ABSTRACT

Title of Dissertation:	PHM-BASED PREDICTIVE MAINTENANCE SCHEDULING FOR WIND FARMS MANAGED USING OUTCOME-BASED CONTRACTS
	Xin Lei, Doctor of Philosophy, 2018
Dissertation directed by:	Professor Peter A. Sandborn, Department of Mechanical Engineering

Prognostics and Health Management (PHM) technologies have been introduced into wind turbines to forecast the Remaining Useful Life (RUL), and enable predictive maintenance opportunities prior to failure thus avoiding corrective maintenance that may be expensive and cause long downtimes. For a wind turbine, when an RUL is predicted, a predictive maintenance option is triggered that the maintenance decision-maker has the managerial flexibility to decide if and when to exercise before the turbine fails. By implementing the predictive maintenance, the high cost of corrective maintenance can be avoided; however a portion of the RUL will be thrown away that can be translated into cumulative revenue loss.

In this dissertation, a simulation-based European-style Real Options Analysis (ROA) approach is used to schedule the predictive maintenance for a single wind turbine with an RUL prediction managed using an as-delivered payment model. When an RUL is predicted for the wind turbine, the predictive maintenance value paths are

simulated by considering the uncertainties in the RUL prediction and wind speeds. By valuating the European-style predictive maintenance option at all possible predictive maintenance opportunities, a series of predictive maintenance option values can be obtained, and the predictive maintenance opportunity with the highest expected predictive maintenance option value can be selected.

By extending the approach for a single wind turbine, a wind farm managed using an outcome-based contract, specifically a Power Purchase Agreement (PPA), with multiple turbines indicating RULs concurrently can be analyzed. The predictive maintenance value for each wind turbine with an RUL indication depends on the operational state of all the other turbines, the amount of energy delivered, and the energy delivery target, prices and penalization mechanism for under-delivery defined in the PPA. A case study is provided demonstrating that the selected predictive maintenance opportunity for a PPA-managed wind farm is different from the same wind farm managed using an as-delivered payment model, and also differs from the selected predictive maintenance opportunities for the individual turbines with RULs managed in isolation.

Finally, the magnitude of the life-cycle benefit that the developed approach can bring to the wind farm owner is estimated through a simple case study. Using the European-style ROA approach to determine the wind farm maintenance policy, the improvement to the wind farm expected life-cycle net revenue is significant compared with the state-of-art wind farm maintenance policies, i.e., up to 25% higher than the corrective maintenance policy, and up to 83% higher than the predictive maintenance at the earliest opportunity policy.

PHM-BASED PREDICTIVE MAINTENANCE SCHEDULING FOR WIND FARMS MANAGED USING OUTCOME-BASED CONTRACTS

by

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Dedication

I dedicate this dissertation to my wife (Yuexin Liu), mother (Huifang Jia), father (Xuanmin Lei) and to you as a reader.

Acknowledgements

I would like to sincerely express my gratitude to my academic advisor Prof. Peter Sandborn. I truly appreciate the opportunity to work with him and also learn from him: his in-depth academic advising, professional engineering coaching as well as the generous financial support have guided and helped me to overcome one difficulty after another and finally reach the completion of this dissertation and also my PhD study.

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List of Abbreviations and Nomenclature

A	Wind turbine rotor disc area
AP_{CM}	Material availability penalty rate
$ARUL_C$	RUL sample in calendar time
$ARUL_{C,k}$	RUL sample in calendar time for wind turbine k
$ARUL_{C,min}$	Shortest $ARUL_{C,k}$
$ARUL_F$	RUL_F sample in cycles
B	Buoy height
$C_A(t)$	Avoided corrective maintenance cost if predictive maintenance is scheduled at time t
C_{CM}	Corrective maintenance parts, service and labor cost
$C_{CM,k}$	Corrective maintenance parts, service and labor cost of turbine k
$C_{CM,K}$	Corrective maintenance parts, service and labor cost of all K turbines
C_{PM}	Predictive maintenance parts, service and labor cost
$C_{PM,k}$	Predictive maintenance parts, service and labor cost of turbine k
$C_{PM,K}$	Predictive maintenance parts, service and labor cost of all K turbines
$CE(t_0)$	Cumulative energy delivered by the whole wind farm from time 0 to t_0
$CF(t_0)$	Cumulative operating time from time 0 to t_0
$CE_{CM}(t)$	Cumulative energy delivered by the whole wind farm from time 0 to t if corrective maintenance is going to be implemented
$CE_{PM}(t)$	Cumulative energy delivered by the whole wind farm from time 0 to t if predictive maintenance is going to be implemented

