Equivalent Age-based Opportunistic Maintenance for Wind Farms

by

Ali Aldubaisi

A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
May 2, 2020

Keywords: maintenance, wind energy, reliability

Approved by

Jorge Valenzuela, Chair, Professor of Industrial and Systems Engineering
Richard Sesek, Associate Professor of Industrial and Systems Engineering
LuAnn Carpenter, Assistant Professor of Industrial and Systems Engineering
Fadel Megahed, Assistant Professor of Information Systems and Analytics

Abstract

The wind industry is facing new challenges due to the rapid growth of wind farms all around the world. Farm size, turbine size and a rising number of sophisticated components, the industry has to face the challenge to develop sustainable maintenance procedures in order to meet the planned cost and time. Important limiting factors for wind farms life cycle management are weather conditions and maintenance strategies. Hence, optimal strategies need to take weather conditions into account. In this context, the focus of this research is to develop an effective approach to maintain wind farms while incorporating the effects of weather conditions on aging and accessibility. This is achieved through the implementation of a discrete-event simulation approach which captures the impact of environmental conditions (wind speed, temperature) on the aging process of wind turbines.

First, we explore SCADA data of four wind turbines to study the impact of wind speed and air temperature on the uptime of wind turbines. This built-in system collects operational and ambient data at 10-minute resolution. Statistical analysis on SCADA data has shown significant impact of high wind speed on uptime. We investigate two years SCADA data of four turbines based on status and fault codes to evaluate the impact of weather condition during each uptime periods. The four wind turbines are identical Senvion MM82. This type of turbines is a variable-speed, three bladed with a hub height of 78 m and a rotor diameter of 82 m. They operate within a wind speed range between 3 m/s and 25 m/s. Results have shown that uptime is significantly reduced if the average wind speed during that period is higher than 7 m/s. On the other hand, the effect of air temperature on uptime is not clear and a larger dataset is needed to investigate further.

Second, we propose a new weather-based maintenance approach for wind turbine systems based on Equivalent Age models, which account for the effect of wind speed and ambient temperature on turbine aging. We develop a weather based age prediction model and the associated

maintenance threshold values for devising optimal maintenance strategies that reduce the maintenance costs while enhancing the availability of wind power. We consider a single wind turbine subject to variable weather conditions. We examine wind speed and air temperature and how they affect the aging of the turbine and the feasibility of maintenance. This makes the proposed age modeling and resulting maintenance strategy weather-dependent.

Finally, we propose a farm-level equivalent age-based opportunistic maintenance threshold driven by wind speed data. Maintenance decisions consider the trade-off between the optimal preventive maintenance schedule for individual turbines and the cost reduction due to the grouping maintenance actions of multiple turbines together in one maintenance event. Economic and accessibility constraints are also considered. We use a simulation approach to experiment with different weather conditions, economic dependencies, and location scenarios . We then present a numerical example to find the optimal maintenance thresholds for a wind farm under different weather conditions. Experiments conducted on a 100-turbine wind farm case demonstrate the advantages of our proposal over traditional policies. The model is solved using the Nelder–Mead method which produces scenario specific results. We highlight the benefits of our approach through a numerical example using hourly wind speed and air temperature data from three different regions in the United States. The results show an optimal policy can be adapted to weather conditions, showing the cost-effective action for each specific location. Compared with traditional age-based maintenance, our approach can achieve improvement in both availability and costs.

Acknowledgments

First and foremost, all praise to God, the most merciful and compassionate. I would like to thank all my friends and family for their support during my doctoral studies. I would also like to thank my dissertation committee members for their support and encouragement. I'd like especially to thank my adviser Dr. Valenzuela for all his guidance, support and patience throughout my research. I cannot express my gratitude enough for his help and support . I'm particularly grateful for Mr. Devall who I've worked with over the years in the Lego Lab at Auburn University. I'm very thankful for his mentorship and support over the years.

This dissertation is dedicated to my parents, for their love and encouragement.

Table of Contents

List of Figures

List of Tables

Chapter 1

INTRODUCTION

Wind power is rapidly emerging as one of most important renewable energy sources in the world. There is a significant growth in both size and number of wind turbines globally. This rapid growth accounts for 44% of the total planned electric generation capacity additions in the Untied States [1]. Modern wind turbines are one of the largest machinery with very sophisticated system of components and a long service life of 20 years. Hundreds of turbines are often installed together in wind farms that are connected to the grid. The significant investment increase in generation capacity comes with a key challenge to manage wind farms to achieve the lowest operation and maintenance cost. More effective maintenance strategies are needed for successful future growth in wind industry. A common goal of maintenance is to reduce the overall maintenance cost and improve the availability of the systems.

Maintenance activities can be classified based on the time they are carried out. Activities performed after a failure or breakdown are classified as corrective maintenance (CM). Activities performed before a failure while the turbine is still operational are classified as preventive maintenance (PM). Preventive maintenance is preferred for many safety, quality, unavailability and cost benefits. However, performing maintenance too often result in undesirable cost and therefore a balance between preventive maintenance and risk of failure has to be found. In Figure 1.1 a schematic overview of maintenance strategies is depicted. Preventive maintenance can be divided into time-based maintenance (TBM), condition based maintenance (CBM), and opportunistic maintenance (OM). TBM only depends on the time (age or number of time blocks) that a unit is in service and is therefore relatively easy to implement. However, it is possible that the item is still in reasonable condition when maintenance is performed or is deteriorating faster than expected and need maintenance earlier. CBM, on the other hand, results in maintenance that is performed just before failure and is generally more effective. Condition-based maintenance continuously monitors the components health to schedule maintenance when needed. However, with CBM, the availability of data-driven maintenance models is a big challenge for wind power systems. Therefore, it can only be applied if conditions can be monitored by inspections or continuously and if benefits outweigh the efforts and cost required to apply it. By performing a preventive or corrective maintenance action their might be an opportunity to maintain other units as well. In such cases, the maintenance strategy is called opportunistic.

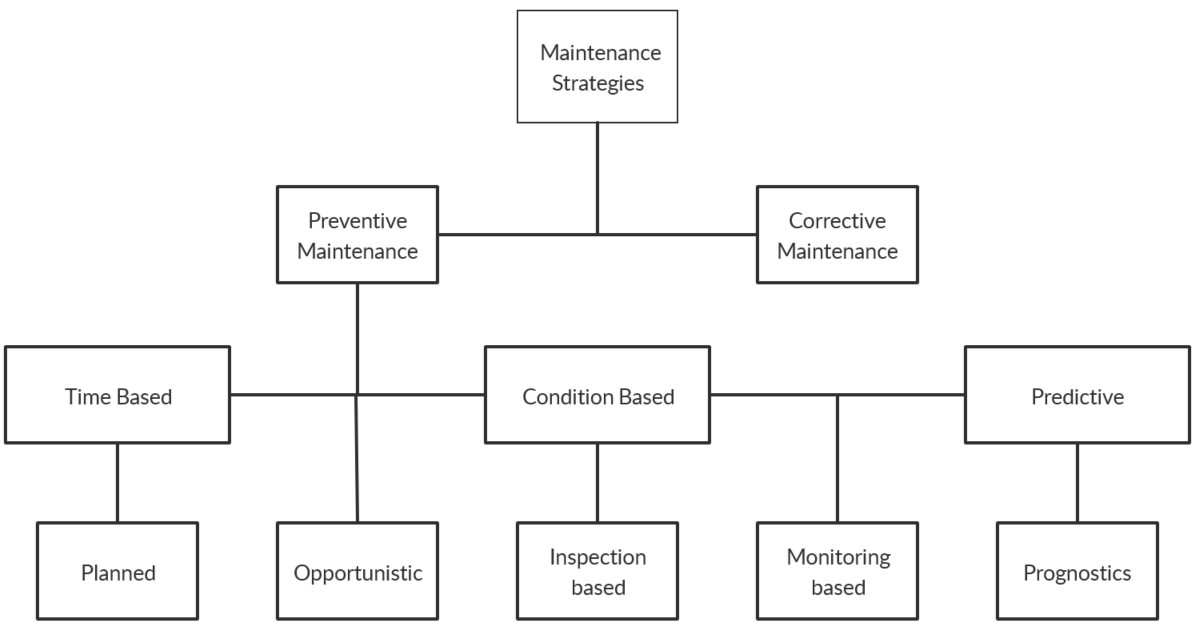


Figure 1.1: Schematic overview maintenance strategies

Currently, most maintenance activities in the wind power industry are performed at regular intervals. Variety of TPM strategies are used in the wind power industry, which take advantage of ease of management, particularly in the case of extreme condition and remote locations. However, they have not been studied adequately and more effective methods need be developed. TBM may result in unnecessary costly activities since turbines have to be shut down abruptly and energy production has to be stopped. Typical maintenance schedules contain little information on the degradation evolution of individual turbines. Therefore, different types of maintenance strategies have been discussed in the literature. In addition, the existing methods for wind turbine systems deal with individual components, but pay much less attention to the wind farm as a whole which generally consists of multiple wind turbine systems, and each wind turbine has multiple components with different failure distributions. Economic dependencies exist among wind turbine systems and their components in the wind farm. Therefore, an opportunistic maintenance approach may be more cost-effective by taking advantage of already allocated resources and time. In Table 1.1, the advantages of CBM and TBM are listed in comparison with each other.

Table 1.1: Comparison of CBM and TBM advantages

Condition-Based Maintenance	Time-Based Maintenance
• Just-in-time maintenance to avoid over maintenance • Better utilization of the equipment • Better utilization of maintenance resources • Increases equipment life cycle • Reduces unplanned maintenance activities	• No need for expensive condition-monitoring sensors • No skilled workers necessary to analysis data • Easier inventory planning • Widely used and easy to implement

In opportunistic maintenance, whenever a planned maintenance or a failure occur, the maintenance crew is sent to the wind farm to perform maintenance activities, and take this opportunity to simultaneously perform maintenance on multiple turbines utilizing maintenance resources and reducing the number of visits to the farm. The other disadvantage of existing methods is considering preventive maintenance as perfect replacement, which completely renews the system to the initial health state. In practice, maintenance activities are mostly imperfect maintenance or minor repair actions. The majority of repair actions for wind turbine components can be an addition to a new part, exchange of parts, or minimal repairs [2].

Gustavsson et al.[3] consider grouping TBM activities for several components dealing with a fixed set-up costs shared by components. The gains are combined with the extra costs so that it can be determined if a certain maintenance activity is profitable. TBM contains a number of parameters, such as average lifetime, whose values are optimized numerically or analytically. However, these parameters are not related to the condition of components but to the estimated lifetime of it. A component far from average can therefore result in performing maintenance too early or too late. CBM strategies have been thoroughly discussed in literature [4, 5]. According to [6], 99% of all machine failures are preceded by certain signs, conditions, or indications that a failure was going to occur. By implementing closed loop maintenance control, sensor feedback information from assembly installations and equipment is utilized in making maintenance-planning decisions. Moreover, continuous collection and interpretation of data regarding the equipment conditions can predict time to failure and an appropriate decision strategy can be applied [7]. Firstly, data from various parameters is measured and interpreted continuously, such as vibration, temperature, oil composition, power, and noise levels, which is called the condition monitoring process. This result in maintenance that is performed just before failure, or just in time (JIT). Secondly, the knowledge of failure causes, effects and deterioration patterns of equipment is increased. Within CBM, diagnostics and prognostics are two important aspects where diagnostics are used for detection, location and identification of faults that occur and prognostics are used to predict the faults before it occurs [8]. Furthermore, Jardine et al. [8] and Goyal et al [9] describe that a CBM program consists of three key steps that will be elaborated on briefly: Data acquisition, Data processing, and Maintenance decision making.

Data acquisition

Acquiring data is the first step in implementing a CBM program for fault diagnostics and prognostics. This data can be categorized into event-data and condition monitoring data. Event-data is a description of what happened, for example breakdown, oil pollution or installation and what is done to restore it, for example repair, preventive maintenance or oil replacement. Condition monitoring data are measurements related to the condition health/state of the equipment and installations. As mentioned above there is a wide variety of possible condition monitoring data with as many sensors. The data can be obtained continuously through the supervisory control and data acquisition system (SCADA) or by inspections. Golmakani eta al. [10] describe an age-based inspection approach where at each step, based on the age of the system, the best time for next inspection is determined.

Data processing

After cleaning, the data can be analyzed by using various models, algorithms and tools that are available in literature to understand and interpret the data. The type of data determines the models, algorithms and tools that are useful and can be categorized into three groups [8]:

- *Value type*: Data collected at a specific time epoch for a condition monitoring variable are a single value. For example, oil composition, temperature, pressure and humidity are all value type data.
- *Waveform type*: Data collected at a specific time epoch for a condition monitoring variable are time series, which is often called time waveform. For example, vibration data and acoustic data are waveform type.
- *Multi-dimension type*: Data collected at a specific time epoch for a condition monitoring variable are multidimensional. The most common multidimensional data are image data such as infrared thermographs, X-ray images, visual images, etc.

The listed types of data are discussed extensively in literature [11, 12].

Decision making

The last step of a CBM program is maintenance decision-making and is crucial for taking maintenance actions. As mentioned before, techniques for this process are diagnostics and prognostics. Where prognostics is superior to diagnostics since it can save extra unplanned maintenance cost [8]. Faults and failures that are not predictable have to be detected by diagnostics. Besides, results from diagnostics can be utilized by prognostics to build a better CBM model.

The remaining useful life of the component given the current condition is the most widely used type of prognostics. The remaining useful lifetime (RUL) refers to the time left before observing a failure given the current machine age and condition, and the past operation profile [8]. The RUL of the subsystem can be determined by the operating history up to time. However, it is necessary to embed this into an appropriate decision model which takes accounts of the cost associated with failure and maintenance [13]. Predicting the RUL involves uncertainty and therefore it must be treated as a probabilistic process in which the predicted RUL is represented by a probability density function (PDF) [14].

However, the availability of real time data and prediction models combined with the lack of experience might be a problem for companies that are interested in implementing CBM [15] and is therefore an advantage of TBM. Furthermore, applying CBM to a large wind farm requires a dynamic scheduling of maintenance activities. Companies have to be able to adopt such flexible planning to the already existing planning methods. Due to the high maintenance activity level, TBM has relatively low repair cost and high prevention cost. For CM it is the other way around, repair cost are high when breakdowns occur and there are no prevention cost since maintenance takes place only when equipment fails. CBM makes sure that equipment is utilized at maximum and therefore the optimum lays within this sector. Above explanation only holds in theory, if specific component failure cannot be monitored the most efficient model can also depend on TBM or a combination of both strategies.

In the ideal situation, CBM is able to detect problems so that equipment can be replaced or repaired before a failure. However, as is described by [16], CBM may not be 100% accurate. It is possible that failure occurs before problems are predicted, and on other occasions, conditions will dictate equipment replacement and repair when the equipment could continue to operate for some time. If these prediction mistakes occurs frequently a combination with TBM should be developed where a trade-off between using TBM and CBM is considered.

In the efforts to address the issues listed above, we propose a series of opportunistic maintenance optimization models, under imperfect maintenance and two-level maintenance thresholds. These policies will be based the equivalent age approach that utilizes weather information to estimate the age of the turbine at any giving time. Simulation methods will be developed to evaluate the costs of proposed opportunistic maintenance policies. Numerical examples will be provided to illustrate the proposed approaches as compared to time-based maintenance policies and demonstrate the advantages of the proposed opportunistic maintenance methods. This dissertation consists of three papers relating to opportunistic maintenance models for wind farms.

In Chapter 2, we explore two years of SCADA data for four wind turbines in the same wind farm. The goal of this chapter is to study the impact of weather conditions on the uptime length for each turbine. Statistical analysis of SCADA helps to establish data driven aging model, and assess more accurately the overall reliability of the turbine.

In Chapter 3, we consider the equivalent age model for one wind turbine under different wind and temperature profiles. Because typical studies do not include the effect of weather conditions on aging of turbines and, detecting faults using operation data tends to be quite difficult. Equivalent age modeling is useful in this context because it provides a mechanism by which weather information provides estimation of differences in aging rates while not depending strongly on acquiring and analyzing multiple streams of sensors data. We propose the application of a deterministic equivalent age approach coupled with typical Weibull-based life distribution that uses hourly wind speed and air temperature to estimate the age of the turbine at the end of each day and implement two-level threshold maintenance strategy.

In Chapter 4, we apply our model from Chapter 2 to a wind farm with multiple wind turbines, where the key research questions are centered on the grouping of maintenance actions among turbines under economic dependencies assumptions. We conduct a simulation study to show that the new method produces results that are scenario based and compare it to other existing methods.

Finally, in Chapter 5, we summarize our main findings and provide potential directions for future work.

References

[1] EIA, "Annual energy outlook 2020." https://www.eia.gov/outlooks/aeo/, January 2020. [Accessed March 2020].

[2] F. Spinato, P. J. Tavner, G. J. W. V. Bussel, and E. Koutoulakos, "Reliability of wind turbine subassemblies," *IET Renewable Power Generation*, vol. 3, pp. 387–401, December 2009.

[3] E. Gustavsson, M. Patriksson, A.-B. Strömberg, A. Wojciechowski, and M. Önnheim, "Preventive maintenance scheduling of multi-component systems with interval costs," *Computers & Industrial Engineering*, vol. 76, no. Supplement C, pp. 390 – 400, 2014.

[4] Y. Han and Y. H. Song, "Condition monitoring techniques for electrical equipment-a literature survey," *IEEE Transactions on Power Delivery*, vol. 18, pp. 4–13, Jan 2003.

[5] R. Ahmad and S. Kamaruddin, "An overview of time-based and condition-based maintenance in industrial application," *Computers & Industrial Engineering*, vol. 63, no. 1, pp. 135 – 149, 2012.

[6] H. P. Bloch and F. K. Geitner, *Machinery Failure Analysis and Troubleshooting*. Gulf Houston TX, 1983.

[7] L. Mann, A. Saxena, and G. M. Knapp, "Statistical-based or condition-based preventive maintenance?," *Journal of Quality in Maintenance Engineering*, vol. 1, no. 1, pp. 46–59, 1995.

[8] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mechanical Systems and Signal Processing*, vol. 20, no. 7, pp. 1483 – 1510, 2006.

[9] D. Goyal, B. S. Pabla, S. S. Dhami, and K. Lachhwani, "Optimization of condition-based maintenance using soft computing," *Neural Computing and Applications*, vol. 28, pp. 829–844, Dec 2017.

[10] H. R. Golmakani and F. Fattahipour, “Age-based inspection scheme for condition-based maintenance,” *Journal of Quality in Maintenance Engineering*, vol. 17, no. 1, pp. 93–110, 2011.

[11] T. Heger and M. C. Pandit, “Optical wear assessment system for grinding tools,” *Journal of Electronic Imaging*, vol. 13, pp. 13 – 12, 2004.

[12] C. Ellwein, S. Danaher, and U. Jager, “Identifying regions of interest in spectra for classification purposes,” *Mechanical Systems and Signal Processing*, vol. 16, no. 2, pp. 211 – 222, 2002.

[13] P. A. Scarf, “On the application of mathematical models in maintenance,” *European Journal of Operational Research*, vol. 99, no. 3, pp. 493 – 506, 1997. Eleventh EURO Summer Institute: Operational Research Models in Maintenance.

[14] G. W. Vogl, B. A. Weiss, and M. Helu, “A review of diagnostic and prognostic capabilities and best practices for manufacturing,” *Journal of Intelligent Manufacturing*, Jun 2016.

[15] E. Zio and M. Compare, “Evaluating maintenance policies by quantitative modeling and analysis,” *Reliability Engineering & System Safety*, vol. 109, no. Supplement C, pp. 53 – 65, 2013.

[16] B. Al-Najjar, “Accuracy, effectiveness and improvement of vibration-based maintenance in paper mills: Case studies,” *Journal of Sound and Vibration*, vol. 229, no. 2, pp. 389 – 410, 2000.

Chapter 2

SCADA DATA EXPLORATION FOR WIND SPEED EFFECT ON TURBINE UPTIME

2.1 INTRODUCTION

Effective maintenance models of wind turbines are essential to drive more investments in wind energy as a more economic source of energy, reducing the O&M cost relative to the electricity price. This can only be achieved by having better knowledge about turbine failures, degradation and age, particularly for wind turbines operating in extreme weather conditions and remote areas such as offshore wind farms. Maintenance approaches that utilize condition monitoring systems to continuously track turbine health states, increase the maintenance effectiveness significantly by reducing costs and failures by 20 % to 25% [1]. Recently, as wind power has gained more interest in many countries, the concept of condition based maintenance has been studied widely in the literature. The objective of the majority of those studies is to reduce maintenance costs and improve farm availability. Wind farm condition based maintenance research can be divided into two main categories: condition monitoring systems and maintenance optimization mathematical models.

Nonetheless, current maintenance solutions are not entirely capable of using the large amount of condition monitoring data produced by multi-sensors in modern wind turbines. In order to enhance power forecasts, the service life of turbines, the maintenance plans and wind farms logistics, the use of sensors data can be enhanced as digitization accelerates in the energy industry. In addition to traditional visual inspection, vibration analysis is the most common condition monitoring method to assess the health of wind turbines. Visual inspection, which usually involves shutting down the turbine, is a labor intensive method and can only identify some types of failures [2] hence, a minimum number of inspections is desirable. Vibration analysis, which requires additional sensors is a very effective tool for rotating equipment including the wind turbine gearbox, however, wind turbines are complex systems. A study conducted by the National Renewable Energy Laboratory (NREL) shows that current vibration analysis systems have on average 50 % detection accuracy [3]. Other sensor-based condition monitoring methods have been studied as well including oil and thermal analysis, which have been successful in detecting early signs of specific failure modes [4]. These methods, however, tend to require additional equipment and can be expensive to implement in large scale. Thus, they are usually associated with the most expensive parts of turbines such as blades and gearboxes [5, 4].

