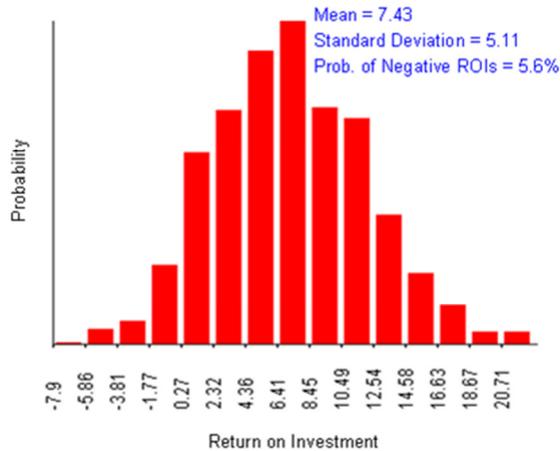


**Figure 9. (a) Life cycle cost per socket for a fixed-interval scheduled maintenance approach. (b) Life cycle cost per socket for a data-driven PHM approach. 1000-socket population.**

We now wish to estimate the return on investment (ROI) of the data-driven PHM approach relative to a fixed-interval scheduled maintenance approach. The mean total life cycle cost per blade, for a data-driven PHM approach, was €173,213 (mean), with an effective investment cost per blade of €25,408 (mean), representing the cost of developing, supporting, and installing PHM in the blade. This cost was compared to the fixed-interval scheduled maintenance approach, where the total life cycle cost per blade was €356,999 (mean). Note that the investment cost for the fixed-interval scheduled maintenance policy is by definition zero; since the ROI is computed to support an economic justification in investing in PHM, as opposed to the fixed-interval scheduled maintenance case where there is no investment (i.e., zero investment) in PHM.

Figure 10 shows the histogram of the computed ROIs for 1000-socket population (due to uncertainties in all quantities, each socket in a population will have a unique ROI). In this example, the computed mean ROI of investing in a data-driven PHM approach for the population of blades

was 7.43. Notice that some of the ROI values in Figure 10 are negative. This means that there is a risk that implementing a data-driven PHM approach for the blades could result in an economic loss, i.e., you could end up being worse off than fixed-interval scheduled maintenance. Based on Figure 10, this example predicts that a data-driven PHM approach would result in a positive ROI (cost benefit) with a 94.4% confidence.



**Figure 10. Histogram of ROI for a 1000-socket population.**

## 6 CONCLUSIONS

This paper an overview of the failure of the major subsystems in wind turbines and their effect on availability. PHM is a possible solution for guaranteeing high availability of wind turbines eventually allowing them to compete with traditional energy sources. A PHM system, TRIADE, is presented as a possible solution for the health monitoring of blades and gearboxes in wind turbines, and a return on investment analysis is presented to support the economic benefit of the implementation.

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