$CF_{CM}(t)$ Cumulative operating time from time 0 to t if corrective maintenance is going to be implemented

$CF_{PM}(t)$ Cumulative operating time from time 0 to t if predictive maintenance is going to be implemented

$CR_{CM,K}(\tau_1, \tau_2)$ Cumulative revenue earned by turbine k from time τ_1 to τ_2 if corrective maintenance is going to be implemented

$CR_{CM}(\tau_1, \tau_2)$ Cumulative revenue earned from time τ_1 to τ_2 if corrective maintenance is going to be implemented

$CR_{PM}(\tau_1, \tau_2)$ Cumulative revenue earned from time τ_1 to τ_2 if predictive maintenance is going to be implemented

$CR_{PM,k}(\tau_1, \tau_2)$ Cumulative revenue earned by turbine k from time τ_1 to τ_2 if predictive maintenance is going to be implemented

$D(\tau)$ RUL consumption from time τ-1 to τ in cycles

DT Downtime of the corrective maintenance

$E[v(t, x)]$ Expected value of scheduling the predictive maintenance at time t

$E_j(\tau)$ Energy generated by turbine j from time τ-1 to τ

$E_{CM,k}(\tau)$ Energy generated by turbine k from time τ-1 to τ if corrective maintenance is going to be implemented

$E_{CM}(\tau)$ Energy generated from time τ-1 to τ if corrective maintenance is going to be implemented

$E_{PM}(\tau)$ Energy generated from time τ-1 to τ if predictive maintenance is going to be implemented

$E_{PM,k}(\tau)$	Energy generated by turbine k from time τ-1 to τ if predictive maintenance is going to be implemented
E_R	Wind energy generated in rated power from time τ-1 to τ
$EN_{PM}(t)$	Number of the extra predictive maintenance events as a result of the predictive maintenance at time t
$ENPV_{PM}(t)$	Expected predictive maintenance NPV if predictive maintenance is scheduled at time t
$ENPV_{PM,K}(t)$	Expected predictive maintenance NPV if predictive maintenance is scheduled for all K turbines at time t
$EOV_{PM}(t)$	Expected predictive maintenance option value if predictive maintenance is scheduled at time t
$EOV_{PM,K}(t)$	Expected predictive maintenance option value if predictive maintenance is scheduled for all K turbines at time t
ET	Energy delivery target for the wind farm from time 0 to T defined in PPA
$f(\cdot)$	Probability density function of the wind speed data
$F_{CM}(\tau)$	Operating time if corrective maintenance is going to be implemented
$F_{PM}(\tau)$	Operating time if predictive maintenance is going to be implemented
FT	Operating time target at from time 0 to T
FV	Future value
$g(\cdot)$	Wind turbine power curve function
H	Wind turbine hub height
$h(\cdot)$	Stationary PDF for RUL_C in calendar time

i	Index of the Monte Carlo simulation trial
I	Number of wind turbines are down in the wind farm at time t_0
J	Number of wind turbines operating normally in the wind farm at time t_0
K	Number of wind turbines indicating *RULs* in the wind farm at time t_0
l	Simulation time step length
L_{CM}	Life-cycle length if corrective maintenance is always implemented
L_{PM}	Life-cycle length if predictive maintenance is always implemented
M	Number of simulation paths
n	Number of time periods for discounting
N	Fixed number of maintenance cycles
NPV	Net present value
$NPV_{PM}(t)$	Predictive maintenance NPV if predictive maintenance is scheduled at time t
$NPV_{PM,K}(t)$	Predictive maintenance NPV if predictive maintenance is scheduled for all K turbines at time t
$OV_{PM}(t)$	Predictive maintenance option value if predictive maintenance is scheduled at time t
$OV_{PM,K}(t)$	Predictive maintenance option value if predictive maintenance is scheduled for all K turbines at time t
P	Theoretical power available from the wind
P_A	Material availability penalty rate
P_C	Energy price in the as-delivered payment model, or the contract price in the PPA