An alternative to physics-based methods is data-driven methods that use SCADA (Supervisory Control and Data Acquisition) data to predict changes in the turbines health state. A SCADA system is available in the majority of industrial wind turbines. This built-in system collects operational and ambient data at 10-minute resolution [6, 7]. Several studies have used SCADA for energy prediction and power curve analysis [8]. Meanwhile, implementing statistical analysis on SCADA data to predict normal or anomalous operating conditions has shown significant accuracy in predicting early faults. Kusiak and Li [9] investigated 3 months SCADA data of four turbines based on status and fault codes to predict fault points. They reported prediction accuracy of 70 % and 49 % at failure and one hour in advance, respectively. Godwin and Matthews [10] studied pitch faults using 2 years SCADA data of eight wind turbines with known pitch faults. They combined that with maintenance logs to predict faults two days in advance with an average prediction accuracy of 85 %.

In this paper, we explore SCADA data for four turbines to study the impact of wind speed and air temperature on the uptime of each turbine. We use linear regression as our statistical approach to assess the significance of each variable through combination of failure information and SCADA observations. This paper therefore presents preliminary results based on the available SCADA data.

2.2 SCADA DATA

We utilize an open source SCADA database from Engie Renewables [11]. The datasets contains 10-minute data for 4 turbines with a rated power of 2 MW covering the period between 2013 and 2020 in La Haute Borne, France. The SCADA data has 30 fields, summarized in Table 2.1. The four wind turbines are identical Senvion MM82. This type of turbines is a variable-speed, three bladed with a hub height of 78 m and a rotor diameter of 82 m. MM82 has an asynchronous type generator of 2MW. Senvion MM82 operates within a wind speed range between 3 m/s and 25 m/s. The wind turbine has a rated power of 2MW at a rated wind speed of 13 m/s. Table 2.2 and Figure 2.1 show Senvion MM82 information and its power curve, respectively.

Table 2.1: Summary of SCADA fields.

Variable	Description	Unit	Variable	Description	Unit
Va2	Second wind vane on the nacelle	deg	Cm	Converter torque	Nm
Ws2	Second anemometer on the nacelle	m/s	Ds	Generator speed	rpm
Ws	Average wind speed	m/s	Gb2t	Gearbox bearing 2 temperature	°C
Wa_c	Absolute wind direction corrected	deg	Gost	Gearbox oil sump temperature	°C
Na_c	Nacelle angle corrected	deg	Ya	Nacelle angle	deg
Ot	Outdoor temperature	°C	Wa	Absolute wind direction	deg
Yt	Nacelle temperature	°C	Va	Vane position	deg
Nf	Grid frequency	Hz	Rs	Rotor speed	rpm
Nu	Grid voltage	V	Ba	Pitch angle	deg
Rm	Torque	Nm	Rt	Hub temperature	°C
Dst	Generator stator temperature	°C	P	Active power	kW
Git	Gearbox inlet temperature	°C	S	Apparent power	kVA
Q	Reactive power	kVAr	Db1t	Generator bearing 1 temperature	°C
DCs	Generator converter speed	rpm	Db2t	Generator bearing 2 temperature	°C
Va1	Vane position 1 (first vane)	deg	Gb1t	Gearbox bearing 1 temperature	°C
Rbt	Rotor bearing temperature	°C	Ws1	Wind speed (first anemometer)	m/s

In addition to the 10-minutes condition data, the dataset contains the current operational status of the turbine in each time period. In this paper we use status data to determine uptime periods for each turbine. Table 2.3 summarizes the available status data.

Table 2.2: Senvion MM82 wind turbine information

Parameter	Description	Value
Pw_{rated}	Rated power (kW)	2050
v_{rated}	Rated wind speed (m/s)	13
v_{in}	Cut-in wind speed (m/s)	3
v_{out}	Cut-out wind speed m/s	25
L	Service life$(years)$	20
d_r	Rotor diameter (m)	82
h_2	Hub height (m)	78

Table 2.3: Summary of major status fields.

ID	Category	No./Turbine/Year	Downtime/Turbine/Year	Total
19	Hub	0.928	8.687373	6
16	Tower	3.424	6.535387	7
9	Hydraulics	3.632	7.891067	8
3	Rotor Brake	4.096	9.541907	9
22	Other	5.264	12.966022	10
2	Anemometry	5.744	16.484427	11
18	Cable Unwind	7.648	2.849724	12
13	Customer Stop	8.848	157.337409	13
7	Yaw System	9.824	15.684973	14
20	Rotor Blades	10.976	95.650022	15
6	Generator	13.856	83.986507	16
5	Gearbox	17.952	200.734276	17
15	Scheduled Maintenance	31.488	24.981791	18
8	Electrical Controls	32.672	129.02232	19
10	Electrical System	50.912	135.32332	20
11	Pitch Control	92.64	326.015871	22

2.3 POWER CURVE ANALYSIS

Turbine output power and performance at any given wind speed can be described by its power curve. Fig 2.1 shows the power curve and the operating regions of the Senvion MM82 turbine. In the first region the turbine is idle or not generating power due to low wind speeds that are below the required cut-in wind speed value to generate power. When wind speeds are higher than the cut-in value, the turbine enters the second region. During the second and third regions, the control system keeps the pitch angle constant and the yaw actuator keeps the turbine orientated to the main direction of the wind. In the fourth region, the pitch actuator starts as wind speeds approach the rated wind speed while the blade pitch angle is adjusted to maintain the recommended rotor speed. In the fifth region, the control system maintains the output power level at the rated power value by controlling the pitch angle until wind speeds exceed 25 m/s.

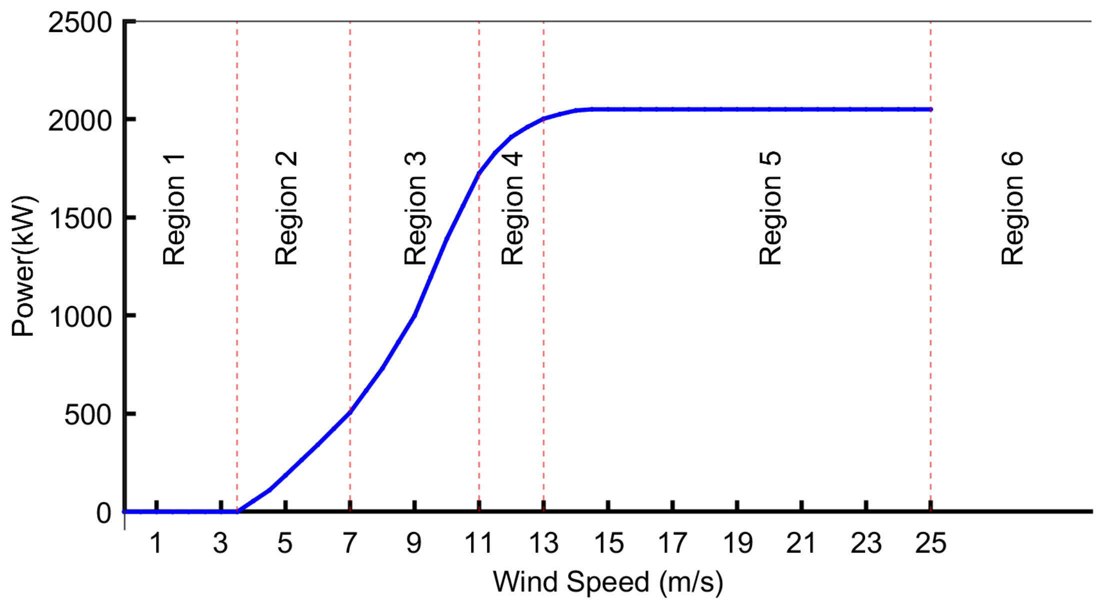


Figure 2.1: Power curve for the Senvion MM82 wind turbine

The general equation relating wind power Pw to swept area (A), wind speed (v), density of air (ρ), power coefficient (C_p) and rated power Pw_{rated} is:

$$
Pw(v) = \begin{cases} 0 & v < v_{in} \\ \frac{1}{2}\,\rho\, C_p\, A\, v^3 & v_{in} \leq v < v_{rated} \\ Pw_{rated} & v_{rated} \leq v \leq v_{out} \\ 0 & v > v_{out} \end{cases} \tag{2.1}
$$

Ideally, C_p is between 0.2 and 0.5 for all wind speed values between v_{in} and v_{out}. Grid and rotor data are another interesting observations to identify farm level conditions since wind farms are connected to power grids with fluctuations in demand. However, there are many factors that influence the output of the turbine. Under ideal conditions we expect the four turbines to follow the power curve shown in Fig. 2.1. However, the raw data contains many imperfections. Rows of data with missing values are removed from the corresponding wind speed and power measurements. Measurements are recorded for a given condition's minimum, maximum, and average. For the purpose of this study, only average values are considered. First we look at the power curve of all observations of average active power and average winds speed as shown in Fig. 2.2.

Power curve will be key to determine the state of operation as any deviation from the expect curve or trends in the observations will be points of interest. To explore the raw power data, we plot the observed power of the four wind turbines side by side. While the four turbines are identical and in the same wind farm, their power curves are significantly different with steep power deviation to the left of the expected power curve. To explore this area of interest of their power curves while keeping the same visualization, we assign data clusters to color which shows clear deviation from the power curve in different regions in each turbine as shown in Fig. 2.3.

Looking at the power data we notice that their is steep spikes in the early data to the left of the power curve. One explanation is that turbines experience performance degradation over time. To further explore those clusters, we plot the power curve over time by mapping the power data to time intervals over the entire period . The plots show that wind speeds trends are generally following the trend in the average power as expected from the power curve. However, the plots

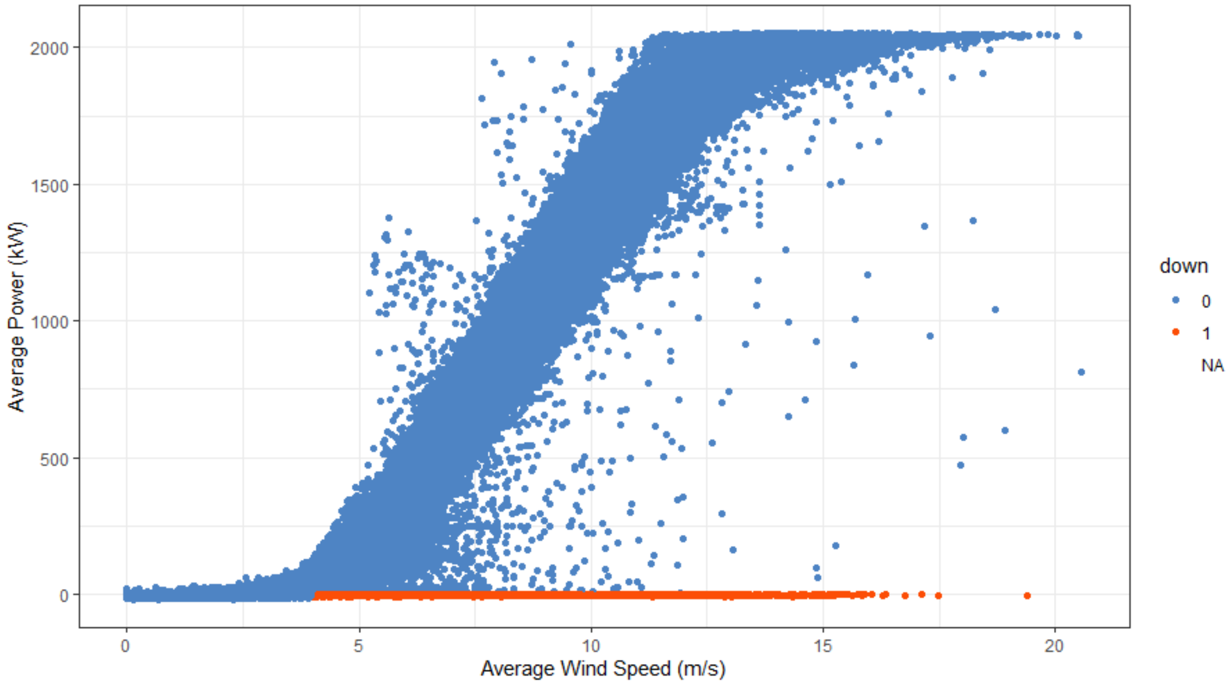


Figure 2.2: Average power (kW) vs. average wind speed (m/s) with 'downtime' points highlighted

shows significant clusters of zero output power values at high wind speeds as indicated by the dark spikes in Fig 2.3.

In this dataset, operational wind speed is between 3 m/s and 25 m/s. Since the four turbines are in one location, we can look at the entire dataset and remove all the non-operational data points using status data. Fig 2.4 shows the power curve of all turbines using normalized wind speed and power measurements and filtered by turbine status. Normalized measurements are defined as the ratio of recorded values over the maximum value.

Previous and current condition of the turbine at any given time affect the power observations. Power outputs cannot be used directly to define uptime periods without considering the status of the turbine. This allows us to better identify the length of each uptime period.

In this paper, we define uptime as the operational period between two downtime periods of length longer than 5 hours. Fig. 2.5 shows summary of the major downtime categories. We exclude low or high wind related idle times from our uptime calculation to limit downtime data to either failure or maintenance related data. Grid issues and high temperature are among major causes of

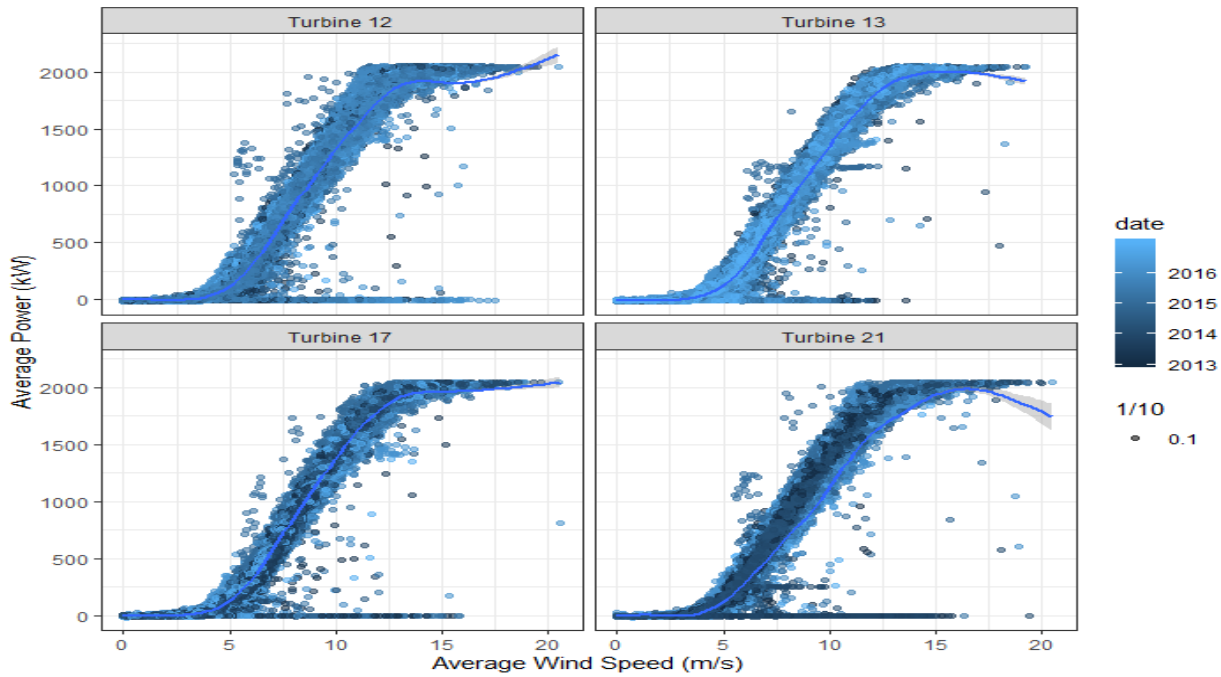


Figure 2.3: Mapped wind speed (m/s) vs. average power (kW)

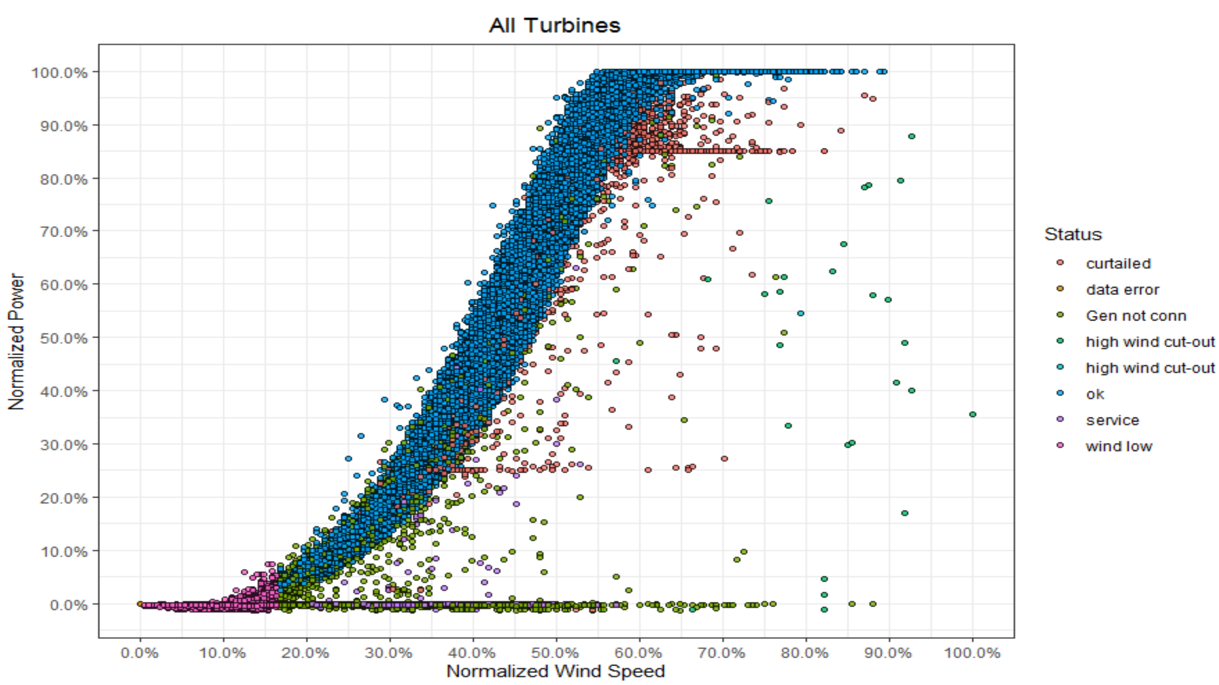


Figure 2.4: Normalized power vs. normalized wind speed with 'status' points highlighted

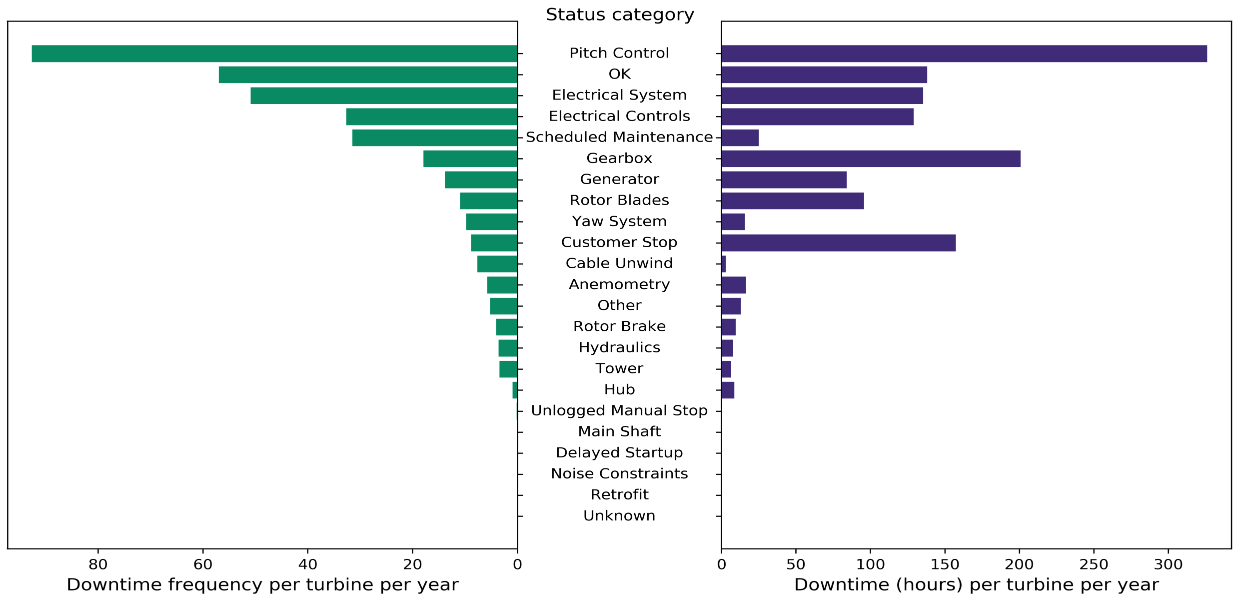


Figure 2.5: Summary of downtime data

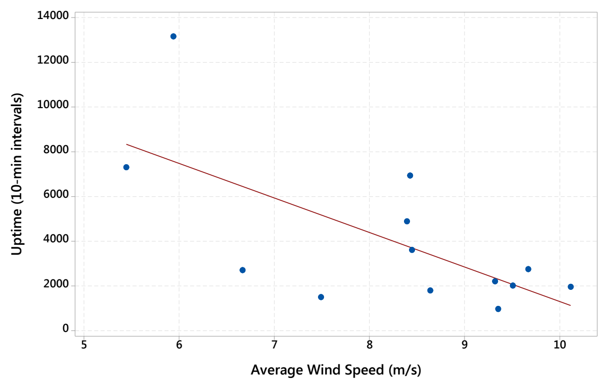
downtime. However, there is not a direct relationship between them and maintenance activities. Again, we exclude those two factors from our major downtime consideration. Table 2.4 shows the uptime periods for each turbine as the number of 10-minutes intervals between two major downtime events. Note that while all turbines are located in the same location their wind and power measurements show significant difference during specific periods mainly due to curtailment in order to reduce turbulence and minimize the wake effect. Moreover, certain periods do not have the corresponding status data for all turbines, therefore those periods were eliminated from this analysis.