$P_{CM}(\tau)$	Energy price at time τ if corrective maintenance is going to be implemented
P_E	Excess energy price in the PPA
$P_{PM}(\tau)$	Energy price at time τ if predictive maintenance is going to be implemented
P_R	Replacement energy price in the PPA
PV	Present value
r	Discount rate
$R_{CM,k}(\tau)$	Revenue earned by turbine k from time τ-1 to τ if corrective maintenance is going to be implemented
$R_{CM}(\tau)$	Revenue earned from time τ-1 to τ if corrective maintenance is going to be implemented
$R_G(t)$	Cumulative revenue gained during the corrective maintenance downtime by implementing predictive maintenance at time t
$R_L(t)$	Cumulative revenue loss if predictive maintenance is going to be implemented at time t
$R_{PM}(\tau)$	Revenue earned from time τ-1 to τ if predictive maintenance is going to be implemented
$R_{PM,k}(\tau)$	Revenue earned by turbine k from time τ-1 to τ if predictive maintenance is going to be implemented
RUL_C	Predicted remaining useful life in calendar time
RUL_F	Predicted remaining useful life in cycles
S	Wind speed

$S_B(\tau)$	Simulated buoy height wind speed from time τ-1 to τ
S_{CI}	Wind turbine cut-in wind speed
S_{CO}	Wind turbine cut-out wind speed
$S_H(\tau)$	Simulated wind turbine hub height wind speed from time τ-1 to τ
S_{RW}	Wind turbine rational wind speed
t	Time of the predictive maintenance opportunity
T	End of the simulation time period, time 0 is the beginning of the simulation time period
t_c	Time when corrective maintenance will start
t_m	Mission starting time
t_{PHM}	Time from the maintenance event to the next RUL indication
t_{PM}	Time from the RUL indication to the predictive maintenance opportunity
t_0	Time when RUL is predicted
u	Revenue per unit time
$UP_{CM,K}$	Under-delivery penalty allocated to the K turbines if corrective maintenance is going to be implemented
$UP_{PM,K}$	Under-delivery penalty allocated to the K turbines if predictive maintenance is going to be implemented
$v(t, x)$	Benefit of predictive maintenance at time t
$V_{PM}(t)$	Predictive maintenance value if predictive maintenance is scheduled at time t

$V_{PM,K}(t)$	Predictive maintenance value if predictive maintenance is scheduled for all K turbines at time t
x	Uncertain parameters
x_i	Sample of x
α	Power Law exponent
β	Shape parameter of the wind speed data Weibull distribution
η	Scale parameter of the wind speed data Weibull distribution
μ	Mean of the wind speed data
ρ	Air density
σ	Standard deviation of the wind speed data
τ	Simulation time step
ω	Wind turbine rotor nominal rotation speed

Chapter 1: Introduction

1.1 Wind Energy

1.1.1 Global wind energy

As a source of renewable energy, wind power is growing throughout the world. The global annual and cumulative installed wind energy capacity growth are shown in Figure 1-1 and Figure 1-2. The annual growth rate has been more than 10% for over 15 years [1]. Although the expectations for wind energy growth were uncertain at the end of 2013 due to the economic slowdown in Europe and the political uncertainty in the

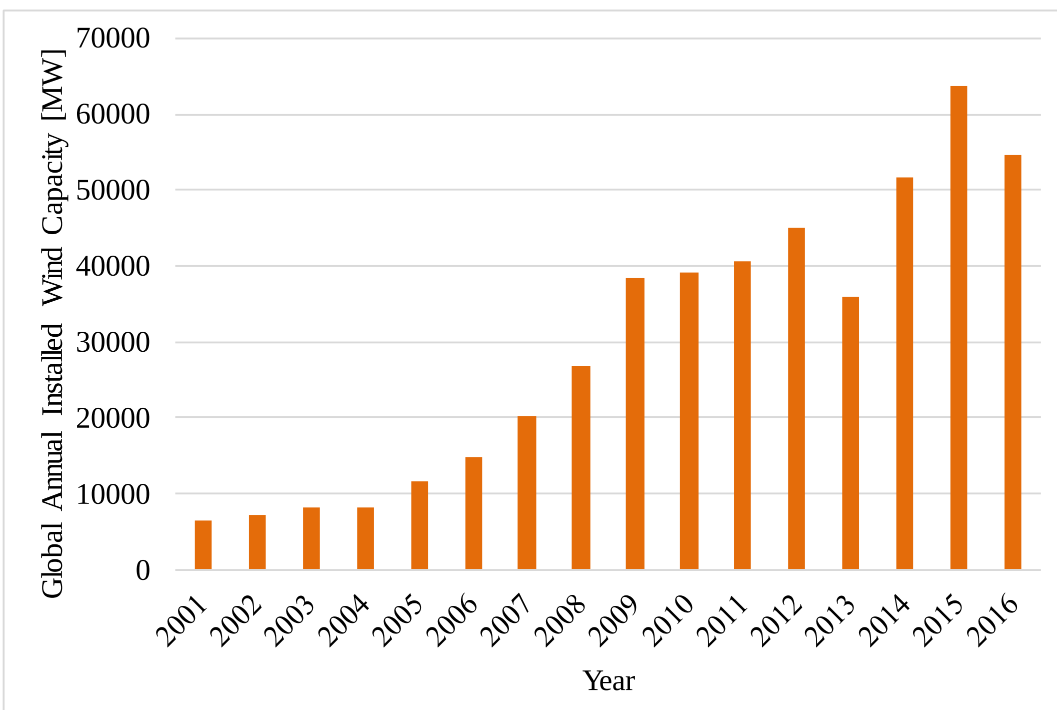

Figure 1-1. Global annual installed wind energy capacity from 2001 to 2016 [1].

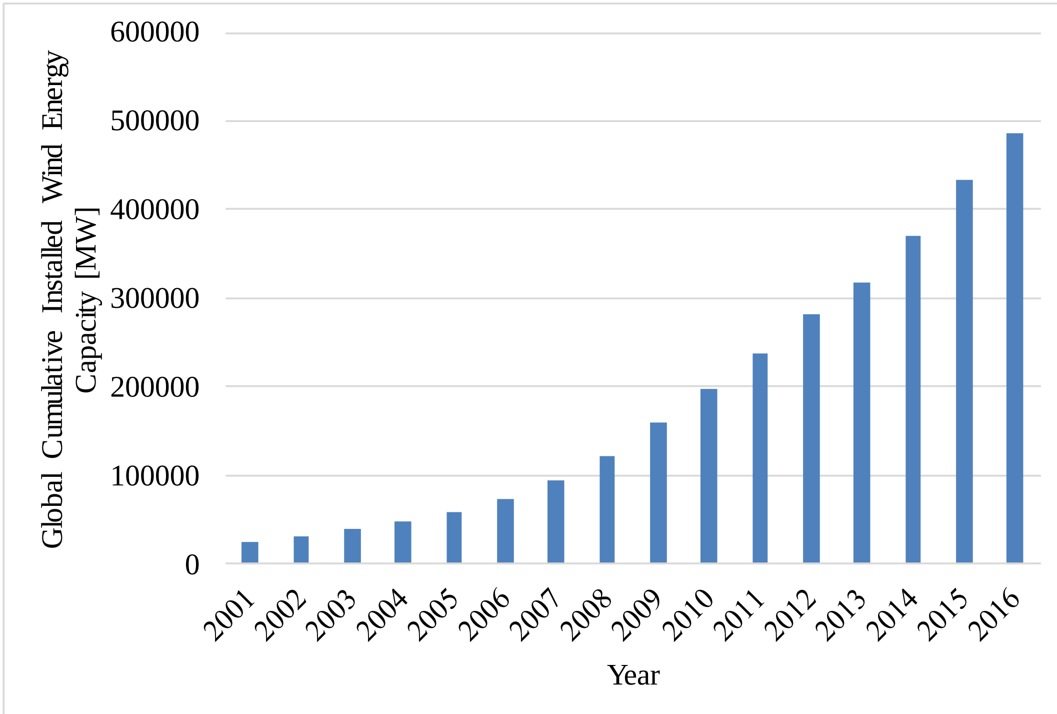

Figure 1-2. Global cumulative installed wind energy capacity from 2001 to 2016 [1].