Table 2.4: Uptime periods as the number of 10-minutes intervals between two major downtime events

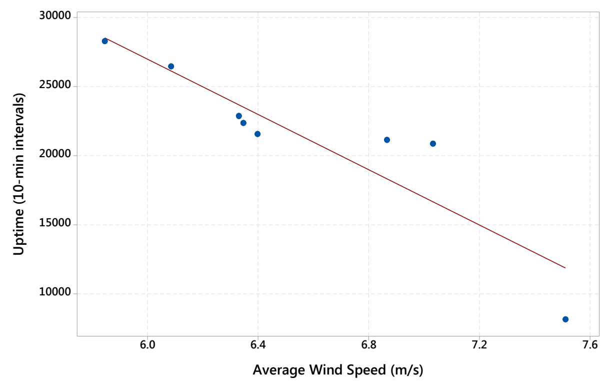
Turbine No.	Uptime Periods										
	1	2	3	4	5	6	7	8	9	10	11
Turbine 12	2751	2018	1797	4887	2706	1501	3610	2207	6935	1961	972
Turbine 13	22367	21567	8159	26466	20871	22869	28288	-	-	-	-
Turbine 17	4304	4287	3404	3194	1901	3989	-	-	-	-	-
Turbine 21	23276	20019	19400	26456	15012	28449	16351	27440	-	-	-

2.4 IMPACT OF WIND SPEED

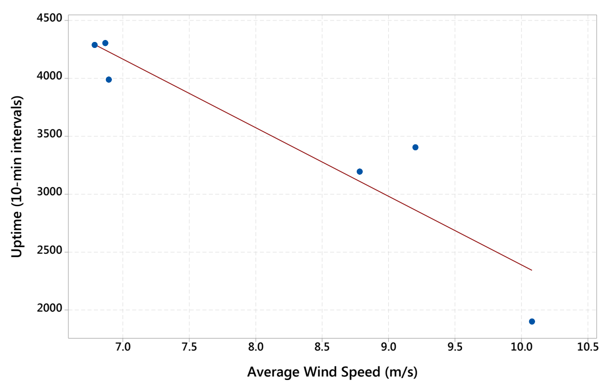
In this section, we look at the trends in uptime data versus the average wind speed during each period for each turbine. We assume that turbines are operational during the entire uptime period and subjected to the same weather conditions. Fig. 2.6 shows plots of the uptime and the expected average wind speed during each uptime period. All turbines show a declining trend in uptime as the average wind speed increases.



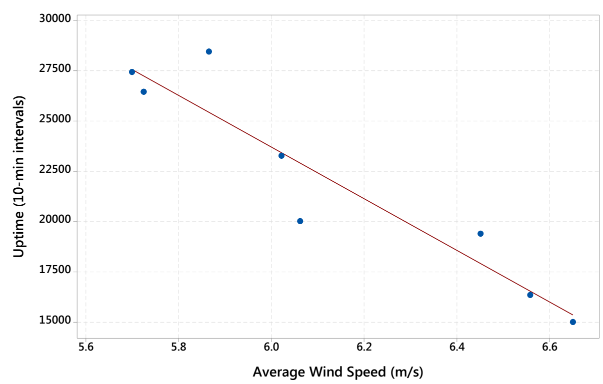
(a) Turbine 12



(b) Turbine 13



(c) Turbine 17



(d) Turbine 21

Figure 2.6: Average wind speed (m/s) vs. uptime (10-min intervals)

It is worth mentioning that this trend is more prevalent when the average wind speed exceeds $7m/s$. This wind speed value corresponds with the maximum power coefficient C_p as shown in Fig. 2.7. All uptime data shows significant reduction if a turbine spends more time operating beyond its most efficient power coefficient value.

Second, we conduct a linear regression analysis for each turbine. We reveal that all p-values are smaller than $alpha = 0.05$ and all R-square values are greater than 0.9 which indicates statistical significance. Fig. 2.8 shows normal probability plots performed in Minitab which shows most points clustered near the straight line hence the model is deemed fit. Table 2.5 shows a summary of the regressing analysis results.

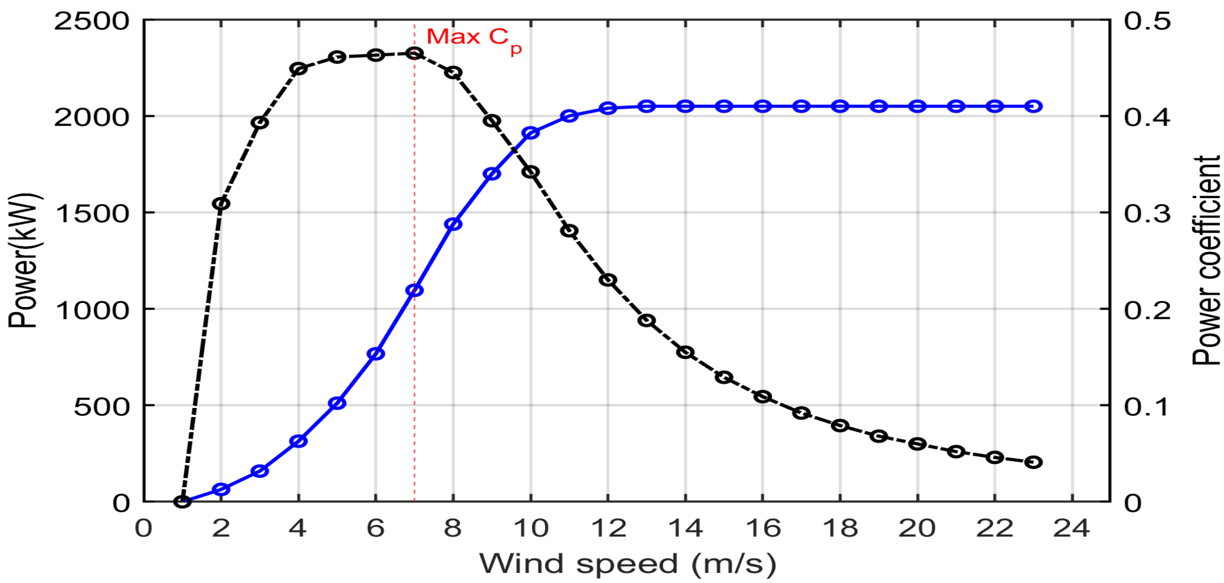


Figure 2.7: MM82 power coefficients and power curve

2.5 DISCUSSION

The results show significant variation of uptime between four identical turbines. Due to the limited size of the dataset, it is difficult to assess the impact of turbine age on uptime under different weather conditions. Moreover, status data are not available for the entire length of the dataset and there are overlapping status of normal and faulty states even under operational conditions. Based on the regression results, wind speeds higher than $7m/s$ are least influential in reducing uptime. Higher wind speeds beyond the maximum power coefficient region in the power curve have clear impact on uptime with significant reduction up to 60% under average wind speeds higher than the rated speed compared to periods of low wind speeds.

Table 2.5: Summary of regression analysis results

Source	DF	Adj MS	F-Value	P-Value
Regression	1	6190915	8.82	0.013
Wind Speed	1	6190915	8.82	0.013
Error	11	7020268		
Total	12			

(a) Turbine 12

Source	DF	Adj MS	F-Value	P-Value
Regression	1	208165013	28.58	0.002
Wind Speed	1	208165013	28.58	0.002
Error	6	7283173		
Total	7			

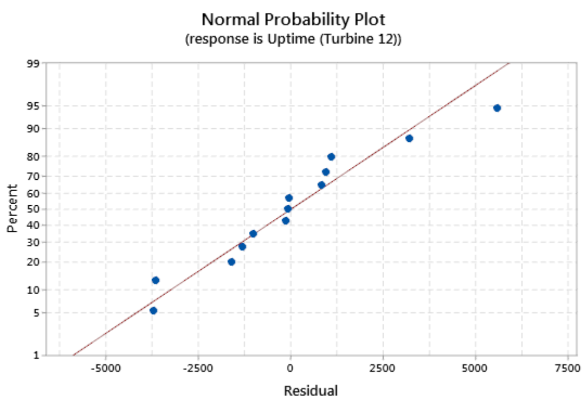
(b) Turbine 13

Source	DF	Adj MS	F-Value	P-Value
Regression	1	3607555	25.96	0.007
Wind Speed	1	3607555	25.96	0.007
Error	4	138991		
Total	5			

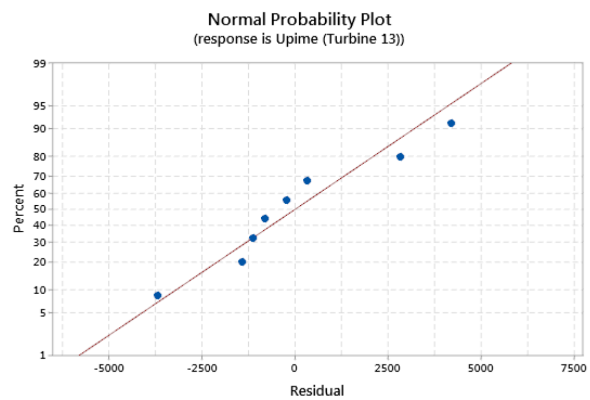
(c) Turbine 17

Source	DF	Adj MS	F-Value	P-Value
Regression	1	163621391	48	<0.0001
Wind Speed	1	163621391	48	<0.0001
Error	6	3408888		
Total	7			

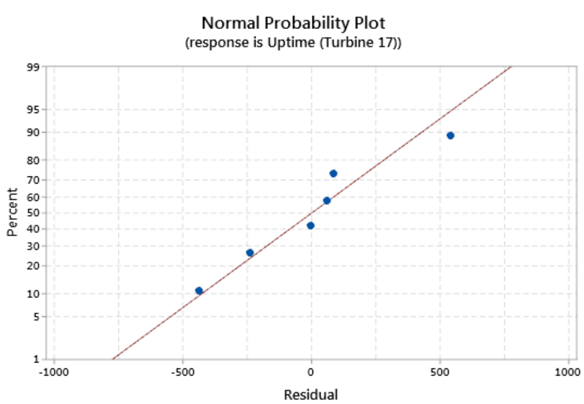
(d) Turbine 21



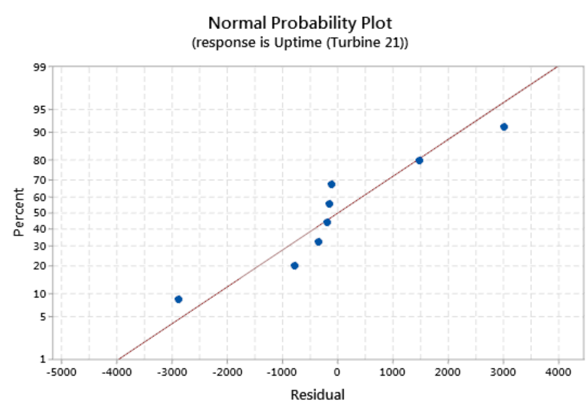
(a) Turbine 12



(b) Turbine 13



(c) Turbine 17



(d) Turbine 21

Figure 2.8: Normal probability plots for each turbine

However, SCADA data discussed in the previous section show no clear relationship between ambient air temperature and uptime of wind turbine (see Fig. 2.9). FBG sensors are widely used to detect fatigue in turbine blades. The main effect of ambient temperature can be related to thermal strain which is a function of temperature difference. Plotting the average standard deviation of temperature during each uptime period did not reveal a clear trend.

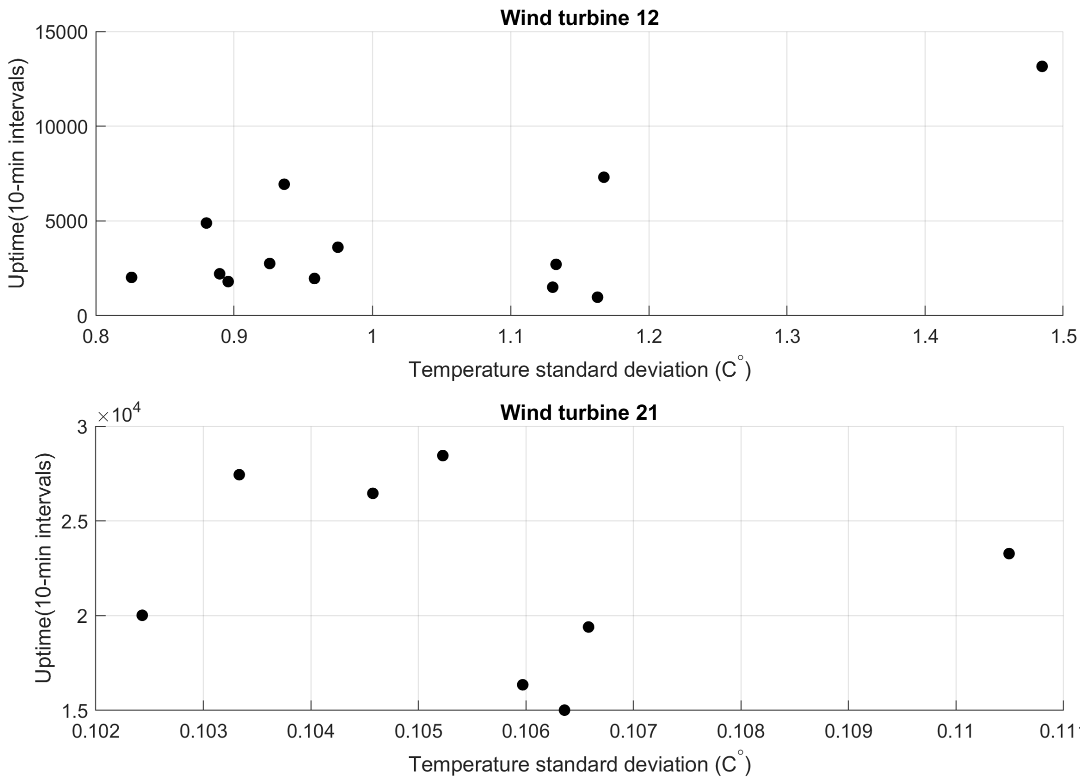


Figure 2.9: Temperature standard deviation vs. Uptime

Grid and farm management data were not analyzed in this study and they can be important in the classification of uptime periods. Faults in the grid are reflected in the electrical system observations and can be linked to environmental conditions.

2.6 CONCLUSION

This paper focuses on the impact of wind speed on the availability of turbines. We explored SCADA data of four wind turbines for the impact of wind speed on uptime. We analyzed the power curve and status data to determine the length of uptime periods for each turbine. We showed that higher wind speeds (above 7 m/s) have significant impact of uptime reduction. Compared to low wind speed periods, periods of wind speeds above the rated speed can experience up to 60% uptime reduction. The effect of ambient temperature on the other hand is not clear. Temperature data does not show any clear trend with respect to up time data. Conducting more in-depth analysis to improve prediction of the impact of weather conditions on turbine aging requires larger datasets of the same turbine types at different geographical locations . The reason behind this is that for any statistical analysis, the effect of weather conditions must be separated from the effect of time. Given the available data, our conclusion is that turbines operating at rated wind speeds or higher will experience significant reduction in uptime. Conducting a statistical analysis with larger datasets of the same turbine types at different geographical locations is a next step to gain better understanding of the effect of wind speed and other weather conditions on the uptime of wind turbines and improve wind farms condition based maintenance models .

References

[1] P. Tchakoua, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. A. Tameghe, and G. Ekemb, “Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges,” *Energies*, vol. 7, no. 4, pp. 2595–2630, 2014.

[2] H. Niemann, N. Kjølstad Poulsen, M. Mirzaei, and L. C. Henriksen, “Fault diagnosis and condition monitoring of wind turbines,” *International Journal of Adaptive Control and Signal Processing*, vol. 32, no. 4, pp. 586–613, 2018.

[3] J. Tautz-Weinert and S. J. Watson, “Using scada data for wind turbine condition monitoring – a review,” *IET Renewable Power Generation*, vol. 11, no. 4, pp. 382–394, 2017.

[4] F. P. García Márquez, A. M. Tobias, J. M. Pinar Pérez, and M. Papaelias, “Condition monitoring of wind turbines: Techniques and methods,” *Renewable Energy*, vol. 46, pp. 169–178, 2012-10-01.

[5] K. Leahy, R. L. Hu, I. C. Konstantakopoulos, C. J. Spanos, and A. M. Agogino, “Diagnosing wind turbine faults using machine learning techniques applied to operational data,” in *2016 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pp. 1–8, 2016-06.

[6] J. Tautz-Weinert and S. J. Watson, “Using SCADA data for wind turbine condition monitoring – a review,” *IET Renewable Power Generation*, vol. 11, no. 4, pp. 382–394, 2017.

[7] W. Yang, P. J. Tavner, C. J. Crabtree, Y. Feng, and Y. Qiu, “Wind turbine condition monitoring: Technical and commercial challenges,” *Wind Energy*, vol. 17, no. 5, pp. 673–693, 2014.

[8] S. Gill, B. Stephen, and S. Galloway, “Wind turbine condition assessment through power curve copula modeling,” *IEEE Transactions on Sustainable Energy*, vol. 3, pp. 94–101, 2012.

[9] A. Kusiak and W. Li, “The prediction and diagnosis of wind turbine faults,” *Renewable Energy*, vol. 36, no. 1, pp. 16–23, 2011-01-01.

[10] J. L. Godwin and P. Matthews, “Classification and Detection of Wind Turbine Pitch Faults Through SCADA Data Analysis,” *International Journal of Prognostics and Health Management*, vol. 4.

[11] “La haute borne data.” https://opendata-renewables.engie.com/. Accessed: 2020-02-30.

Chapter 3

MAINTENANCE OPTIMIZATION OF WIND TURBINES USING WEATHER-DEPENDENT EQUIVALENT AGE MODEL

3.1 INTRODUCTION

Maintenance policies are crucial to ensure products quality, machines reliability and operator safety. Despite recent technological advances in condition sensing, Time Based Maintenance (TBM) strategy is still widely used in many industries [1]. Condition Based Maintenance (CBM) on the other hand, is quickly gaining interest within the wind power industry as more sophisticated sensors and complex systems are incorporated into wind turbines. It is critical to operational costs and availability to utilize more precise information about remaining turbine useful life to avoid catastrophic failures and reduce cost of maintenance.

The central idea of CBM is to maintain systems or components at exactly the right time, by utilizing information about their actual condition to maintain high reliability while reducing operating costs. In this context, a trade-off is made between the risk of failure during operation (resulting in costly system downtime) and the cost of premature maintenance. Unlike TBM, CBM depends less on the failure history and focuses more on inspections and real time data monitoring of equipment to predict remaining useful life (RUL) and failure rate. The goal for any maintenance policy is to restore the system to a functional state and avoid downtime losses while keeping maintenance cost minimized within technical and financial constraints. Hence, decision support systems are very critical for CBM policies to be successful.

Maintenance optimization models have been intensively studied in the literature mostly focusing on two optimality criteria; cost and availability [2, 3, 4]. Several multi-objective and multi-component time-based maintenance models for short term planning horizon have been proposed to mitigate the risk associated with the traditional TBM such as assuming constant operating conditions and depending on historical data [5, 6, 7]. Due to the complex nature of aging in complex systems, several studies have developed probabilistic optimization models with imperfect maintenance [8, 9], failure dependencies [10, 11] or economic dependency among components [12, 13]. These maintenance strategies consider the economic dependencies between different wind turbines and/or their turbine components.

The implementation of CBM in wind farms has been studied extensively in the last decade, utilizing the deterioration state information to determine the maintenance plan and reduce O&M cost [14, 15, 16, 17]. Recently, Zhang et al [18] proposed an opportunistic imperfect maintenance policy for wind turbines. The authors proposed a two-threshold policy, where maintenance actions are triggered by the first wind turbine to reach the failure threshold. A lower failure threshold is then applied to the remaining turbines in an effort to group maintenance actions. Besnard and Bertling [19] proposed a CBM strategy using Markov chain to represent the deterioration states of turbine blades. They classified the deterioration state based on the severity of the damage. Shafiee et al. [20] investigated the impact of environmental shocks on blade cracking. They considered crack length threshold to find the optimal CBM policy for a wind farm under harsh marine environments. Mazidi et al. [21] proposed a proportional hazard based maintenance model for wind turbines using SCADA data to determine the stress conditions of wind turbines. However, they did not consider weather conditions or other external factors in their model. Haddad et al. [22] studied the advantages of delaying maintenance actions after a prognostic indication to find the optimal remaining useful life. Their maintenance approach utilizes health condition prediction information to minimize lead time for wind farms. Although these studies propose CBM policies with some weather restrictions, they do not necessarily consider the complex weather conditions as a factor in reliability models.

These maintenance models do not account for the impact of the actual weather conditions on aging. CBM has better performance when it develops a targeted maintenance plan for each wind turbine under variable weather and load conditions. Despite the number of studies in wind farms maintenance, only few have studied the effect of weather conditions on wind turbine aging. Byon et al. [23] have investigated the weather conditions impact on CBM decisions. They proposed a partially observed Markov decision process model to obtain a closed-form solution, however they only considered the impact of weather conditions on the accessibility of the farm. The primary objectives of condition monitoring systems is to accurately represent the stochastic behavior of the aging process, assess the system reliability and make a maintenance decision. Operating and environmental conditions in many scenarios, are easy to identify. Since diagnostic covariates cannot reflect precisely the degradation state of the system, decision rules rely on the estimated degradation level reconstructed from these noisy covariates [24]. However, in many cases system degradation is hidden, and system failure is non-self-announcing [25]. This means the system reveals only its degradation state and its failure through a monitoring procedure. However, some factors that cause the degradation turbine components are uncertain and difficult to predict [26].