US, 2014, 2015 and 2016 have been proven to be good years for the wind industry. 51,675 Megawatts (MW), 63,633 MW and 54,600 MW were installed in 2014, 2015 and 2016 individually, bringing the global total wind energy capacity to 486,749 MW by the end of 2016 [1].

Driven by the growth in China and India, Asia has become the world's largest wind energy regional market in 2016, followed by Europe and North America [1]. By the end of 2016 there were 29 countries with more than 1,000 MW of installed wind energy capacity: 17 in Europe, 5 in Asia-Pacific, 3 in North America, 3 in Latin America and 1 in Africa [1], [2]. Nine countries had more than 10,000 MW of installed wind energy capacity: China (168,690 MW), US (82,184 MW), Germany (50,018 MW), India (28,700 MW), Spain (23,074 MW), UK (14,543 MW), France (12,066 MW), Canada (11,900 MW), and Brazil (10,740 MW). The 2016 global annual and

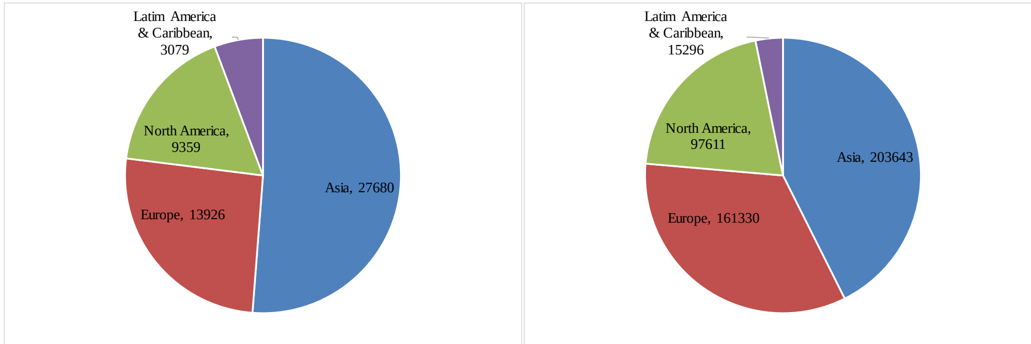

Figure 1-3: Left - 2016 global annual wind energy capacity (in MW) distribution by region and right - 2016 global cumulative wind energy capacity (in MW) distribution by region [1].

cumulative wind energy capacity distribution by region and country are shown in Figure 1-3 and Figure 1-4 [1].

In Asia, China nearly tripled its wind energy capacity from 62 GW in 2011 to 168.7 gigawatts (GW) by the end of 2016, and 23,328 MW was added during 2016 [1]. China is aiming to double its wind energy capacity to 200 GW by the end of 2020 [3], and has already entered a steady development stage. As the second largest wind energy market in Asia, India saw 3,612 MW of newly installed wind energy capacity during 2015, which kept India in the global top five wind energy markets [1]. The new Indian government has committed to a 170 GW renewable energy target by 2022, including 60 GW of wind capacity.

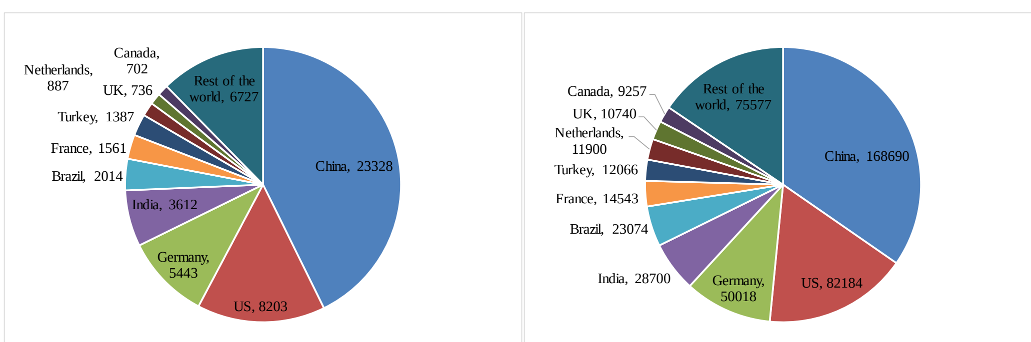

Figure 1-4: Left - 2016 global annual wind energy capacity (in MW) distribution by country and right - 2016 global cumulative wind energy capacity (in MW) distribution by country [1].

In Europe 13,926 MW of wind energy capacity was installed during 2016, with the European Union (EU) members accounting for 12,491 MW [1]. By the end of 2016 the grid-connected wind energy was enough to cover 10.4% of the EU's electricity consumptions. Germany and the France installed 5,443 MW and 1,561 MW respectively in 2016, accounting for 56.1% of the total 2016 EU wind energy installations. Turkey also installed 1,387 MW in 2016 [2].

The US was the second largest wind energy market, and wind provided 6.99% of total installed generation capacity by the end of 2016 [4]. The US Department of Energy has set the goal to obtain 20% of its electricity from wind by 2030 [5]. In 2016 702 MW of new wind energy capacity came online, which made Canada the tenth largest market globally [1].

1.1.2 Wind turbines and farms

Wind turbines are categorized as horizontal axis and vertical axis based on the direction of the shaft, or onshore and offshore based on the location. A typical modern utility-scale wind turbine has a horizontal axis with three blades and an average capacity of 1,958 kilowatts (kW) [6], including following major components as shown in Figure 1-5 [7]:

The components shown in Figure 1-5 are described as:

- **Pitch system**

  The pitch system is mounted in each blade to control the angle for the blade as it turns about its longitudinal axis to optimize the wind energy captured, and also act as an aerodynamic brake [8].

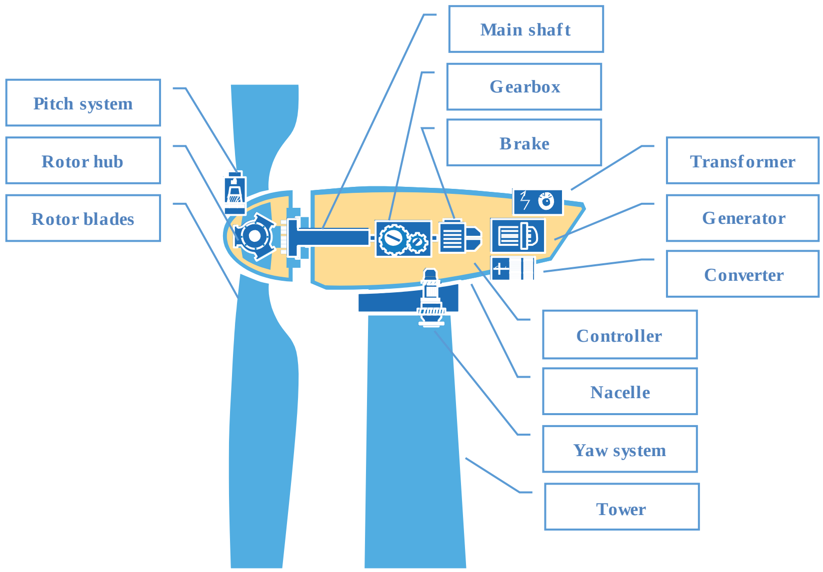

Figure 1-5: The components of a horizontal axis three blades wind turbine [7].

- **Rotor blades**

  Blades transmit the wind to mechanical energy through the low speed shaft, gearbox and the high speed shaft to the generator [8]. Modern blades are typically made by fiberglass-reinforced polyester or epoxy resin [9].

- **Rotor hub**

  The rotational force generated by the blades are transmitted to the main shaft through the rotor hub through a main bearing. The rotor hub is usually covered by a nose cone, and spins at 10 to 25 revolutions per minute (rpm) [9].

- **Main shaft**

  The main shaft connects the rotor hub to the gearbox, and transmits the rotational force [10].