In this paper, we propose a new age based maintenance model in absence of an observable degradation signal for wind turbine systems, but where the weather conditions (wind speed and ambient temperature) can be monitored continuously. In this situation, one can use system reliability, with respect to monitored conditions, to directly calculate the system conditional probability of failure at a given time and base maintenance policy for the system on this distribution. Specifically, this work makes two major extensions from previous work: (1) builds a weather based aging model for wind turbines using EA; and (2) derives a two-level threshold maintenance policy that considers weather restrictions.

The new decision-making model described in this paper utilizes real-time weather information to evaluate system health, with a set of maintenance thresholds. Using field data, mainly from the literature and real wind measurements, the case study demonstrates that the proposed method addresses practical O&M planning issues and reduces the O&M costs by planning preventive maintenance in low wind conditions to avoid failure during harsh weather seasons.

3.2 PROPOSED MODEL

Consider a wind turbine with repairable components, each subjected to deterioration. Let $L : \Omega \to \mathbb{R}$ be a random variable that represents the lifetime of a wind turbine in a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. During their lifetime, we assume turbines deteriorate contentiously until they experience a fault. Let $F_\tau(t)$ be the lifetime distribution function which describes the failure probability before a given moment of time $P(\tau \le t)$. In this paper, we assume that the turbine lifetime distribution follows a two-parameter Weibull distribution $F(t)$, where t denotes current time, with scale parameter η and shape parameter β:

$$F(t) = 1 - exp\left[-\left(t/\eta\right)^{\beta}\right] \tag{3.1}$$

It is natural to expect weather conditions and their corresponding impact on the degradation process to change over the lifetime of the turbine. It has been reported [27] that wind turbines located at higher elevations with high wind speed conditions, experience higher failure rates. Wilkinson et al. [28] studied the correlation between air temperature and the reliability of wind turbines and concluded that higher ambient air temperatures cause higher failure rates. Tavner et al [29] has shown that high humidity can reduce the reliability of the drivetrain components. According to Slimacek and Lindqvist [30], external weather factors such as ambient temperature, icing and high winds can increase the failure rate of wind turbines by a factor of 1.7.

The traditional approach to preventive maintenance estimates the Weibull parameters using historical failure data, then schedule maintenance activities based on mean time to failure (MTTF). This approach assumes time independent covariates and linear proportionality with the hazard rate, which is in most cases unrealistic. Data-driven techniques, on the other hand, utilize monitored operational data related to system health. They can be beneficial when the understanding of the system operation is not straightforward or when the system is so complex that developing an accurate model is prohibitively expensive.

Henry and Nachlas [31], have developed a new concept that overcomes those limitations and represents equipment aging in a more accurate model called Equivalent Age. The model reflects the continuous degradation in equipment life (which usually differs from calendar time) based on operation conditions $X_i(t)$ and usage intensity $Y_j(t)$ which are both time dependent. In this paper, we adopt this concept to model the equivalent age of a wind turbine subjected to variable wind speed and air temperature conditions. While other weather conditions may have impact on wind turbine reliability, in this paper we will only consider wind speed and air temperature because they have higher impact on wind turbine failures [32] than humidity and icing and they are applicable to both onshore and offshore farms as oppose to wave height.

3.2.1 Equivalent Age Model

Consider a wind turbine system with wind speed measures $V(t)$, and ambient temperature measures $T(t)$, then the equivalent age $\alpha(t)$ at any time t is:

$$\alpha(t) = \int_{0}^{t} (\alpha_0)^{q(k)} dk \tag{3.2}$$

Where α_0 is a nominal aging factor, and $q(t)$ is a linear additive function of two time series: wind speed ($V(t)$) and ambient temperature ($T(t)$):

$$q(t) = \delta(V(t)) + \gamma(T(t)) \tag{3.3}$$

This model combined with the Weibull distribution can represent a wide range of applications under various assumptions. The equivalent age $\alpha(t)$ described in 4.2) will replace the calendar time t in (Eq. 4.1). If we assume constant wind speed and temperature conditions, this model is identical to proportional hazards models and age is the same as calendar time. Flexibility of the model is crucial and provides the means for robust decision making within the CBM field.

Wind Speed Effect Function

One of the most important parameters in determining electric power obtained from wind-based resources is wind speed. The general equation relating wind power Pw to swept area (A), wind speed (v), density of air (ρ) , a wind turbine power coefficient (C_o) and rated power Pw_{rated} is [33]:

$$Pw(v) = \begin{cases} 0 & v < v_{in} \\ \frac{1}{2}\rho C_o A v^3 & v_{in} \leq v < v_{rated} \\ Pw_{rated} & v_{rated} \leq v \leq v_{out} \\ 0 & v > v_{out} \end{cases} \tag{3.4}$$

Assume the turbine experiences nominal degradation rate at the rated wind speed v_rated, and negligible degradation below the cut-in wind speed v_{in} and above the cut-out wind speed v_{out} , then the effect of the intensity wind speed on the equivalent age model can be defined as follow:

$$\delta(V(t)) = \begin{cases} \frac{v(t)^3 - v_{rated}^3}{v_{rated}^3} & \text{if } v_{in} \leq v(t) \leq v_{out} \\ \delta_0 & \text{otherwise} \end{cases} \tag{3.5}$$

δ_0 is a negative number to reflect the slow-down of aging when the wind speed is not within operating conditions and the turbine is idle.

Ambient Temperature Effect Function

Fiber Bragg grating (FBG) sensors have been widely used in the literature to study failure modes and fatigue related issues of wind turbine blades [34, 35, 36]. These studies primarily focus on the application of FBG sensors for condition monitoring of thermal strain as a function of temperature. The change in ambient temperature causes thermal expansion and thermo-optic effect. The shift difference of the Bragg wavelength (λ_B) (In case of a pure thermal strain) is given by [36]:

$$\frac{\Delta\lambda_B}{\lambda_B} = (\epsilon_s + \epsilon_e)\Delta T \tag{3.6}$$

Where ϵ_s, ϵ_e and ΔT are the thermal expansion coefficient, the refraction index and the change in temperature, respectively.

Experimental evidence shows this linear dependence between temperature and wavelength shift is valid for fairly large strain and temperature variations [37]. In the equivalent age model, let the following equation represents the effect of ambient air temperature as a linear function of temperature difference:

$$\gamma(T(t)) = \begin{cases} \frac{|\Delta T| - \Delta T_n}{\Delta T_n} & \text{if } \Delta T \neq 0 \\ \gamma_0 & \text{if } \Delta T = 0 \end{cases} \tag{3.7}$$

γ_0 is a negative number to reflect the slow-down of aging when the change in ambient temperature is zero.

Let the equivalent age of a turbine be denoted by θ. Then the Weibull lifetime distribution is given as follows :

$$F(\theta) = 1 - exp\left[-\left(\theta \Big/ \eta\right)^{\beta}\right] \tag{3.8}$$

Equation 3.8 together with the equivalent age model allows inclusion of wind speed and ambient temperature information from the monitored system.

3.2.2 Maintenance Model

Modern wind turbines are equipped with automated alarm systems within the condition monitoring equipment so that when a sensor signal exceeds a certain threshold, an alarm is sent to a wind farm operator [38]. Several threshold-type maintenance policies have been presented in the literature by either maximizing the availability or minimizing total costs. In these policies, a component is assigned for maintenance when the conditional probability of failure exceeds a certain level threshold value. The conditional probability of failure in the next day $Pr(1)$, can then be written as:

$$Pr(1) = \frac{F(1+\theta) - F(\theta)}{1 - F(\theta)} \tag{3.9}$$

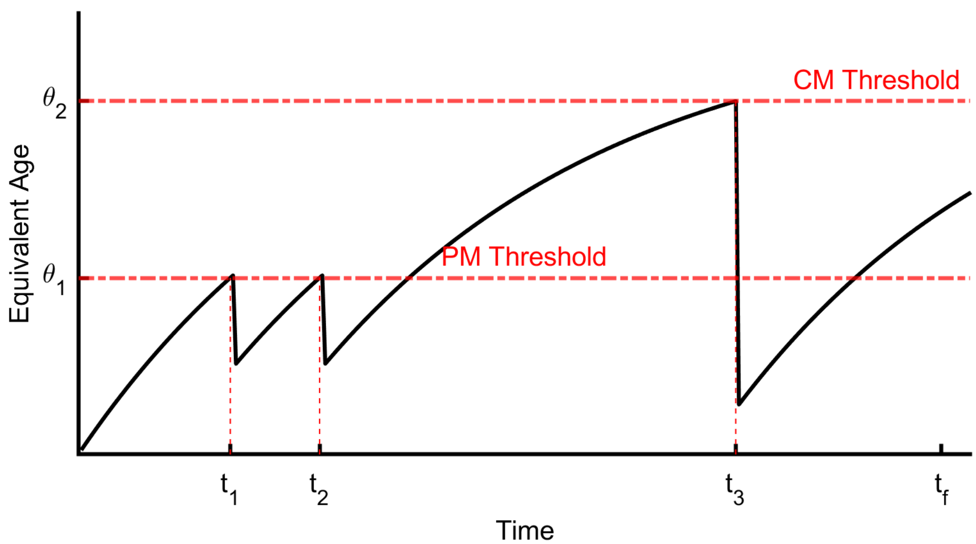


Figure 3.1: Two-level threshold condition-based maintenance policy.

In our proposed maintenance model, two thresholds (preventive threshold p^{pm} and corrective threshold p^{cm}) and three types of maintenance actions are considered:

- Preventive maintenance; a minimal repair with associated cost of C^P, triggered when the probability of failure exceeds the preventive threshold ($Pr(1) \geq p^{pm}$) ,
- Scheduled corrective maintenance; a major repair with associated cost of C^R, triggered when the probability of failure reaches the corrective threshold ($Pr(1) \geq p^{cm}$),
- Unscheduled corrective maintenance; a major repair after an unexpected failure with associated cost of failure C^F.

For simplicity, we also assume that these activities are instantaneous (as shown in Fig. 3.1), i.e., the time required to maintain the turbine is negligible relative to its age and thus all maintenance activities are assumed to be carried and completed during the same day. However, different costs associated with each maintenance type are imposed.

Maintenance actions reduces the equivalent age of the system at the start of the next period by a certain proportion $M(t)$ of the equivalent age at the time of maintenance or failure. We assume that weather conditions are monitored continuously over the entire period with inspection interval of one day. At the end of each interval, the system is either maintained or no action is taken. We assume that maintenance activities at any time are imperfect and thus reduce the equivalent age of the system but do not bring the system back to the original state (as good as new). The objective of our maintenance model is to find the optimal threshold values such that expected total cost is minimized.

First, we define x_i and y_i , as binary variables, to represent the preventive and corrective maintenance actions in day i as:

$$x_i = \begin{cases} 1 & \text{if the system is in PM} \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

$$y_i = \begin{cases} 1 & \text{if the system is in CM} \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

The following objective function computes the expected total cost $E(C(t))$ as a summation of the costs in each day i based on the cost of; preventive maintenance C^P, corrective maintenance C^R, system failure C^F and loss of production $C(i)^L$:

$$E(C(t)) = \sum_{i=1}^{N} \{(C^P + C(i)^L)(x_i) + (C^R + C(i)^L)(y_i)$$
$$+ (1 - x_i)(1 - y_i)[F(\theta(i))(C^F + C(i)^L)$$
$$- (1 - F(\theta(i)))C(i)L]\} \tag{3.12}$$

Any downtime due to delay of corrective maintenance causes loss of production $C(i)^L$. This daily loss of production is defined as follows:

$$C(i)^L = Pw(v(i)) \times W^{price} \tag{3.13}$$

Where W^{price} is the energy price per kWh. To account for the imperfect maintenance and its impact on the equivalent age, let $M(i)$ be a maintenance function that acts as an age reduction after a maintenance activity in day i. This definition affects aging behavior directly after maintenance and restores equipment age to a younger state but not to a perfect condition. While the turbine might experience some performance degradation after maintenance actions, in this paper we assume that the turbine will operate in full power after each maintenance. However, the equivalent age of the turbine must be updated to reflect any age reduction due to maintenance. Let $M^P(i)$ and $M^R(i)$ be the age reduction for PM and CM actions respectively:

$$M(i) = \begin{cases} 0 & \text{if the system is functioning} \\ M^P = e^{-2i/L} & \text{if the system is in PM} \\ M^R = r & \text{if the system is in CM} \end{cases} \tag{3.14}$$

Where L is the planned lifetime of the turbine and r is a constant proportion of the equivalent age at the time of the corrective maintenance. Then the equivalent age $\theta(i)$ at any give day (i) is:

$$\theta(i) = \sum_{k=1}^{i} (\alpha_0^{q(k)} - M(k)) \tag{3.15}$$

After each maintenance action, the nominal aging rate α_0 increases by a small increment λ to describe the aging evolution of the system with a faster deterioration rate after each imperfect maintenance. Assuming constant weather conditions, this problem can be solved as a simple age-based maintenance policy. The probabilistic behavior of aging under different weather conditions are often neglected in condition based maintenance literature. Another major weather-related consideration in wind farm maintenance is the accessibility of a turbine. To ensure safe access to a wind farm, weather conditions must be suitable to perform required maintenance.

To perform maintenance, we assume weather conditions should be within allowed limits during the day of maintenance. In this paper, we assume a turbine is only accessible if wind speed is below a safe threshold v_s and the ambient temperature is within the range of $(T_l$ to $T_u)$. Therefore, we can rewrite the binary maintenance variables x_i and y_i as:

$$x_i = \begin{cases} 1 & \text{if} \begin{cases} (p^{pm} \leq Pr(1) < p^{cm}), \\ (v(i) < v_s), \\ (T_l < T(i) < T_u) \end{cases} \\ 0 & \text{otherwise} \end{cases} \tag{3.16}$$

$$y_i = \begin{cases} 1 & \text{if} \begin{cases} (Pr(1) \geq p^{cm}), \\ (v(i) < v_s), \\ (T_l < T(i) < T_u) \end{cases} \\ 0 & \text{otherwise} \end{cases} \tag{3.17}$$

Assuming current and near future weather conditions are known, any triggered maintenance action is delayed until weather conditions become favorable. When weather conditions are unfavorable upon reaching the first maintenance threshold, PM work is delayed and the turbine continues to operate until the weather becomes favorable. If the turbine fails or the CM threshold is reached, any delay due to harsh weather incurs $C(i)^L$ production losses per day because the turbine cannot operate until CM is completed.

Determining the next maintenance decision, daily, can only indicate whether maintenance actions should be taken in that particular day and may result in lower or higher cost per maintenance action. Due to the probabilistic nature of this maintenance model with varying wind speed and temperature, it is very difficult to be modeled using analytical models only, as the parameters involved are time variant and their values cannot be captured analytically. However, simulation models are very helpful to address dynamic conditions in the study of condition-based maintenance.

3.3 SOLUTION APPROACH

To evaluate the performance of the proposed maintenance model over the 20 years' service life of a wind turbine, weather conditions are required for the entire period. Due to the complexity of weather forecasting, we use historical weather data to generate hourly wind speed and temperature measurements. To illustrate the stochastic nature of weather conditions, we first fit the historical data to a statistical distribution, then use Markov Chain Monte Carlo (MCMC) method to generate N samples of wind speed and temperature profiles. MCMC has been widely used in literature to generate synthetic wind speed and wind power time series due to its ability to accurately replicate the statistical properties of hourly wind speeds compared to other approaches like autoregression and wavelet-based models [39, 40, 41].

Suppose failure distribution of a wind turbine is known, and the equivalent age values at each instant can be computed. The simulation model of the proposed maintenance model can then calculate the average cost for each weather profile. Algorithm 4 shows a pseudo-code of simulation. The detailed simulation steps are:

Step 1: Define model inputs for a specific wind turbine and a specific location. Specify Weibull parameters, maintenance costs, age reduction values of each maintenance action, nominal wind and temperature effect values, power curve parameters and wind turbine specifications.

Step 2: Obtain weather data from land weather stations near the selected site. Extract hourly wind speed and temperature measurements into monthly time series to capture the seasonal variations and trends in weather conditions. Wind speed measurements are typically taken from land stations at low height h_1. Therefore, all wind speed v_1 values at height h_1 are extrapolated using the power law to estimating wind speed v_2 values at the hub height h_2:

$$v_2 = v_1(\frac{h_2}{h_1})^{\kappa} \tag{3.18}$$

Where κ is the power exponent for different types of terrain and atmospheric stability conditions. Fit data to their corresponding statistical distributions. Hourly air temperature measurements are fit to normal distribution with mean μ and standard deviation σ [42]. Weibull distribution is widely used to model wind speed v [43, 44, 45]. The probability density function is given by

$$f(v; c, k) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k}, \quad v \geq 0 \tag{3.19}$$

where k and c are the shape and scale parameters respectively, and $k, c > 0$. Note, this procedure is applied month by month to preserve seasonality. Statistical parameters can be different from month to month, meaning each month has an associated normal and Weibull parameters defining hourly air temperature and wind speed distributions from that month.

Step 3: Using MCMC, generate Z time series of size $(m \times n)$ of hourly wind speeds $(v_z(\cdot))$ and ambient temperatures $T_z(\cdot))$ using their corresponding distributions previously obtained in Step 2. $T_z(i, j)$ and $v_z(i, j)$ represent the values in the weather profile z of ambient temperature and wind speed during hour i and month j . Where n is the number of months and m represents the number of hours in a month.

Step 4: Set initial age and time to zero, total simulation time to $time^{max}$ (hours), the maximum number of iterations to $iter^{max}$, and define initial aging rate α_0 and maintenance thresholds p^{pm} and p^{cm}. Generate the first random failure time t_f from the Weibull distribution defined in step 1.

Step 5: Start the simulation model for weather profile z with discrete time steps in 1-hour intervals i. Calculate hourly weather effects $q(i)$, cumulative equivalent age $\theta(i)$, output power $Pw(v_i)$ following the IEC 61400-12-1 standard [46].

Step 6: Every 24 hours, check $\theta(i)$ against t_f. If $\theta(i) < t_f$, then check $Pr(1)$ against CM threshold p^{cm}. Otherwise, if $\theta(i) < t_f$ and $Pr(1) < p^{cm}$, then check $Pr(1)$ against PM threshold p^{pm}. If $\theta(i) < t_f$ and $Pr(1) < p^{pm})$ then no action is required. Skip steps 7-8.

Step 7: If $\theta(i) \geq t_f$ or $Pr(1) \geq p^{cm}$ and weather conditions are favorable then perform corrective maintenance. set m to zero and z to one, set $M(i)$ to M^R. Update current equivalent age $\theta(i)$, aging rate α_0, random failure time t_f and maintenance cost C. If weather conditions are not favorable, wind turbine is assumed down for the next 24 hours, production loss cost $C(i)^L$ is accumulated for each 24 hours till weather conditions are favorable.

Step 8: If $\theta(i) < t_f$, $p^{pm} \leq Pr(1) < p^{cm}$ and weather conditions are favorable then perform preventive maintenance. set m to one and z to zero, set $M(i)$ to M^P. Update current equivalent age $\theta(i)$, aging rate α_0, random failure time t_f and maintenance cost C. If weather conditions are not favorable, PM is delayed until weather conditions become favorable and wind turbine is assumed operating until the next inspection.

Step 9: If $i < time^{max}$, return to step 5. If $i \geq time^{max}$ and $j < N$, calculate total cost TC and return to step 4. If $i \geq time^{max}$ and $j \geq N$, end simulation and calculate the expected total cost $E(TC)$:

$$E(TC) = \frac{\sum_{j=1}^{N} TC(j)}{N} \tag{3.20}$$

Finally, a minimum search algorithm (Nelder-Mead) is applied to update the initial threshold values in step 4 and determine the optimal values of p^{pm} and p^{cm} that minimize the expected total cost $E(C)$. We follow the procedure described in the algorithm 3:

3.4 NUMERICAL EXAMPLE

In this section, we present a numerical example illustrating the proposed maintenance policy. We assume that the wind farm maintenance decisions are made on daily basis. Appropriate parameter values are selected based on the published data or discussions with our industry partners. We present four simulation scenarios to highlight the performance of the proposed model at different geographical locations and compare it to traditional age-based models. First, we select a specific wind turbine (Enercon E-126 [47]) with wind curve parameters as shown in Table 4.3. We also identify three different regions and obtain their historical weather data from the National Oceanic and Atmospheric Administration (NOAA) [48]. Hourly data measurements were collected from 15 land-based weather stations in three states (Texas, California, and Illinois) for the period from 2015 to 2018. The raw data are then extrapolated from the land station height ($h_1 = 3m$) to hub height ($h2 = 135$) using Equation 4.15. After fitting the historical wind speed and temperature data with their corresponding distributions, MCMC was used to generate 5 stochastic hourly weather condition time series for each state for the entire service life of 20 years. Table 3.2 shows summary statistics for the raw historical data.