- **Gearbox**

Gearboxes are used to convert the low-speed-high-torque rotor rotation at 10 to 25 rpm to high-speed-low-torque rotation at approximately 1,500 rpm. Note there are also direct drive wind turbines that do not have gearboxes [9].

- **Break system**

  The hydraulic disc brakes can halt the turbine rotation when required [9].

- **Transformer**

  The transformer transforms the medium-voltage output from the converter to 10 to 35 kilovolt (kV) for transmission [9].

- **Generator**

  Typically a doubly-fed induction generator is used to convert the mechanical energy from the rotor to electrical energy [9].

- **Converter**

  The converter converts the direct current of the generator into alternating current (AC) [12].

- **Controller**

  The controller monitors the operational and environmental conditions of the wind turbine using the sensors. It also decides what actions to take such as changing the pitch angles or yaw angles to maintain the wind turbine within its operating limit [9], [10], [12]. Parameters such as the rotational speeds, ambient temperature, blade pitch angles, nacelle yaw angles and wind speeds are collected from the sensors placed at critical points in the turbine.

- **Yaw system**

  The yaw system rotates the rotor to face the wind direction [9].

- **Nacelle**

  Nacelle is typically made by fiberglass, to house the gearbox, generator and controller [9].

- **Tower**

  The tower is commonly tapered and made by tubular steel and/or concrete. Tower heights vary depending on the length of the blades and the wind speed profile. Ladders and elevators are inside the tower to allow the access to the nacelle [9].

Wind turbines typically start to generate electricity when wind speed reaches 3 to 5 meters per second (m/s) (the “cut-in” speed), reach maximum power at about 15 m/s and stop operating at around 25 m/s (the “cut-out” speed) [7]. The theoretical power available from wind, P, is given by

$$P = \frac{1}{2}\rho A S^3 \tag{1}$$

where ρ is the air density, A is the rotor disc area and S is the wind speed [11]. According to Betz’s Law, theoretically the wind turbine can convert no more than 59.3% of the kinetic energy from the blowing wind in to output power [11].

Currently there is a significant incentive to develop offshore wind farms, since moving offshore not only brings higher average mean wind speeds, but also the possibility for higher towers (generally the wind speeds are higher and more consistent at higher heights), larger rotor diameters and larger wind farms.

The average size of onshore wind turbines being manufactured today is 2.5 to 3 MW [13]. Compared with onshore wind turbines, offshore wind turbines are at the initial commercial deployment stage. The average capacity of installed offshore wind turbines is 5.9 MW in 2016, and larger turbines are available and expected to dominate future offshore wind turbine installations [14]. The first US offshore wind project with five 6 MW Alstom wind turbines are being developed at Block Island of Rhode Island, which launched commercial operations in 2016 [15]. The offshore wind project using the Vestas 9.5 MW wind turbine by Dong Energy is due to go online in the Irish Sea in 2018 summer [16], which is also the largest wind turbine in the world for now. GE recently announced the Haliade-X 12 MW offshore wind turbine [17].

A wind farm is a group of wind turbines located either onshore or offshore, together with the roads for farm access (if onshore), buildings and the grid connection point, to generate electricity from wind. A large wind farm may have several hundred individual wind turbines and spread in an area of hundreds of square miles. For example the largest wind farm in the world is Gansu Wind Farm in China, which had a total capacity of over 6,000 MW as in 2014 and a goal of 20,000 MW by 2020 [18]. The London Array in the UK is the largest offshore wind farm in the world, with a 630 MW total capacity and 175 3.6 MW wind turbines [19].

Usually, the wind farm owners purchase wind turbines with a two year all-in-service contract, including warranties, consumables, spare parts, 24-hours monitoring, preventive maintenance (time-based) and corrective maintenance services [20]. The contract usually specifies an availability target that specifies the required portion of time that the turbine must be operating or ready to operate. Therefore the service provider, in many cases the service department of the wind turbine manufacturer, must maximize the availability rather than maximize the profit or minimize the production loss [21]. The contract can be extended to five years [20]. After that the contract expires, the turbine owners have to pay for the maintenance themselves, or purchase a new contract from the manufacture or a third party. However not all manufacturers are willing to provide all-in-service contracts after five years, one reason is that the maintenance costs can become unpredictable [22]–[24]. In this dissertation it is assumed the warranty for the wind farm has expired, and the wind farm owner has to pay for the maintenance.