To compare each scenario, we conduct simulations using the same parameter values explained in Table 4.3. We simulate the turbine equivalent age and weather conditions for each instance with 100 replications, performed over 7300 days (20 years). Then, we obtain the average maintenance cost per day and the failure and maintenance frequencies per year. Table 3.4 and 3.5 summarize the simulation results of each maintenance scenario under both traditional and proposed age models,

Algorithm 1 Proposed simulation procedure

Input:

reliability parameters (η, β, α_0, δ_0, γ_0, t_{max})
maintenance parameters (C^F, C^P, C^R, M^R, M^P, p^{cm}, p^{pm})
power curve parameters (v_{in}, v_{out}, v_{rated}, Pw_{rated})

for $j = 1$ **to** $iter$ **do**
  for $i = 1$ **to** t^{max} **do**
    $q(i) \leftarrow \delta_i(v(i)) + \gamma_i(T(i))$ {compute weather effects}
    $\theta(i) \leftarrow \alpha_0^{q(i)} + \theta(i-1)$ {compute equivalent age}
    $Pw(v(i)) \leftarrow using\ equation(4.13)$ {compute wind power}
    $Pr(1) \leftarrow using\ equation(3.9)$ {compute the conditional failure probability}
    if $\theta(i) \geq t_f$ **then**
      if $((v(i) < v_s)\ \&\ (T_l < T(i) < T_u))$ **then**
        $C(i) \leftarrow C^R + C^F$ {maintenance cost due to failure}
        $\theta(i) \leftarrow \theta(i) - M(i)$ {update the equivalent age}
        $t_f \leftarrow \theta(i) + new\ random.weibull(\eta, \beta)$ {generate new random failure time}
        $\alpha_0 \leftarrow \alpha_0 + \lambda$ {update the nominal aging rate}
      else
        $C(i) \leftarrow C(i)^L$ {delay cost due to unfavorable weather conditions}
      end if
    else if $Pr(1) \geq p^{cm}$ **then**
      if $((v(i) < v_s)\ \&\ (T_l < T(i) < T_u))$ **then**
        $C(i) \leftarrow C^R$ {corrective maintenance cost after reaching CM threshold}
        $M(i) \leftarrow M^R$ {age reduction due to corrective maintenance}
        $\theta(i) \leftarrow \theta(i) - M(i)$ {update the equivalent age}
        $t_f \leftarrow \theta(i) + new\ random.weibull(\eta, \beta)$ {generate new random failure time}
        $\alpha_0 \leftarrow \alpha_0 + \lambda$ {update the nominal aging rate}
      else
        $C(i) \leftarrow C(i)^L$ {delay cost due to unfavorable weather conditions}
      end if
    else if $Pr(1) \geq p^{pm}$ **then**
      if $((v(i) < v_s)\ \&\ (T_l < T(i) < T_u))$ **then**
        $C(i) \leftarrow C^P$ {preventive maintenance cost after reaching PM threshold}
        $M(i) \leftarrow M^P$ {age reduction due to preventive maintenance}
        $\theta(i) \leftarrow \theta(i) - M(i)$ {update the equivalent age}
        $t_f \leftarrow \theta(i) + new\ random.weibull(\eta, \beta)$ {generate new random failure time}
        $\alpha_0 \leftarrow \alpha_0 + \lambda$ {update the nominal aging rate}
      end if
    end if
  end for
  $TC(j) \leftarrow \sum_{i=1}^{t_{max}} C(i)$ {compute total cost for each iteration}
end for
return $\leftarrow E(TC)$ {compute the expected total cost from all iterations}

Algorithm 2 Nelder-Mead Method

Input:

call simulation (algorithm 4)

randomly generate an initial solution $x_0(p^{pm}, p^{cm})$

repeat

  order the points of the simplex such that $E(TC(x_0)) >= E(TC(x_1)) >= E(TC(x_2))\dot{>} = E(TC(x_n))$

  compute the centroid of all the points x_g

  compute the reflection of x_n in respect to x_g ($x_r = x_g + (x_g - x_n)$)

  if $E(TC(x_r)) > E(TC(x_{n-1}))$ **then**

    compute the expansion point : $x_e = x_g + 2 * (x_g - x_n)$

    if $E(TC(x_e)) > E(TC(x_r))$ **then**

      replace x_n with x_e

    else

      replace x_n with x_r

    end if

  else

    compute the contraction point : $x_c = x_g + 0.5 * (x_g - x_n)$

    if $E(TC(x_c)) >= E(TC(x_n))$ **then**

      replace x_n with x_c

    else

      shrink the simplex

      for all $x_i, 1 <= i < n$ **do**

        replace x_i with : $x_i = x_0 + 0.5 * (x_i - x_0)$

      end for

    end if

  end if

until convergence

Table 3.1: Enercon E-126 wind turbine information

Parameter	Description	Value
Pw_{rated}	Rated power (kW)	7580
v_{rated}	Rated wind speed (m/s)	17
v_{in}	Cut-in wind speed (m/s)	2.5
v_{out}	Cut-out wind speed m/s	25
L	Service life$(years)$	20
C_o	Maximum power coefficient	0.48
d_r	Rotor diameter (m)	127
h_2	Hub height (m)	135

respectively. The optimal maintenance policy obtained by our proposed approach shows remarkable reductions in both failure frequency and maintenance costs compared with the traditional age-based approach. The daily maintenance costs are decreased by 50%, 39.3% and 23.7% for California, Illinois and Texas respectively, demonstrating the cost reduction that can be achieved by adopting the proposed strategy.

We can compare our policy that uses weather information gained from historical data, with traditional age-based policies that do not include weather conditions. We compare these policies under the same weather accessibility constraints recommended in the literature [49, 50] . We assume maintenance can only be carried out if wind speed is below 10 m/s and ambient temperature is within the range of $-15°$ to $25°$. We use a Weibull-based reliability model, widely used in the literature [18, 51] with Weibull parameters and maintenance costs as given in Table 4.4.

Table 3.2: Summary statistics of raw hourly weather data

	$Wind\,Speed\,(m/s)$			$Air\,Temperature\,(C°)$			
	max	μ	σ	max	min	μ	σ
Texas	50	6.5	4	41	-11	20	8.2
California	43	4.2	3.5	42	-6	15.5	6.9
Illinois	36	3.2	2	38	-30	10	11

We repeat this simulation procedure 100 times for each weather profile with different initial random failure time and calculate the optimal threshold values that minimize the average daily cost of maintenance over the entire period for each scenario. We also track average daily operational revenue, average number of unexpected failures and preventive and corrective maintenance, for better comparison. To verify that our results from the proposed simulation model and the Nelder-Mead algorithm are indeed optimal or near optimal, we run our model several times with different randomly generated initial feasible solutions. The algorithm is implemented in MATLAB 2018b and all experiments are run with an Intel Core i7-4790K 4.0 GHz CPU Windows 10 machine with 24 GB RAM. Each simulation run takes 20 seconds on average while the average time till convergence is 8.1 minutes. The stopping criteria used to terminate the optimization procedure is an error of 10^{-6} of the function values. Fig. 3.2 shows an example of the number of iterations until convergence required by the Nelder-Mead algorithm for each weather scenario.

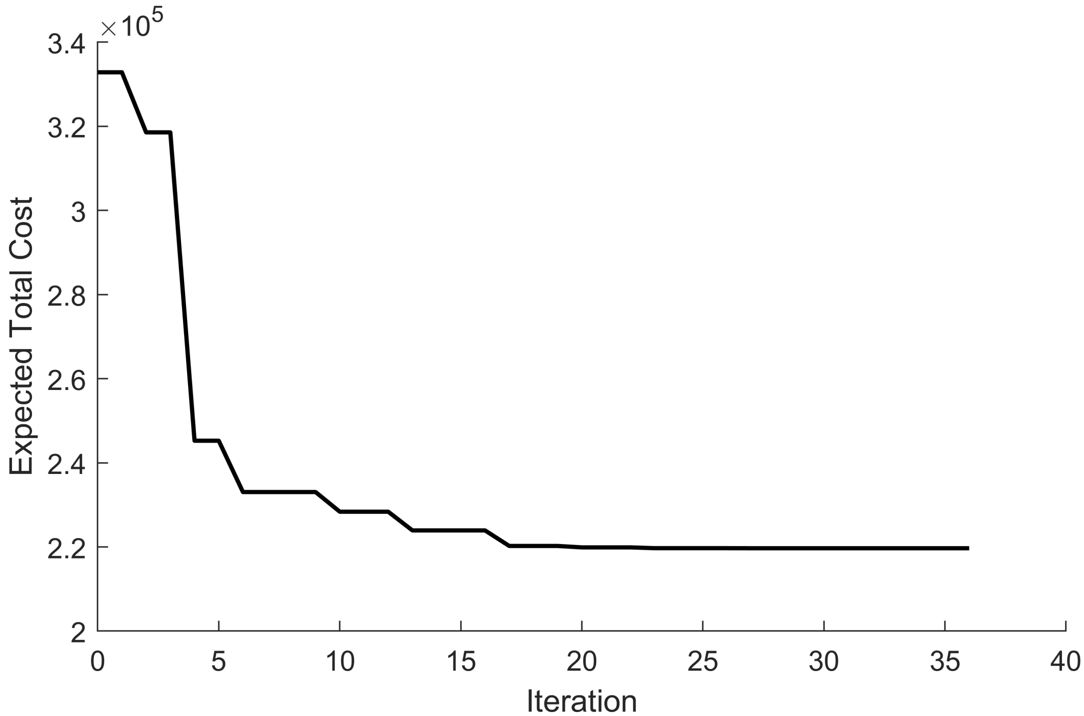


Figure 3.2: Number of iterations for convergence of the proposed model to the optimal solution (100 replications per iteration) .

First, we run the simulation model under traditional age-based preventive maintenance using only the Weibull distribution function described in Table 4.4. In the case of California, the optimal preventive maintenance threshold is 0.054 with an average maintenance cost of ($62.9 per day), which is twice the average maintenance cost obtained by the proposed model as shown in Table 3.5. The expected number of failures, PM, CM and downtime days per year are all higher as well. In this example, California represent the least harsh environment and thus, under our model the turbine will have slower aging and lower failure rate. However, the traditional approach does not take that into account, resulting in over maintaining the system over the entire service life. The lifetime distribution function in traditional models is independent of weather conditions and thus the optimal solution may underestimate or overestimate the component lifetimes under different

Table 3.3: Main reliability and maintenance parameters

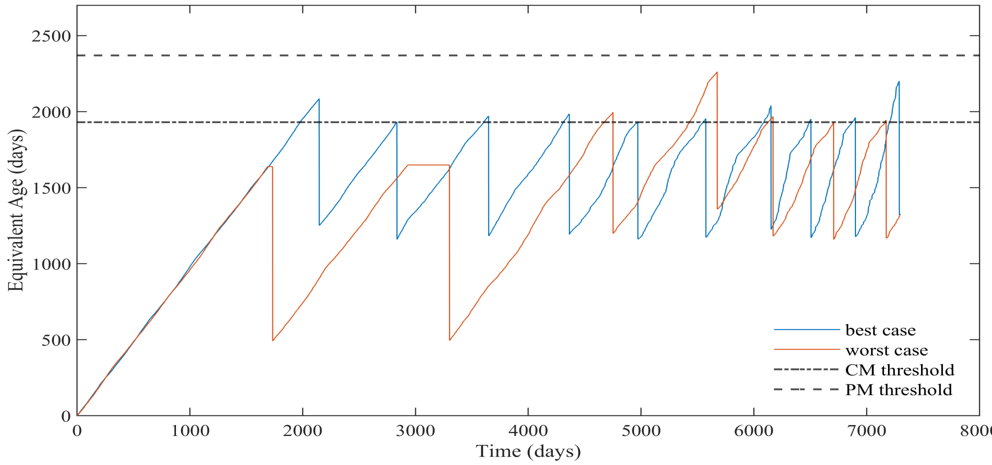
Parameter	Description	Value
β	Weibull Shape	3
η	Weibull Scale (days)	2400
C^P	PM Cost (1000 \$)	38
C^R	CM Cost (1000 \$)	63
C^F	Failure Cost (1000 \$)	150
w^{price}	Wind Price (\$/kWh)	0.05
M^P	PM age reduction factor	0.3
M^R	CM age reduction factor	0.6
α_0	Nominal aging rate	1.3
δ_0	Effect of ambient temperature	-5
γ_0	Effect of idle wind turbine	-10

usage and weather conditions. In the case of Texas and Illinois, the proposed model shows significant improvement in availability over the traditional approach, reducing the average downtime from 24.8 days/year to 15.85 days/year in Texas. Texas has harsh weather with a wide range of temperatures and high wind speeds, causing higher downtime and revenue losses. The failure rate in the Illinois case is also significantly lower under our model (0.005 failure per year) compared to (0.035 failure per year) using the traditional approach. All scenarios presented in this section are

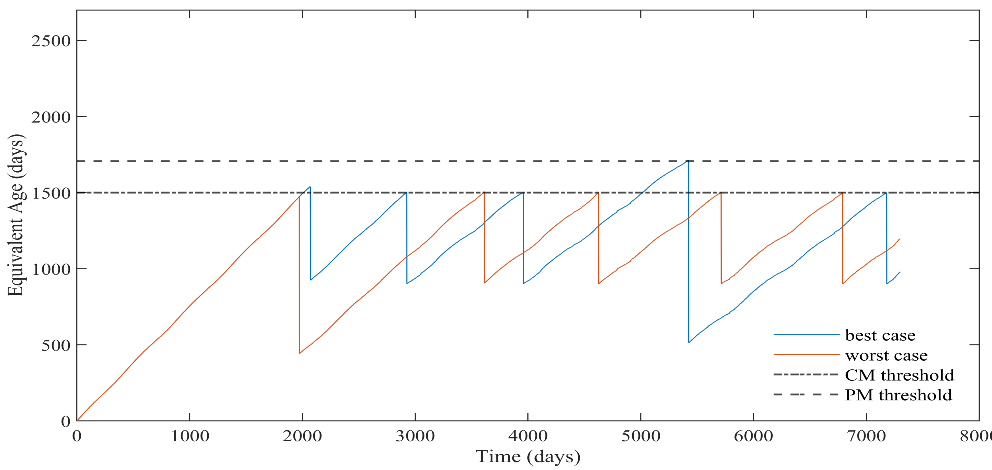
Table 3.4: Optimal maintenance thresholds and costs using the traditional model

	Texas	California	Illinois
PM Threshold (%)	0.069	0.054	0.109
CM Threshold (%)	0.105	0.059	0.118
PM Rate (per year)	0.45	0.6	0.35
CM Rate (per year)	0.025	0.055	0.007
Failure Rate (per year)	0.032	0.01	0.035
Downtime (days/year)	24.8	7.75	10.25
Maintenance Cost (\$/day)	83.0	62.9	69.5

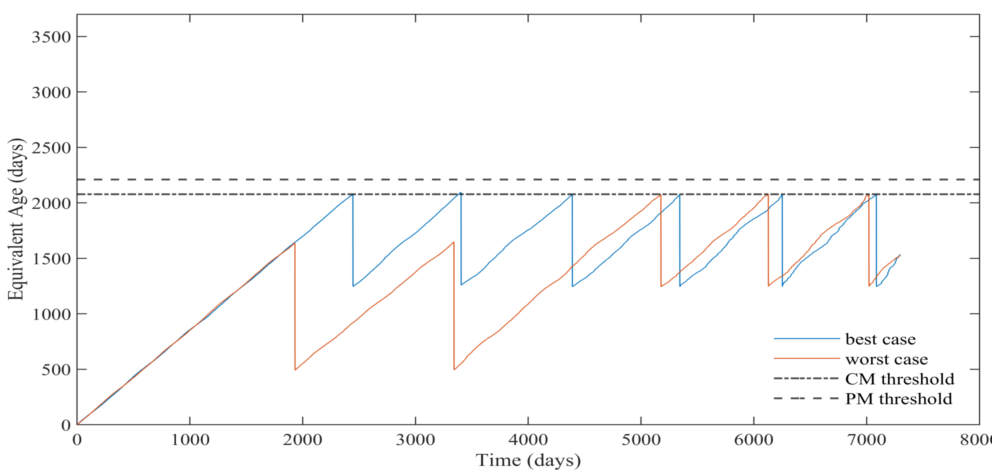
used to illustrate the effect of weather conditions at different locations over the same type of wind turbine. The equivalent age is obtained by simulating the proposed model using the optimal threshold values and various weather profiles for all three states. Fig. 3.3 shows the best and worst case



(a) Texas



(b) California



(c) Illinois

Figure 3.3: Best and worst case simulation results for each state

results for each state from the simulation study with 100 iterations, where each iteration consists of 5 weather profiles.

Table 3.5: Optimal maintenance thresholds and costs using the proposed model

	Texas	California	Illinois
PM Threshold (%)	0.081	0.038	0.093
CM Threshold (%)	0.127	0.046	0.108
PM Rate (per year)	0.405	0.29	0.31
CM Rate (per year)	0.045	0.005	0.007
Failure Rate (per year)	0.025	0.0165	0.005
Downtime (days/year)	15.85	3.8	4.35
Maintenance Cost ($/day)	63.3	31.42	42.2

Moreover, Fig. 3.3 illustrates the effect of imperfect maintenance, weather constraints and weather profiles on overall aging of the system. The optimal threshold values with the lowest average daily maintenance cost were obtained using the Nelder-Mead method. Texas has the highest expected maintenance cost of ($63.3 per day) with thresholds values of $p^{cm} = 0.081\%$ and $p^{pm} = 0.127\%$. Texas weather profiles have higher wind speeds and temperatures on average as presented in Table 3.2 which results in faster aging process and more inaccessible days due to weather constraints. California on the other hand, has the lowest expected maintenance cost of ($31.42 per day) with thresholds values of $p^{cm} = 0.038\%$ and $p^{pm} = 0.046\%$. As shown in the results, the threshold values are higher under harsh environment reflecting the faster aging of the turbine and thus, reaching the thresholds faster. The width of the preventive maintenance window (the difference between the two thresholds) is also higher under harsh weather as we can see in the case of Texas and Illinois compared to California. This is to allow operators more time because of the limited accessibility to the farm due to unfavorable weather conditions.

The results presented in Table 3.5 demonstrates the advantage of the proposed model over the traditional age-based policy in Table 3.4 in providing more scenario specific results.

3.5 CONCLUSION

In this paper we construct a weather based equivalent age model for choosing the most cost-effective maintenance actions under specific weather scenarios. We develop a simulation based optimal policy to respond to the time-varying weather conditions. We examine the impact of wind speeds and air temperatures on wind turbine maintenance with imperfect repairs, accessibility constraints and revenue losses. A new equivalent age-based maintenance policy is proposed for wind turbines using historical weather data to simulate 20 year long weather measurements for given locations, and propose to use equivalent age model with Weibull distribution to evaluate wind turbine aging under different weather profiles. We show the advantage of our approach to generate scenario-based results that are less dependent on generic lifetime distributions. The case study demonstrates the benefits of adopting the equivalent age model. Maintenance cost, failure rate and maintenance frequencies can be significantly reduced when the proposed model is applied instead of simply using traditional age models. Also, we show that considering the weather effects can potentially improve the availability of the turbine and avoid potential production losses.

There are several aspects in our modeling that warrant further investigation. In this paper, we assume that aging can be calculated precisely via monitoring. However, in many cases, aging is a stochastic process with more than two conditions involved, requiring to more data intensive models. Extending the model to account for other operating and environment conditions would allow for more accurate condition-based maintenance policy using the adaptive strength of this model. We also assume the entire turbine is one component with known Weibull parameters. We used this simplified model to allow for an intuitive and clear demonstration of our proposed approach. In practice, wind turbines should be modeled as a system of components with their own parameters. Future work could extend the model to incorporate multiple wind turbines. In this study we assume maintenance is instantaneous. However, when a turbine fails, maintenance activities may not start immediately and repairing activities may take up to several days.

3.6 NOMENCLATURE

$V(t)$: wind speed measure

$T(t)$: ambient temperature measure

$\delta(t)$: effects function of intensity of wind

$\gamma(t)$: effects function of ambient temperature

$q(t)$: overall weather effects function

α_0: nominal aging rate

β: Weibull distribution shape parameter

η: Weibull distribution scale parameter

Θ: equivalent age of the unit at failure

θ: instantaneous equivalent age

$F(t)$: life distribution function

$R(t)$: reliability function

C^R: cost of imperfect CM

C^P: cost of imperfect PM

C^F: cost of failure

$C(i)^L$: cost of loss of production

$E(TC)$: expected total cost

p^{pm}: PM conditional failure probability threshold

p^{cm}: CM conditional failure probability threshold

$M(t)$: imperfect maintenance improvement function

W^{price}: wind energy price

References

[1] W. Qiao and L. Qu, "Prognostic condition monitoring for wind turbine drivetrains via generator current analysis," *Chinese Journal of Electrical Engineering*, vol. 4, pp. 80–89, Sep. 2018.

[2] R. Ahmad and S. Kamaruddin, "An overview of time-based and condition-based maintenance in industrial application," *Computers & Industrial Engineering*, vol. 63, no. 1, pp. 135–149, 2012.

[3] A. Jardine and A. Tsang, *Maintenance, Replacement, and Reliability: Theory and Applications, Second Edition*. 01 2013.

[4] W. Yaping and H. Pham, "A multi-objective optimization of imperfect preventive maintenance policy for dependent competing risk systems with hidden failure," *Reliability, IEEE Transactions on*, vol. 60, no. 4, pp. 770–781, 2011.

[5] M. L. A. W. Alardhi, "Preventive maintenance scheduling of multi-cogeneration plants using integer programming," *The Journal of the Operational Research Society*, vol. 59, no. 4, pp. 503–509, 2008.

[6] R. Nicolai and R. Dekker, "A review of multi-component maintenance models," *Proceedings of the European Safety and Reliability Conference 2007, ESREL 2007 - Risk, Reliability and Societal Safety*, vol. 1, pp. 289–296, 01 2007.

[7] S. Zhong, A. A. Pantelous, M. Beer, and J. Zhou, "Constrained non-linear multi-objective optimisation of preventive maintenance scheduling for offshore wind farms," *Mechanical Systems and Signal Processing*, vol. 104, pp. 347 – 369, 2018.

[8] C.-C. Chang, "Optimum preventive maintenance policies for systems subject to random working times, replacement, and minimal repair," *Computers & Industrial Engineering*, vol. 67, no. 0, pp. 185–194, 2014.

[9] F. Ding and Z. Tian, "Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions," *International Journal of Reliability, Quality & Safety Engineering*, vol. 18, no. 5, pp. 463–481, 2011.

[10] J. Lei, F. Qianmei, and D. W. Coit, "Reliability and maintenance modeling for dependent competing failure processes with shifting failure thresholds," *Reliability, IEEE Transactions on*, vol. 61, no. 4, pp. 932–948, 2012.

[11] F. Hongdong, H. Changhua, C. Maoyin, and Z. Donghua, "Cooperative predictive maintenance of repairable systems with dependent failure modes and resource constraint," *Reliability, IEEE Transactions on*, vol. 60, no. 1, pp. 144–157, 2011.

[12] H. P. Hong, W. Zhou, S. Zhang, and W. Ye, "Optimal condition-based maintenance decisions for systems with dependent stochastic degradation of components," *Reliability Engineering & System Safety*, vol. 121, no. 0, pp. 276–288, 2014.

[13] H. C. Vu, P. Do, A. Barros, and C. Bérenguer, "Maintenance grouping strategy for multi-component systems with dynamic contexts," *Reliability Engineering & System Safety*, vol. 132, no. 0, pp. 233–249, 2014.

[14] S. K. Hasnida Ab-Samat, "Opportunistic maintenance (om) as a new advancement in maintenance approaches: A review," *Journal of Quality in Maintenance Engineering*, vol. 20, no. 2, pp. 98–121, 2014.

[15] M. Shafiee and J. D. Sørensen, "Maintenance optimization and inspection planning of wind energy assets: Models, methods and strategies," *Reliability Engineering & System Safety*, 2017.

[16] S. Alaswad and Y. Xiang, "A review on condition-based maintenance optimization models for stochastically deteriorating system," *Reliability Engineering & System Safety*, vol. 157, pp. 54 – 63, 2017.

[17] J. Kang, J. Sobral, and C. G. Soares, "Review of condition-based maintenance strategies for offshore wind energy," *Journal of Marine Science and Application*, vol. 18, pp. 1–16, Mar 2019.

[18] C. Zhang, W. Gao, S. Guo, Y. Li, and T. Yang, "Opportunistic maintenance for wind turbines considering imperfect, reliability-based maintenance," *Renewable Energy*, vol. 103, pp. 606 – 612, 2017.

[19] F. Besnard and L. Bertling, "An approach for condition-based maintenance optimization applied to wind turbine blades," *IEEE Transactions on Sustainable Energy*, vol. 1, pp. 77–83, July 2010.

[20] M. Shafiee, M. Finkelstein, and C. Bérenguer, "An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks," *Reliability Engineering & System Safety*, vol. 142, pp. 463 – 471, 2015.

[21] P. Mazidi, L. B. Tjernberg, and M. A. S. Bobi, "Wind turbine prognostics and maintenance management based on a hybrid approach of neural networks and a proportional hazards model," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 231, no. 2, pp. 121–129, 2017.

[22] G. Haddad, P. A. Sandborn, and M. G. Pecht, "Using maintenance options to maximize the benefits of prognostics for wind farms," *Wind Energy*, vol. 17, no. 5, pp. 775–791, 2014.

[23] E. Byon, L. Ntaimo, and Y. Ding, "Optimal maintenance strategies for wind turbine systems under stochastic weather conditions," *IEEE Transactions on Reliability*, vol. 59, pp. 393–404, June 2010.

[24] K. T. Huynh, A. Barros, and C. Bérenguer, "Adaptive condition-based maintenance decision framework for deteriorating systems operating under variable environment and uncertain condition monitoring," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 226, no. 6, pp. 602–623, 2012.

[25] X.-S. Si, Z.-X. Zhang, and C.-H. Hu, *Prognostics for Age- and State-Dependent Nonlinear Degrading Systems*, pp. 217–246. Berlin, Heidelberg: Springer Berlin Heidelberg, 2017.

[26] J. Wen, Y. Zheng, and F. Donghan, “A review on reliability assessment for wind power,” *Renewable and Sustainable Energy Reviews*, vol. 13, no. 9, pp. 2485 – 2494, 2009.

[27] S. Faulstich, B. Hahn, and P. J. Tavner, “Wind turbine downtime and its importance for offshore deployment,” *Wind Energy*, vol. 14, no. 3, pp. 327–337, 2011.

[28] M. Reder and J. J. Melero, “Modelling the effects of environmental conditions on wind turbine failures,” *Wind Energy*, vol. 21, no. 10, pp. 876–891, 2018.

[29] P. Tavner, D. Greenwood, M. Whittle, R. Gindele, S. Faulstich, and B. Hahn, “Study of weather and location effects on wind turbine failure rates,” *Wind Energy*, vol. 16, no. 2, pp. 175–187, 2013.

[30] V. Slimacek and B. H. Lindqvist, “Reliability of wind turbines modeled by a poisson process with covariates, unobserved heterogeneity and seasonality,” *Wind Energy*, vol. 19, no. 11, pp. 1991–2002, 2016.

[31] A. J. Henry and J. A. Nachlas, “An equivalent age model for condition-based maintenance,” in *2012 Proceedings Annual Reliability and Maintainability Symposium*, pp. 1–6, Jan 2012.

[32] G. Wilson and D. McMillan, “Assessing wind farm reliability using weather dependent failure rates,” *Journal of Physics: Conference Series*, vol. 524, p. 012181, jun 2014.

[33] A. A. Teyabeen, F. R. Akkari, and A. E. Jwaid, “Power curve modelling for wind turbines,” in *2017 UKSim-AMSS 19th International Conference on Computer Modelling Simulation (UKSim)*, pp. 179–184, April 2017.

[34] U. Sampath, H. Kim, D.-G. Kim, Y.-C. Kim, and M. Song, “In-situ cure monitoring of wind turbine blades by using fiber bragg grating sensors and fresnel reflection measurement,” *Sensors (Basel, Switzerland)*, vol. 15, pp. 18229–18238, 07 2015.

[35] T.-Y. Hsu, S.-Y. Shiao, and W.-I. Liao, “Damage detection of rotating wind turbine blades using local flexibility method and long-gauge fiber bragg grating sensors,” *Measurement Science and Technology*, vol. 29, p. 015108, dec 2017.

[36] A. Turner and T. W. Graver, “Structural monitoring of wind turbine blades using fiber optic bragg grating strain sensors,” in *Experimental Mechanics on Emerging Energy Systems and Materials, Volume 5* (T. Proulx, ed.), (New York, NY), pp. 149–154, Springer New York, 2011.

[37] B. F. S. Lars Glavind, Ib Svend Olesen and M. V. Kristensen, “Fiber-optical grating sensors for wind turbine blades: a review,” *Optical Engineering*, vol. 52, no. 3, pp. 1 – 10 – 10, 2013.

[38] R. Steenbergen, P. Gelder, S. Miraglia, and T. Vrouwenvelder, *Safety, Reliability and Risk Analysis: Beyond the Horizon*. 09 2013.

[39] A. Carpinone, M. Giorgio, R. Langella, and A. Testa, “Markov chain modeling for very-short-term wind power forecasting,” *Electric Power Systems Research*, vol. 122, pp. 152 – 158, 2015.

[40] K. Xie, Q. Liao, H. Tai, and B. Hu, “Non-homogeneous markov wind speed time series model considering daily and seasonal variation characteristics,” *IEEE Transactions on Sustainable Energy*, vol. 8, pp. 1281–1290, July 2017.

[41] H. Chao, B. Hu, K. Xie, H. Tai, J. Yan, and Y. Li, “A sequential mcmc model for reliability evaluation of offshore wind farms considering severe weather conditions,” *IEEE Access*, vol. 7, pp. 132552–132562, 2019.

[42] J. Goffart, T. Mara, and E. Wurtz, “Generation of stochastic weather data for uncertainty and sensitivity analysis of a low-energy building,” *Journal of Building Physics*, vol. 41, no. 1, pp. 41–57, 2017.

[43] C. L. Archer and M. Z. Jacobson, "Spatial and temporal distributions of u.s. winds and wind power at 80 m derived from measurements," *Journal of Geophysical Research: Atmospheres*, vol. 108, no. D9, 2003.

[44] R. N. Clark, "Chapter one - site evaluation: Examining the proposed site to ensure that it has adequate wind and space," in *Small Wind* (R. N. Clark, ed.), pp. 11 – 27, Boston: Academic Press, 2014.

[45] G. Li and J. Zhi, "Chapter 2 - analysis of wind power characteristics," in *Large-Scale Wind Power Grid Integration* (N. Wang, C. Kang, and D. Ren, eds.), pp. 19 – 51, Oxford: Academic Press, 2016.

[46] International Electrotechnical Commission, *IEC 61400-12: Wind turbines - Part 12: Power performance measurements of electricity producing wind turbines*. No. 12, Geneva, Switzerland: International Electrotechnical Commission, 1st PPUB ed., 2005.

[47] ENERCONE GmbH, "Enercon Product Overview." https://www.enercon.de/en/products/ep-8/e-126/. Accesssed: 04-28-2019.

[48] A. Arguez, I. Durre, S. Applequist, M. Squires, R. Vose, X. Yin, and R. Bilotta , "NOAA's U.S. Climate Normals (1981-2010)," 2010. Accessed: 3.15.2019.

[49] S. Carlos, A. Sánchez, S. Martorell, and I. Marton, "Onshore wind farms maintenance optimization using a stochastic model," *Mathematical and Computer Modelling*, vol. 57, no. 7, pp. 1884 – 1890, 2013.

[50] J. Zhang, S. Chowdhury, J. Zhang, and A. Messac, *Optimal Scheduling of Preventive Maintenance for Offshore Wind Farms*.

[51] B. Le and J. Andrews, "Modelling wind turbine degradation and maintenance," *Wind Energy*, vol. 19, no. 4, pp. 571–591, 2016.

Chapter 4

OPPORTUNISTIC MAINTENANCE FOR WIND FARMS BASED ON EQUIVALENT AGE

4.1 INTRODUCTION

Wind power capacity in the United States is expected to exceed 20% of the total power capacity by 2030 [1]. Most of wind farms are located remote areas or offshore where high wind speeds are prevalent. They experience harsh weather conditions and significant seasonal variations which subject wind turbines to variable loads and forces and contribute to their degradation process. Visiting those remote wind farms for repairs or inspections requires significant planning, resources and potential revenue losses due to downtime. Consequently, minimizing the number of visits to the farm while avoiding catastrophic failures is critical. Due to the complex nature of the uncertain environment conditions and the stochastic nature of turbines aging, it is difficult to accurately estimate the health state of a wind turbine for maintenance purposes.

Time-based maintenance (TBM) is a common practice in wind industry where the frequency of preventive maintenance is largely based on historical statistical data and industry recommendations. Recently, the industry has recognized the benefits of condition monitoring and using sensors data to help preventing catastrophic failures. However, deciding when and what type of action to undertake is still a key challenge in wind farm maintenance. Similarly, most work in the literature also presents time-based maintenance models for wind farm maintenance. Successful maintenance strategy requires significant knowledge about the current health of each turbine and the type of failures to assign and schedule the right type maintenance actions and resources.

Traditionally, the age of a turbine is defined as a linear function of time and failure age is been estimated based on historical data and engineering expertise rather than on weather and usage conditions. While some failure patterns are common among specific turbine populations, these traditional failure models often fall short of representing specific weather scenarios of individual farms. To address this problem, sensors data has been used to predict the actual health condition of wind turbines. Current wind turbines maintenance literature can be categorized under two main areas of research: i) Time based opportunistic maintenance methods that do not consider sensor data, and ii) condition-based methods that focus on remaining useful life prediction. The goal of the first approach is to find the optimal fixed time-based periodic schedules while considering maintenance grouping.

Recent models attempt to capture the economic dependencies between different maintenance actions [2, 3, 4, 5, 6]. For instance, Zhang et al. [7, 8] present a simulation model for a time-based opportunistic maintenance of multi-component wind turbines. The authors consider a generic turbine model with predetermined maintenance thresholds values under weather and spare parts constraints. Wang et al. [9] present similar study using a semi-Markov decision process to find the optimal threshold value for two-unit system. Song et al. [10] consider a periodic inspection policy under different accessibility conditions and farm layouts for offshore farms. They present an opportunistic optimization model and Monte Carlo simulation to sampling weather data along the New Jersey coast. Ding et al. [11] propose an opportunistic maintenance with two-level preventive maintenance considering both perfect and imperfect repairs. Their simulation model is based on time-based approach and the mean time to failure but does not consider weather constraints. Erguido et al.[12] present a mathematical model of a dynamic time-based opportunistic maintenance under multiple failure modes with weather and capacity constraints. However, these studies do not account for the actual condition of turbines and the effect of weather conditions on aging when planning maintenance actions, and therefore do not reflect the impact of different environment factors on failures. These policies may result in conservative maintenance plans with expensive frequent unnecessary maintenance and downtime events.

CBM models, on the other hand focus primarily on predicting the remaining useful life for individual wind turbine systems [13, 14, 15]. Evidently, these models do not capture dependencies between different maintenance actions, and often perform poorly in a wind farm setting. Very few papers have used weather information while also capturing economic dependencies. Recently, Lu et al. [16] has proposed a maintenance scheduling policy that considers opportunistic maintenance for wind turbines subject to condition monitoring. In this work, the authors suggest a two-threshold policy, whereby a strict failure threshold applies to the first wind turbine to be maintained, and a more conservative failure threshold is imposed on the remaining wind turbines in an effort to group them with the first wind turbine. Although this work proposes an opportunistic policy, it does not necessarily consider the impact of weather conditions. Fault diagnosis of wind turbine gearbox is one of the popular approaches to evaluate the health of turbines. In practices, when a vibration based degradation signal reaches to a certain alarming level, maintenance is scheduled to prevent failure and also to ensure certain level of power production. However, as earlier mentioned, deterioration process is a complex and it progresses in various rates under different weather conditions [17].

In reality, the physical condition of a turbine component is not known exactly, but may be estimated from the condition monitoring sensor signals. Estimations rarely reveal perfectly the system conditions and health status due to a wide variety of reasons, such as imperfect models linking measurements to specific faults, as well as noises in sensor signals. Furthermore, weather conditions have a significant impact on the deterioration process. Faultsich et al. (2011) [18] studied factors causing wind turbine failures and concluded that turbines close to seawater and at high land locations with high wind speed suffer higher failure rates. Slimacek and Lindqvist [19] found that external weather factors such as ambient temperatures and wind speeds increase the failure rate of offshore wind turbines by a factor of 1.7 compared to onshore turbines. Shafiee et al. [14] present a stochastic model to estimate the impact of environmental shocks on the development of cracks in turbine blades. In their maintenance model they assume that environmental shocks follow a two-parameter Weibull distribution while the crack growth process follows gamma distribution.

Table 4.1: Summary of model considerations in recent literature on opportunistic maintenance for wind farms

Ref.	TBM	CBM	Weather Effect*	Imperfect Repair	Repair Time	Accessibility	Crew Capacity	Energy Price	Lead Time
[7]	✓					✓			✓
[8]	✓			✓					
[10]		✓						✓	
[11]	✓			✓					
[12]		✓		✓	✓		✓		✓
[14]		✓	✓						
[17]		✓				✓	✓	✓	
[20]		✓				✓			✓
[21]	✓			✓					
[22]	✓			✓	✓	✓		✓	
[23]	✓			✓	✓			✓	
[24]	✓			✓		✓	✓		
[25]	✓			✓	✓		✓	✓	

* the impact of weather conditions on turbine aging

The study however does not consider the impact of different weather patterns of maintenance cost or availability. Several studies addressed this issue by adjusting the Weibull parameters using the availability onshore reliability data as shown in Table 4.2. However, only few studies considered the impact of weather conditions on each individual turbine or any subsystem. Table 4.1 and Table 4.2 summarize the recent opportunistic maintenance models considerations and failure distributions parameters in the literature, respectively.

This paper considers opportunistic age-based maintenance approach for wind farm O&M planning. A detailed analytical models of wind farms are complex to be adequately captured in closed form, thus this work will focus on studying weather-based equivalent age model and failures of multiple wind turbines under economic dependency and accessibility constraints. Discrete event simulation is used to study different scenarios of wind farms maintenance under different weather

Table 4.2: Summary of Weibull lifetime distribution parameters for major wind turbine components

	Onshore		Offshore	
	$\eta(days)$	β	$\eta(days)$	β
Gearbox	2400	3	1477	3
Generator	3300	2	1594	2
Blade	3000	3	1847	3
Pitch	1858	3	1144	3
Main Bearing	3750	2	2400	2

conditions and capture the effects of alternative actions on the overall system. The proposed strategy considers economic dependencies among maintenance actions under stochastic weather conditions, particularly wind speed. In this paper, we develop a simulation model of multiple wind turbines and study the impact of imperfect maintenance actions over time under economic and weather constraints. Specifically, this work makes two major contributions:

1. Wind farm simulation model using equivalent age concept and opportunistic maintenance.

2. Optimization approach to find the optimal opportunistic and preventive maintenance thresholds that minimize the expected total cost of maintenance.

4.2 PROPOSED MODEL

Consider a wind farm with repairable and maintainable wind turbines, each subject to deterioration under variable weather and load conditions. Let $L : \Omega \to \mathbb{R}$ be a random variable that represents the lifetime of a wind turbine in a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. During their lifetime, we assume turbines follow a two-parameter Weibull distribution $F(\theta_n(t))$, where $\theta_n(t)$ is the equivalent age for turbine n at time t, with scale parameter η and shape parameter β. In this paper, we assume that turbines are independent and identically distributed:

$$F(\theta_n(t)) = 1 - exp\left[-\left(\theta_n(t)\Big/\eta\right)^{\beta}\right] \tag{4.1}$$

Consider a wind farm with wind speed $V(t)$ time series, then the equivalent age $\theta_n(t)$ for turbine n at any time t is:

$$\theta(t) = \int_0^t (\alpha_n)^{q(t)} \tag{4.2}$$

Where α_n is a nominal aging factor for turbine n, and $q(t)$ is a function of :

$$q(t) = \delta(V(t)) \tag{4.3}$$

Equation 4.2 allow us to introduce different aging paths for each turbine while all turbines are identically distributed. Assume turbines age at nominal rate under the rated wind speed v_rated, then we can assume that higher wind speeds cause higher degradation rates (δ and γ) and vice versa as described in equation 4.4.

$$\delta(V(t)) = \begin{cases} \frac{v(t)^3 - v_{rated}^3}{v_{rated}^3} & if\ v_{in} \leq v(t) \leq v_{out} \\ \delta_0 & \text{otherwise} \end{cases} \tag{4.4}$$

Where v_{in} and v_{out} are the cut-in and cut-out wind speed, respectively. δ_0 is a negative number to reflect idle state of aging when the wind speed is not within operating conditions.

4.2.1 Opportunistic Maintenance

In this study, two thresholds (preventive threshold p^{pm} and opportunistic threshold p^{op} as shown in Fig. 4.1) and three types of maintenance actions are considered:

- Preventive maintenance; a preventive repair with associated cost of C^P, triggered when the equivalent age of turbine i exceeds the preventive threshold ($\theta(t)_n \geq p^{pm}$) ,
- Opportunistic maintenance; a preventive repair with associated cost of C^O, triggered when the equivalent age of turbine i exceeds the opportunistic threshold ($\theta(t)_n \geq p^{op}$) during preventive or corrective maintenance event,

- Unscheduled corrective maintenance; a major repair after an unexpected failure of turbine i with associated cost of failure C^F.

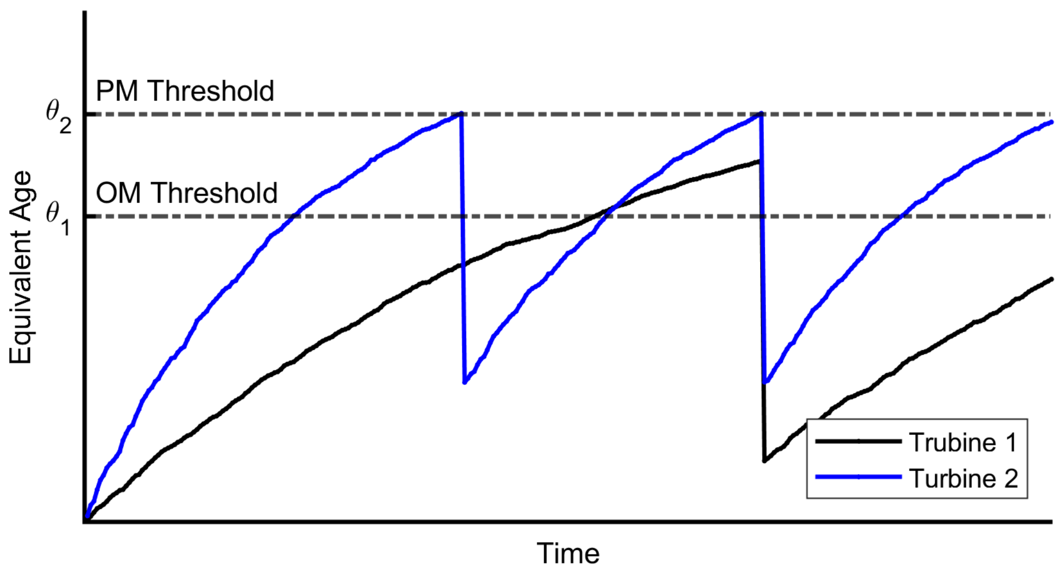


Figure 4.1: Typical two level opportunistic maintenance.

In this model, we assume that all maintenance actions are imperfect. This affects the equivalent age directly after maintenance to reflect any age reduction due to maintenance. Let M_n^P and M_n^R be the age reduction of turbine n for PM and CM actions respectively:

$$M_n(i) = \begin{cases} 0 & \text{if the system is functioning} \\ M_n^P & \text{if the system is in PM} \\ M_n^R & \text{if the system is in CM} \end{cases} \tag{4.5}$$

However, different costs associated with each maintenance type are imposed. Maintenance actions reduces the age of the maintained turbine i at the start of the next period by a certain proportion q_n of the equivalent age $\theta_n(\tau)$ at the maintenance time τ.Then the equivalent age $\theta_n(i)$ at any give day (i) is:

$$\theta(i)_n = \sum_{k=1}^{i} (\alpha_n^{q(k)} - M(k)) \tag{4.6}$$

At the start of a CM or PM maintenance activity for a specific turbine i, all other turbines are checked against the opportunistic threshold p^{op}. Turbines that have an equivalent age greater than the threshold undergo PM as well, in a combined group maintenance activity. Instead of having separate maintenance activities for each turbine, a single group maintenance activity is scheduled. In addition to cost reduction, accessibility of the wind farm is one of the main motivations to perform opportunistic maintenance. In this perspective, utilizing favorable weather conditions to do joint maintenance activity can reduce the risk of unexpected failures during certain seasons. It is also cheaper than performing individual maintenance activities due to high crew deployment cost.

After each maintenance action, the nominal aging rate α_0 increases by a small increment λ to describe the aging evolution of the turbine with a faster aging rate after each imperfect maintenance. To ensure safe access to a wind farm, weather conditions must be suitable to perform the required maintenance. In this paper, we assume a farm is only accessible if wind speed is below a safe threshold v_s and air temperature is within the range of $(T_l$ to $T_u)$.

4.2.2 Cost Model

In order to ensure the optimal scheduling of maintenance for the entire farm, we consider various constraints such as i) crew capacity, ii) production loss and iii) accessibility. We assume that a turbine under maintenance does not produce power and any wind turbine that fails unexpectedly stays down until a corrective maintenance is performed. Depending on the electricity price, production losses is incurred until the turbine is up again .

Let $x_{i,n}$ and $y_{i,n}$ be binary variables, to represent the preventive and corrective maintenance actions in day i for turbine n as:

$$x_{i,n} = \begin{cases} 1 & \text{if the turbine } n \text{ is in PM} \\ 0 & \text{otherwise} \end{cases} \tag{4.7}$$

$$y_{i,n} = \begin{cases} 1 & \text{if the turbine } n \text{ is in CM} \\ 0 & \text{otherwise} \end{cases} \tag{4.8}$$

Assuming current and near future farm accessibility information is known, any triggered maintenance action can only be carried if weather conditions are favorable. When weather conditions are unfavorable upon reaching the first PM threshold, the farm is assumed inaccessible and any maintenance work is delayed. Let g_i and z_i be binary variables representing the farm accessibility and the deployment cost C^D per farm visit as follows:

$$g_i = \begin{cases} 1 & \text{if the farm is accessible} \\ 0 & \text{otherwise} \end{cases} \tag{4.9}$$

$$z_i = \begin{cases} 1 & \text{if the farm is visited} \\ 0 & \text{otherwise} \end{cases} \tag{4.10}$$

Turbines continue to operate until weather becomes favorable. If any turbine fails, production losses due to harsh weather incur $C^L(i,n)$ per turbine n for each delayed day i. The following objective function computes the total cost for all turbines $C(t)$ as a summation of the daily cost of; preventive maintenance $C^P(i,n)$, corrective maintenance $C^R(i,n)$, failure cost $C^F(i,n)$, deployment cost C^D and loss of production $C^L(i,n)$:

$$C(t) = \sum_{i=1}^{T}\sum_{n=1}^{N} \underbrace{(1-x_{i,n})(1-y_{i,n})(C^F(i,n) + (C^L(i,n)))}_{\text{failure cost}} + \underbrace{z_i(C^D)}_{\text{deployment cost}}$$
$$+ \underbrace{(C^P(i,n) + C^L(i,n))(x_{i,n})}_{\text{PM cost}} + \underbrace{(C^R(i,n) + C^L(i,n))(y_{i,n})}_{\text{CM cost}} \tag{4.11}$$

This daily loss of production for turbine n $C^L(i,n)$ is defined as follows:

$$C^L(i,n) = Pw(v(i,n)) \times W^{price} \tag{4.12}$$

Where W^{price} is the energy price per kWh. While the turbine might experience some performance degradation after maintenance actions, in this paper we assume that the turbine will operate in full power after each maintenance. Output power can be calculated as follow [26]:

$$Pw(v(i,n)) = \begin{cases} 0 & v < v_{in} \\ \frac{1}{2}\rho C_o A v^3 & v_{in} \leq v < v_{rated} \\ Pw_{rated} & v_{rated} \leq v \leq v_{out} \\ 0 & v > v_{out} \end{cases} \tag{4.13}$$

Where A is the swept area, ρ is air density and C_o is power coefficient. In this paper we assume that maintenance crew has a limited capacity of cap^{max}. This constraint ensures that the number of turbines scheduled for maintenance at any given period does not exceed the limit on crew capacity.

4.3 SOLUTION APPROACH

Suppose the failure distribution of a wind turbine and wind speed data are known, and the equivalent age values at each instant can be computed. The simulation model of the proposed approach can then calculate the average cost for a specific farm location. Algorithm 4 shows a pseudo-code of simulation. The detailed simulation steps are:

Step 1: Define model inputs for a specific wind farm including: wind speed data, number of turbines, Weibull parameters, maintenance costs, maintenance parameters, nominal wind effect, power curve parameters and wind turbine specifications.

Step 2: Set initial age and time to zero, total simulation time to $time^{max}$ (days), the maximum number of iterations to $iter^{max}$, and define initial aging rate α_0 and maintenance thresholds p^{pm} and p^{om}.

Step 3: Generate random time to failure for all turbines $t_f(n)$ from the Weibull distribution defined in step 1.

Step 4: Start the simulation model with discrete time steps in 1-day intervals i.

Step 5: While $i < time^{max}$: calculate equivalent age $\theta(i, n)$ and output power $Pw(v_{i,n})$.

Step 6: If $\theta(i, n) \geq t_f(n)$:

(a) check farm accessibility. If farm is accessible $(g_(i) = 1)$ then set $z_i = 1$ and schedule corrective maintenance ($y_{i,n} = 1$ and $x_{i,n} = 0$) for failed turbines and preventive maintenance ($y_{i,n} = 0$ and $x_{i,n} = 1$) for turbines with $\theta(i, n) \geq p^{om}$.

(b) limit the number of turbines available for maintenance to cap^{max}

(c) update $\theta(i, n)$ using equation 4.10 and $C(i)$ using equation 4.11.

(d) increase α_0 by λ

(e) generate a new random time to failure $t_f(n)$ for all maintained turbines.

Step 7: Else if $(g_(i) = 0)$ shutdown failed turbine, then set ($z_i = 0$, $y_{i,n} = 0$ and $x_{i,n} = 0$) and accumulate production losses $C^L(i, n)$ for each inaccessible day for failed turbines.

Step 8: Else if $\theta(i, n) \geq p^{pm}$:

(a) check farm accessibility. If farm is accessible ($g_(i) = 1$) then set $z_i = 1$ and schedule preventive maintenance ($y_{i,n} = 0$ and $x_{i,n} = 1$) for turbines with $\theta(i, n) \geq p^{pm}$ and $\theta(i, n) \geq p^{om}$.

(b) limit the number of turbines available for maintenance to cap^{max}

(c) update $\theta(i, n)$ using equation 4.10 and $C(i)$ using equation 4.11.

(d) increase α_0 by λ

(e) generate a new random time to failure $t_f(n)$ for all maintained turbines.

Step 9: Else maintenance is delayed until weather conditions become favorable and turbines are assumed operating until the next inspection.

Step 10: If $i \geq time^{max}$ and $iter \leq iter^{max}$, calculate total cost and return to step 5.

Step 11: If $i \geq time^{max}$ and $iter \geq iter^{max}$, end simulation and calculate the expected total cost $E(TC)$:

$$E(TC) = \frac{\sum_{j=1}^{iter^{max}} TC(j)}{iter^{max}} \tag{4.14}$$

Finally, a minimum search algorithm (Nelder-Mead) is applied to update the initial threshold values in step 2 and determine the optimal values of p^{pm} and p^{om} that minimize the expected total cost $E(TC)$. We follow the procedure described in the algorithm 3:

4.4 EXPERIMENTAL RESULTS

In this section, we present a numerical example illustrating the proposed maintenance policy. We assume that the wind farm maintenance decisions are made on daily basis. First, we select a specific wind turbine (Enercon E-126 [27]) with wind curve parameters as shown in Table 4.3.

Algorithm 3 Nelder-Mead Method

Input:
call simulation (algorithm 4)
randomly generate an initial solution $x_0(p^{pm}, p^{om})$
repeat
order the points of the simplex such that:
$E(TC(x_0)) >= E(TC(x_1)) >= E(TC(x_2))\dot{>} = E(TC(x_n))$
compute the centroid of all the points x_g
compute the reflection of x_n in respect to x_g $(x_r = x_g + (x_g - x_n))$
if $E(TC(x_r)) > E(TC(x_{n-1}))$ **then**
compute the expansion point : $x_e = x_g + 2 * (x_g - x_n)$
if $E(TC(x_e)) > E(TC(x_r))$ **then**
replace x_n with x_e
else
replace x_n with x_r
end if
else
compute the contraction point : $x_c = x_g + 0.5 * (x_g - x_n)$
if $E(TC(x_c)) >= E(TC(x_n))$ **then**
replace x_n with x_c
else
shrink the simplex
for all $x_i, 1 <= i < n$ **do**
replace x_i with : $x_i = x_0 + 0.5 * (x_i - x_0)$
end for
end if
end if
until convergence

Table 4.3: Enercon E-126 wind turbine information

Parameter	Description	Value
Pw_{rated}	Rated power (kW)	7580
v_{rated}	Rated wind speed (m/s)	17
v_{in}	Cut-in wind speed (m/s)	2.5
v_{out}	Cut-out wind speed m/s	25
L	Service life$(years)$	20
C_o	Maximum power coefficient	0.48
d_r	Rotor diameter (m)	127
h_2	Hub height (m)	135

Algorithm 4 Proposed simulation procedure

Input: reliability & maintenance parameters, power curve parameters, wind farm data

$t \leftarrow zero$
$\theta(i, n) \leftarrow zero$
$t_f(n) \leftarrow generate\ random\ time\ to\ failure\ \forall\ n \in N.$
for $j = 1$ **to** $iter^{max}$ **do**
  for $i = 1$ **to** t^{max} **do**
    $q(i, n) \leftarrow \delta_{i,n}(v(i))$ {compute wind effects}
    $\theta(i, n) \leftarrow \alpha_0^{q(i,n)} + \theta(i - 1, n)$ {compute equivalent age}
    $Pw(v(i)) \leftarrow using\ equation(4.13)$ {compute wind power}
    if $\theta(i, n) \geq t_f(n)$ {failure event} **then**
      if $(g_(i) = 1)$ {farm accessibility} **then**
        if $\theta(i, n) \geq p^{om}$ $\{check\ for\ OM\}$ **then**
          $Cap^{max} \leftarrow \sum_{n=1}^{N} x_{i,n} + y_{i,n} \leq Cap^{max}$ {crew capacity limit}
          $C(i) \leftarrow (z_i = 1, y_{i,n} = 1, x_{i,n} = 0)$ {CM cost due to failure}
          $C(i) \leftarrow (z_i = 1, y_{i,n} = 0, x_{i,n} = 1)$ {OM cost}
          $Update\ equivalent\ age\ \&\ maintenance\ cost \leftarrow \theta(i, n), C(i)$
          $t_f(n) \leftarrow \theta(i, n) + new\ t_f(n)$ {time to failure for maintained turbines}
          $\alpha_0(n) \leftarrow \alpha_0(n) + \lambda$ {update aging rate for maintained turbines}
        end if
      else
        $C(i) \leftarrow C(i)^L(i, n)$ {delay cost due to unfavorable weather conditions}
        $\theta(i, n) \leftarrow t_f(n)$ {turbine is down}
      end if
    else if $\theta(i, n) \geq p^{pm}$$\{check\ for\ PM\}$ **then**
      if $(g_(i) = 1)$ {farm accessibility} **then**
        if $\theta(i, n) \geq p^{om}$ $\{check\ for\ OM\}$ **then**
          $Cap^{max} \leftarrow \sum_{n=1}^{N} x_{i,n} + y_{i,n} \leq Cap^{max}$ {crew capacity limit}
          $C(i) \leftarrow (z_i = 1, y_{i,n} = 0, x_{i,n} = 1)$ {PM & OM cost }
          $Update\ equivalent\ age\ \&\ maintenance\ cost \leftarrow \theta(i, n), C(i)$
          $t_f(n) \leftarrow \theta(i, n) + new\ t_f(n)$ {time to failure for maintained turbines}
          $\alpha_0(n) \leftarrow \alpha_0(n) + \lambda$ {update aging rate for maintained turbines}
        end if
      end if
    end if
  end for
  $TC(j) \leftarrow \sum_{i=1}^{t_{max}} C(i)$ {compute total cost for each iteration}
end for
return $\leftarrow E(TC)$ {compute the expected total cost from all iterations}

Table 4.4: Main reliability and maintenance parameters

Parameter	Description	Value
β	Weibull Shape	3
η	Weibull Scale (days)	2400
C^P	PM Cost (1000 \$)	38
C^R	CM Cost (1000 \$)	63
C^F	Failure Cost (1000 \$)	150
w^{price}	Wind Price ($/kWh)	0.05
M^P	PM age reduction factor	0.3
M^R	CM age reduction factor	0.6
α_0	Nominal aging rate	1.3
δ_0	Effect of ambient temperature	-5
γ_0	Effect of idle wind turbine	-10

To evaluate the aging model for all wind turbines, we utilize a database of hourly wind speed measurements from the National Oceanic and Atmospheric Administration (NOAA) [28]. Measurements were collected from land-based weather stations in three states (Texas, California, and Illinois) at 10 meter height ($h_1 = 10m$). The raw data are then extrapolated to hub height ($h2 = 135$) according to IEC standard procedure [29] using Equation 4.15.

$$v_2 = v_1(\frac{h_2}{h_1})^{\kappa} \tag{4.15}$$

Where κ is the power exponent for different types of terrain and atmospheric stability conditions.

To study the performance of the proposed model. First, we compare our model with the traditional age-based preventive maintenance approach. Second, we study the impact of different electricity prices on the resulting maintenance schedule. Third, we consider the impact of different deployment costs on the maintenance schedule. We also consider multiple wind farm locations with 100 onshore wind turbines. To simulate random failure times in this setup, we use Weibull lifetime distribution function described in Table 4.4, where time to failure for each individual turbine is updated after maintenance action.

Our experimental framework involves two models: simulation model, and an optimization model. In the simulation model, we run 100 iterations to calculate the expected total cost of maintenance for a 7300 day planning horizon, given maintenance thresholds and wind profiles. In the optimization model we a simple Nelder Mead method to obtain threshold values that minimize the total expected cost in the simulation model. The optimization model is solved in MATLAB 2018b on a i7-4790K 4GHz quad core PC with 24 GB of RAM. We use wind data from different land station for each location as representative of wind profiles. For each day within the planing horizon, we determine which wind turbines experience unexpected failure, planned maintenance or an idle period. For every wind turbine $\in N$, an unexpected failure occurs when its equivalent age θ exceeds the generated failure time before reaching its preventive or opportunistic maintenance threshold. The failed wind turbines stay idle until a corrective maintenance occurs. Once maintenance actions occur, we update the equivalent age and maintenance costs for each maintained wind turbine. We also keep track of the following metrics:

1. Production loss: based on the availability of each wind turbine, wind data and electricity price, we calculate the expected revenue loss.

2. Total maintenance cost: we obtain the total maintenance cost by the sum of the number of preventive actions, corrective actions and failures multiplied by C^P, $C^R$and C^F, respectively. We obtain the total deployment cost by the sum of crew visits z_i multiplied by the associate cost C^D.

3. Maintenance metrics: we record the number farm visits, failures, and preventive and reactive actions. We also record the total downtime of wind turbines.

To ensure reaching the optimal solution, we repeat this experimental procedure multiple times with different initial thresholds, and calculate the metrics. We next present the results of our experiments. we compare the total cost of maintenance metrics of traditional age-based maintenance, with our proposed model at three locations under different deployment cost. The traditional age-based model generalizes single turbine maintenance policies to cases with multiple wind turbines.

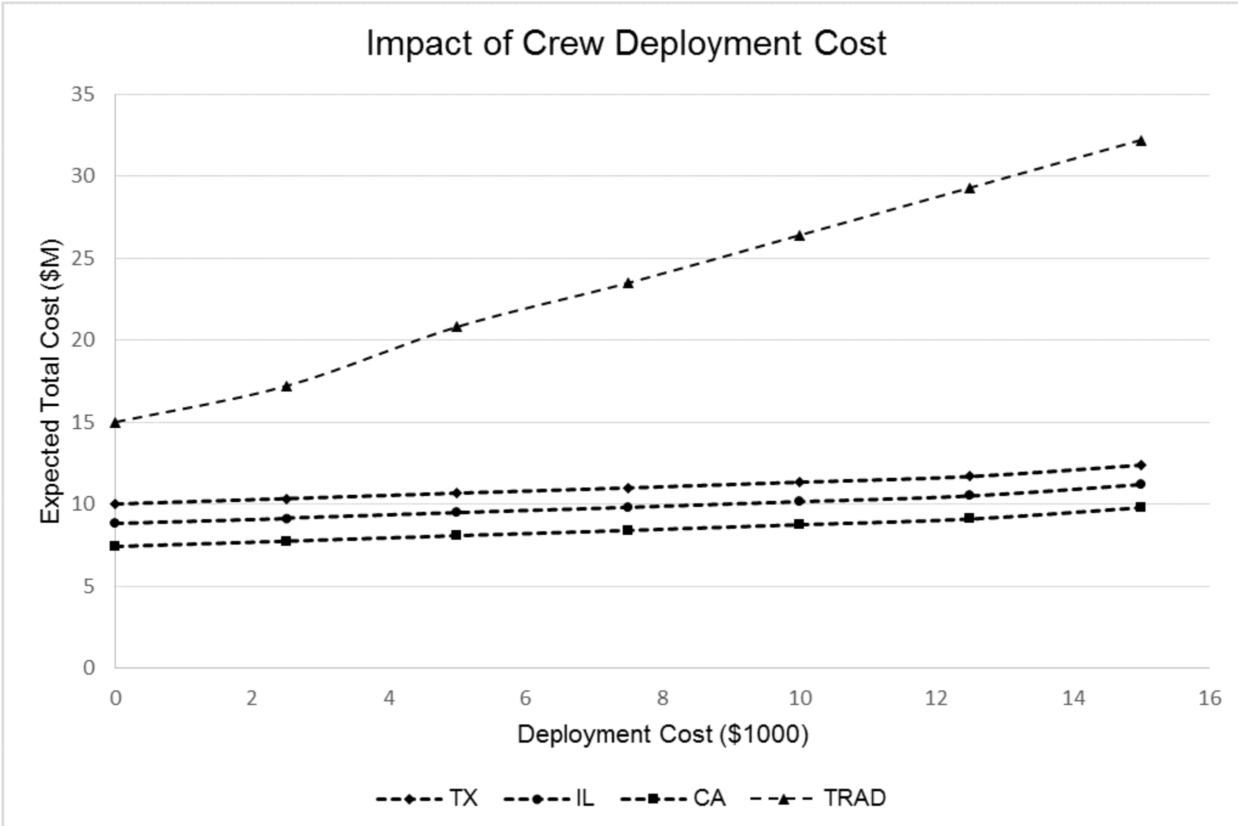


Figure 4.2: Total maintenance cost under different deployment costs.

Depending on the age and type of the wind turbine, periodic maintenance frequencies of wind turbines differ but each turbine is maintained separately. Fig. 4.2 provides the total cost of the two policies under different deployment costs. We fix the price of electricity be $10 per MWh and vary the deployment cost between $0 and $15,000. Opportunistic approach always provides a better results than traditional models.

We next analyze the effect of crew capacity on different farm locations. Tables 4.5– 4.7 compare maintenance metrics under different crew capacity values for Texas, Illinois and California, respectively. All metrics presented refer to the expected numbers per turbine per year.

While decreasing deployment cost the model becomes accessibility driven to find the best threshold value when the wind farm becomes accessible, and performs maintenance when needed. This significantly decreases failure instances, and reduce the number of visits considerably while reducing total maintenance cost. Our model shows significant savings compared to traditional models under high deployment cost. For instance, when the ratio between PM cost and deployment cost is greater than 0.5, our model decreases total cost by more 60% in all cases compared to traditional PM, while reductions in number of failures correspond to more than 40%. Decreasing failure instances reduces total downtime, which ensures that wind farm can meet higher availability targets at any time, meeting demand by increasing available generation capacity.

Table 4.5: The effect of crew capacity per turbine per year: Texas

Crew capacity	1	3	5	7	9	12
Maintenance Actions	5.63	6.915	7.13	7.565	8.195	8.78
Failures	2.29	1.655	1.41	1.315	1.245	1.01
Farm Visits	3.525	2.855	1.755	1.075	0.925	0.835
Downtime Days	20.465	16.56	13.715	10.77	10.075	8.765

Table 4.6: The effect of crew capacity per turbine per year: Illinois

Crew capacity	1	3	5	7	9	12
Maintenance Actions 5.01	5.35	5.715	6.41	6.655	6.925	
Failures	1.615	1.26	1.155	0.935	0.815	0.74
Farm Visits	2.88	2.1	1.755	1.22	1.025	0.865
Downtime Days	15.21	11.05	9.615	8.625	7.91	7.375

Table 4.7: The effect of crew capacity per turbine per year: California

Crew capacity	1	3	5	7	9	12
Maintenance Actions	3.575	4.435	4.94	5.225	5.64	5.935
Failures	1.38	1.06	0.905	0.735	0.565	0.49
Farm Visits	2.08	1.55	1.27	0.915	0.785	0.665
Downtime Days	12.755	9.4	8.335	7.6	7.055	6.36

our model significantly decreases the number of crew visits in comparison to traditional preventive maintenance models for any crew capacity greater than one due to opportunistic maintenance. As the capacity increases, the deployment cost also increase, causing a rise in total cost as a clear consequence. However, increasing the capacity forces the model to group maintenance actions more aggressively, thus decreasing farm visits. As capacity increase, it becomes more expensive to deploy the crew to the farm, leading to higher threshold values. By doing so, we consider the trade-off between the optimal maintenance thresholds, and the cost reduction due to the increase in crew capacity.

4.4.1 Impact of Electricity Price

We next analyze the impact of electricity price on the number of opportunistic maintenance instances. To do so, we run our model of 100 wind turbines with fixed deployment cost ($C^D = \$5000$) and capacity ($Cap^{max} = 5 turbines$). We run the simulation model with electricity prices from \$10/MWh to \$100/MWh to study the impact of electricity price on the frequency of opportunistic maintenance actions as shown in Fig. 4.3. The results reveal that increasing the electricity price increases the production losses, and therefore the cost of downtime. Moreover, there is a significant dependency between farm accessibility, and the price of electricity. If turbines are maintained early on, the production revenue will outweigh the opportunistic maintenance cost and therefore lowering the opportunistic maintenance threshold. However, if the threshold is fixed, then the number of crew visits becomes independent of electricity prices.

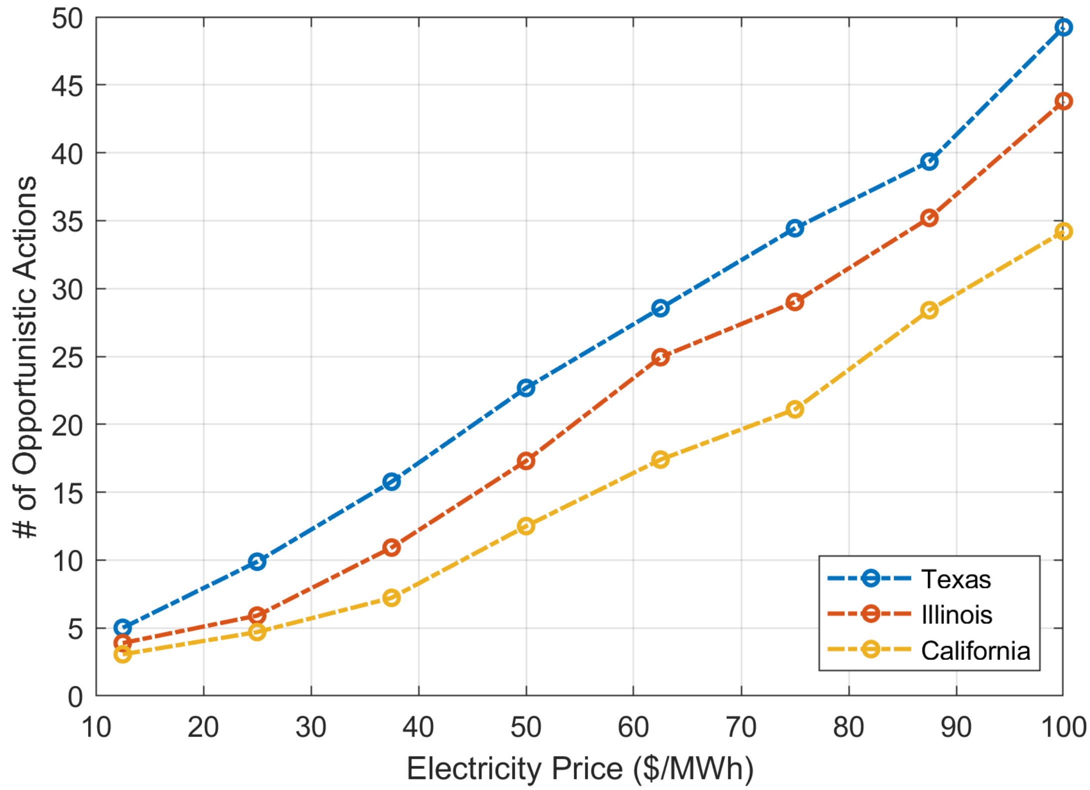


Figure 4.3: Impact of electricity price on opportunistic actions.

Fig. 4.3 shows that opportunistic maintenance actions increase as the electricity prices rise, leading to more crew visits to avoid the loss of production. Since crew capacity is fixed in this example, the need to delay opportunistic maintenance actions increases which in return force the model to lower threshold values. This leads to a slight increase in the rate of increasing at higher prices. However, the increase in the frequency of maintenance is outweighed by production revenues.

4.4.2 Impact of Weather Conditions

In this example, we analyze the impact of wind speed conditions in three wind farms with 100 turbines each in different geographical locations with fixed deployment cost, capacity and electricity price. We set the price of electricity to $10/ MWh, and maximum crew capacity to 5 turbines per

Table 4.8: Optimal equivalent age thresholds and costs using the proposed model

	Texas	California	Illinois
PM Threshold (equivalent age)	2330	1755	2027
OM Threshold (equivalent age)	1401	1333	1212
PM Rate (per turbine per year)	2.74	1.76	2.37
OM Rate (per turbine per year)	1.57	1.23	1.53
Failure Rate (per turbine per year)	0.35	0.20	0.24
Downtime (days/year per turbine)	11.33	8.14	9.35
Maintenance Cost ($1000/year per turbine)	137.9	90.5	110.5

visit. The goal is to find the optimal threshold values for each location under the same economical constraints to evaluate the impact of weather. We run our simulation model for each instance with 100 replications, performed over 7300 days (20 years). Then, we obtain the average maintenance cost per day and the failure and maintenance frequencies per year. Table 4.8 summarizes the simulation results of each maintenance scenario under the proposed age models.

Texas has the highest expected maintenance cost of ($137.9 thousands per turbine per year) with equivalent age thresholds values of 1401 and 2330 for opportunistic and preventive maintenance, respectively. Texas has smaller accessibility windows during summer and spring due to both higher wind speeds and temperatures which results in faster aging process and more maintenance delays due to weather constraints. California on the other hand, has the lowest expected maintenance cost of ($90.5 thousands per turbine per year) with equivalent age thresholds values of 1333 and 1755 for opportunistic and preventive maintenance, respectively . The results show that under harsher weather conditions the width of the opportunistic region between the two threshold values is larger reflecting the higher risk of failure under faster aging turbines and thus, reaching the thresholds faster. note that in this example we fixed the crew capacity to 5 turbines and therefore, the width of the opportunistic maintenance window increases to accounts for delayed maintenance actions due to limited capacity. This also gives the crew more time to reschedule farm visits in the case of unfavorable weather conditions at the time of the requested maintenance.

Finally, we compare California and Illinois cases. We note that the failure rates and downtime days are similar due to comparable accessibility constrains. However,on average Illinois has higher wind speeds causing faster aging process as the wind speed increases. This is reflected in the equivalent age threshold values as Illinois has wider opportunistic window under fixed crew capacity constraint. This means that a turbine in Illinois is expected to stay in the opportunistic maintenance region significantly longer than a turbine in California due to higher number of delayed actions. Even if the farm is accessible, there will be more turbines that reached their opportunistic maintenance threshold in Illinois than California. Thus the model assigns lower opportunistic maintenance threshold as the optimal value to get the maximum benefits of the opportunistic maintenance .

4.5 CONCLUSION

In this paper, we propose an opportunistic maintenance approach that utilizes the effect of wind speed on turbine aging in order to predict the equivalent age of win turbines at different wind farm locations and determine the best maintenance decisions. Unlike the traditional time-based models, the proposed approach uses hourly wind speed measurements to evaluate the equivalent age for each individual turbine and to determine farm accessibility conditions for a specific farm location; this model is then incorporated into an optimization model to find the optimal preventive and opportunistic threshold values for the entire farm. Our model considers the economic dependencies between maintenance actions within a wind farm, and provides scenario-based results. We present numerical examples using real weather and turbine data. The results show improvements in terms of both reliability and total cost for a 100 wind turbine farm at three different locations.

In the future, this work can be extended to incorporate uncertainty in electricity price and dynamic crew capacity. In this paper, we focused on simulating the aging process using available weather conditions and assumed that degradation of the wind turbines is deterministic. One possible extension to this work would to capture the effect of weather conditions at different locations using SCADA data with a more detailed turbine model, and illustrate how a turbine as a system of components ages under different environments. In addition, developing an analytical model to solve the same maintenance problem remains a challenge.

4.6 NOMENCLATURE

$V(t)$: wind speed measure

$\delta(t)$: effects function of intensity of wind

$q(t)$: overall wind effects function

α_0: nominal aging rate

β: Weibull distribution shape parameter

η: Weibull distribution scale parameter

Θ: equivalent age of the unit at failure

θ: instantaneous equivalent age

$F(t)$: life distribution function

$R(t)$: reliability function

C^R: cost of imperfect CM

C^P: cost of imperfect PM

C^F: cost of failure

$C(i)^L$: cost of loss of production

$E(TC)$: expected total cost

p^{pm}: PM conditional failure probability threshold

p^{om}: OM conditional failure probability threshold

$M(t)$: imperfect maintenance improvement function

W^{price}: wind energy price

References

[1] Y. Kumar, J. Ringenberg, S. S. Depuru, V. K. Devabhaktuni, J. W. Lee, E. Nikolaidis, B. Andersen, and A. Afjeh, "Wind energy: Trends and enabling technologies," *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 209 – 224, 2016.

[2] F. DING and Z. TIAN, "Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions," *International Journal of Reliability, Quality and Safety Engineering*, vol. 18, no. 05, pp. 463–481, 2011.

[3] H. Abdollahzadeh, K. Atashgar, and M. Abbasi, "Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups," *Renewable Energy*, vol. 88, pp. 247 – 261, 2016.

[4] X. Zhang and J. Zeng, "Joint optimization of condition-based opportunistic maintenance and spare parts provisioning policy in multiunit systems," *European Journal of Operational Research*, vol. 262, no. 2, pp. 479 – 498, 2017.

[5] A. Gutierrez-Alcoba, E. Hendrix, G. Ortega, E. Halvorsen-Weare, and D. Haugland, "On offshore wind farm maintenance scheduling for decision support on vessel fleet composition," *European Journal of Operational Research*, vol. 279, no. 1, pp. 124 – 131, 2019.

[6] C. Nzukam, A. Voisin, E. Levrat, D. Sauter, and B. Iung, "Opportunistic maintenance scheduling with stochastic opportunities duration in a predictive maintenance strategy," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 453 – 458, 2018. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[7] C. Zhang, W. Gao, T. Yang, and S. Guo, "Opportunistic maintenance strategy for wind turbines considering weather conditions and spare parts inventory management," *Renewable Energy*, vol. 133, pp. 703 – 711, 2019.

[8] C. Zhang, W. Gao, S. Guo, Y. Li, and T. Yang, "Opportunistic maintenance for wind turbines considering imperfect, reliability-based maintenance," *Renewable Energy*, vol. 103, pp. 606 – 612, 2017.

[9] J. Wang, V. Makis, and X. Zhao, "Optimal condition-based and age-based opportunistic maintenance policy for a two-unit series system," *Computers & Industrial Engineering*, vol. 134, pp. 1 – 10, 2019.

[10] S. Song, Q. Li, F. A. Felder, H. Wang, and D. W. Coit, "Integrated optimization of offshore wind farm layout design and turbine opportunistic condition-based maintenance," *Computers & Industrial Engineering*, vol. 120, pp. 288 – 297, 2018.

[11] F. Ding and Z. Tian, "Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds," *Renewable Energy*, vol. 45, pp. 175 – 182, 2012.

[12] A. Erguido, A. C. Márquez, E. Castellano, and J. G. Fernández, "A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms," *Renewable Energy*, vol. 114, pp. 843 – 856, 2017.

[13] P. Zhou and P. Yin, "An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics," *Renewable and Sustainable Energy Reviews*, vol. 109, pp. 1 – 9, 2019.

[14] M. Shafiee, M. Finkelstein, and C. Bérenguer, "An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks," *Reliability Engineering & System Safety*, vol. 142, pp. 463 – 471, 2015.

[15] S. Song, Q. Li, F. A. Felder, H. Wang, and D. W. Coit, "Integrated optimization of offshore wind farm layout design and turbine opportunistic condition-based maintenance," *Computers & Industrial Engineering*, vol. 120, pp. 288 – 297, 2018.

[16] Y. Lu, L. Sun, X. Zhang, F. Feng, J. Kang, and G. Fu, "Condition based maintenance optimization for offshore wind turbine considering opportunities based on neural network approach," *Applied Ocean Research*, vol. 74, pp. 69 – 79, 2018.

[17] M. Yildirim, N. Z. Gebraeel, and X. A. Sun, "Integrated predictive analytics and optimization for opportunistic maintenance and operations in wind farms," *IEEE Transactions on Power Systems*, vol. 32, pp. 4319–4328, Nov 2017.

[18] S. Faulstich, B. Hahn, and P. J. Tavner, "Wind turbine downtime and its importance for offshore deployment," *Wind Energy*, vol. 14, no. 3, pp. 327–337, 2011.

[19] V. Slimacek and B. H. Lindqvist, "Reliability of wind turbines modeled by a poisson process with covariates, unobserved heterogeneity and seasonality," *Wind Energy*, vol. 19, no. 11, pp. 1991–2002, 2016.

[20] P. Zhou and P. Yin, "An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics," *Renewable and Sustainable Energy Reviews*, vol. 109, pp. 1 – 9, 2019.

[21] B. R. Sarker and T. I. Faiz, "Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy," *Renewable Energy*, vol. 85, pp. 104 – 113, 2016.

[22] L. Yang, R. Peng, G. Li, and C.-G. Lee, "Operations management of wind farms integrating multiple impacts of wind conditions and resource constraints," *Energy Conversion and Management*, vol. 205, p. 112162, 2020.

[23] K. Atashgar and H. Abdollahzadeh, "Reliability optimization of wind farms considering redundancy and opportunistic maintenance strategy," *Energy Conversion and Management*, vol. 112, pp. 445 – 458, 2016.

[24] H. Abdollahzadeh, K. Atashgar, and M. Abbasi, “Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups,” *Renewable Energy*, vol. 88, pp. 247 – 261, 2016.

[25] J. Izquierdo, A. Crespo Márquez, J. Uribetxebarria, and A. Erguido, “Framework for managing maintenance of wind farms based on a clustering approach and dynamic opportunistic maintenance,” *Energies*, vol. 12, no. 11, 2019.

[26] A. A. Teyabeen, F. R. Akkari, and A. E. Jwaid, “Power curve modelling for wind turbines,” in *2017 UKSim-AMSS 19th International Conference on Computer Modelling Simulation (UKSim)*, pp. 179–184, April 2017.

[27] ENERCONE GmbH, “Enercon Product Overview.” https://www.enercon.de/en/products/ep-8/e-126/. Accesssed: 04-28-2019.

[28] A. Arguez, I. Durre, S. Applequist, M. Squires, R. Vose, X. Yin, and R. Bilotta , “NOAA’s U.S. Climate Normals (1981-2010),” 2010. Accessed: 3.15.2019.

[29] International Electrotechnical Commission, *IEC 61400-12: Wind turbines - Part 12: Power performance measurements of electricity producing wind turbines*. No. 12, Geneva, Switzerland: International Electrotechnical Commission, 1st PPUB ed., 2005.

Chapter 5

CONCLUSION AND FUTURE WORK

This dissertation investigated a new approach in the wind farm maintenance field that considers a weather-based aging model and economic opportunities. We extended the opportunistic maintenance research in wind farms to take advantage of weather conditions as key factors in aging modeling, which provide an alternative to traditional condition-based maintenance. Opportunistic maintenance actions can be applied to select the turbines of a wind farm to reduce the number of crew visits to the farm and therefore reducing the total maintenance cost.

In this research, we constructed a weather based equivalent age model for choosing the most cost effective maintenance actions under specific weather scenarios. We developed a simulation based optimal policy to respond to the time-varying weather conditions. We examined the impact of wind speeds and air temperatures on wind turbine maintenance with imperfect repairs, accessibility constraints and revenue losses. A new equivalent age-based maintenance policy was proposed for wind turbines using historical weather data to simulate 20 year long weather measurements for given locations. We proposed to use the equivalent age model with the Weibull distribution to evaluate the wind turbine aging under different weather profiles. We showed the advantage of our approach using scenario-based results that are less dependent on generic lifetime distributions. The case study demonstrated the benefits of adopting the equivalent age model. The maintenance cost, failure rate and maintenance frequencies can be significantly reduced when the proposed model is applied instead of simply using traditional age models. Also, we showed that considering the weather effects can potentially improve the availability of the turbine and avoid potential production losses.

In addition, we proposed an opportunistic maintenance approach that utilizes the effect of wind speed on turbine aging in order to predict the equivalent age of wind turbines at different wind farm locations and determine the best maintenance decisions. Unlike the traditional time-based models, the proposed approach uses hourly wind speed measurements to evaluate the equivalent age for each individual turbine and to determine the farm accessibility conditions for a specific farm location. This model is then incorporated into an optimization algorithm to find the optimal preventive and opportunistic threshold values for the entire farm. Our model considers the economic dependencies between maintenance actions within a wind farm, and provides scenario-based results. We presented numerical examples using real weather and turbine data. The results showed improvements in terms of both reliability and the total cost for a 100 wind turbine farm at three different locations.

5.1 CONTRIBUTIONS

This dissertation reports a research in opportunistic maintenance for wind farms, with special attention to the aging process and the effects of weather conditions on maintenance policies.

Chapter 2 explored actual SCADA data to study the impact of wind speed and air temperature on the uptime of a wind turbine. The results showed significant impact of wind speed on uptime while the relationship between the air temperature and uptime was not clear. The results using the available SCADA data demonstrated that the turbines experienced significant reduction in uptime at the wind speeds higher than the wind speed of the maximum power coefficient.

Chapter 3 presented a simulation and an optimization model for a single wind turbine where the effect of wind speed and air temperature of aging is considered. The proposed approach is based on the equivalent age model and two-threshold maintenance. The optimization model finds the optimal threshold values that minimize the expected daily maintenance cost for imperfect preventive and corrective maintenance activities under accessibility constraints. Three scenarios were considered to illustrate the advantage of the proposed approach over traditional time-based models. Real weather data collected from land-based stations were utilized to create hourly weather conditions scenarios for each location for a length of 20 years. The numerical results showed that incorporating weather effect in aging yields a significant maintenance cost saving compared to the traditional PM policies where the accessibility restriction is the only considered weather effect . In particular, the results showed that considering the weather effects on aging can potentially improve the availability of the turbine and avoid potential production losses.

Chapter 4 described the opportunistic maintenance approach for a wind farm. The optimal equivalent age-based opportunistic maintenance strategy is used to study the impact of wind speed on farm the maintenance decisions for a 100-turbine farm with limited crew capacity and high deployment cost. This model also considers imperfect maintenance actions and accessibility restrictions. The total maintenance cost is minimized through two maintenance thresholds, PM and OM thresholds. The proposed model is illustrated through several numerical examples under different electricity prices and crew capacity assumptions. The results showed that our approach yields significant savings in maintenance cost in comparison with the traditional PM policies. The savings of applying the weather based aging model are up to 70% of the maintenance cost under high electricity prices and limited crew capacity. Moreover, the simulation results showed that under harsher weather conditions the width of the opportunistic maintenance window increases to account for delayed maintenance actions and faster turbines aging compared to a fixed window width in the traditional opportunistic maintenance models.

5.2 FUTURE WORK

This research has presented a new approach to wind turbine maintenance that considers a weather based aging model. Opportunities to extend this research in some potential areas are as follows:

1. The SCADA data studied was limited for four turbines in the same location. Conducting a more in-depth analysis with larger datasets of the same turbine types at different geographical locations is a next step to improve the aging model.

2. Turbines are multi-component systems and components experience different degradation processes. Therefore, modeling the reliability of the turbine as a multi-components system can be an extension to our approach.

3. Developing analytical models that combine opportunistic maintenance and weather based stochastic aging is of interest because of its potential benefit in solving large scale problems. The modeling is challenging due to the stochastic nature of aging with a nonlinear objective function. One possible improved approach is to use a two-stage decision model where the external accessibility constraints are considered in the first stage and an agebased grouping policy to select turbines for opportunistic maintenance as the second stage.

4. Considering a dynamic crew capacity based on varying electricity prices and weather conditions is another is another opportunity for future research. The electricity price, which varies significantly and continuously through time, can create some maintenance opportunities when the price is low. In this way, the electricity price can be considered as a continuous opportunity. The maintenance resources (labor, spare parts, etc.) are always limited, and therefore, incorporating a logistic planning for the maintenance is another area for future work

5. Machine learning models have been shown to be appropriate for age prediction. To better classify the operational state of a wind turbine, a machine learning model can be used to predict from SCADA data the status of the turbine based on weather conditions at any given time

Finally, our maintenance approach can be generalized to be applicable to other power systems such as a solar power system or to production systems such as a manufacturing plant. The degradation of the equipment based on usage and ambient conditions is a significant topic to explore. Aging is a stochastic process that depends on many random external factors such as humidity, dust, wind, temperature, etc. Therefore, if there is a maintenance model that can effectively account for external factors, an effective predictive maintenance policy can be developed.