1.1.3 Wind energy market

Wind farms can be owned by landowners, farmers, businesses, schools or electric utilities to serve their own loads, or owned by an Independent Power Producer (IPP) to enter the electricity market for transactions. The commodities in the electricity market include energy and power: the former is the electricity flows through a metered point for a given period measured in kWh or MWh; the latter is the metered net electrical transfer rate at any given moment measured in kW or MW. Energy, as the major product in electricity market [25], will be assumed as the output from the wind farms.

Like other sources of electricity, wind energy can be traded in the wholesale and retail markets as shown in Figure 1-6. The purchase and sale of the wind energy to resellers (the entities that purchase electricity to resell it to a third party) is done in the wholesale market, while the purchase and sale of the electricity to the end users (such as a business, commercial or residential user) is done in the retail market [26], [27]. The wholesale market begins with the wind farms, and the energy produced is bought by a reseller, such as an electric utility company (a company engaging in the generation, transmission, and distribution of the electricity for sale). After the wind energy is

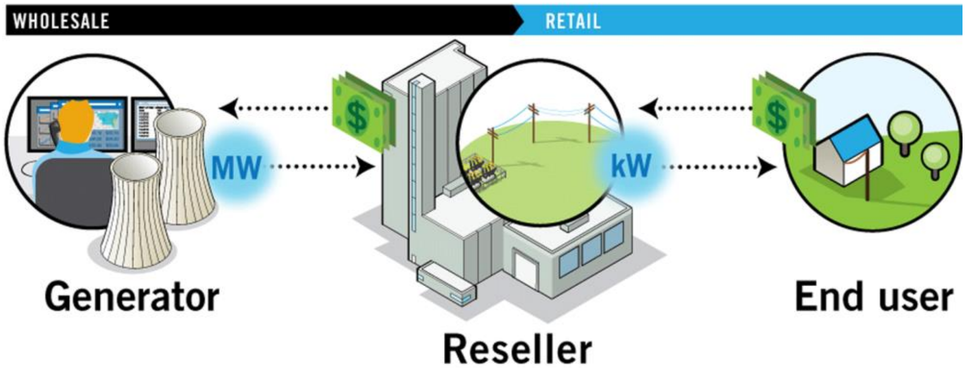

Figure 1-6: The electricity wholesale and retail markets (this dissertation focuses on the wholesale market) [27].

bought by a reseller in the wholesale market, it can be sold to the end users in the retail market. As an illustration, a home as an end-user may pay a local electric utility company for the electricity that it uses monthly.

In this dissertation, it is assumed that the wind farms are owned by the IPPs (e.g., renewable energy companies) to sell the wind energy in the electricity market. It is also assumed that only the electric utilities can sell/resell the electricity in the retail market (as defined by the laws of most states in the US [26]). Therefore under the given assumptions the wind energy can only be traded in the wholesale market, and for simplicity the wind energy is assumed to be purchased by the electric utilities.

The wind energy in the wholesale market can be traded in the short-term through pool or bilateral contracts, or in the long-term through future markets or bilateral contracts (mainly the Power Purchase Agreements (PPAs), which will be introduced in Section 1.2) [25], [28], [29].

In the pool, the producers, including the IPPs submit the maximum supply quantity and minimum selling price bids to the market operator for every hour and every demand from the consumers, while the consumers, including the electric utilities, submit their maximum buying prices for every hour and every demand. If a producer submits a successful bid to contribute their generation to meet the demand, it is said to "clear" the market. The market operator uses an auction based market-clearing procedure to determine the hourly prices and production/consumption schedules, e.g., the least expensive producer will "clear" the market first, followed by the next least expensive and so forth [27], [30], [31].

A futures market is an auction market to buy and sell physical or financial electricity products for delivery in a specified future time period spanning from one week to several years. Transactions in the future markets include forward contracts and options: the former are the agreements to deliver/consume a specified amount of energy at a fixed price in future; the latter are the agreements for having the choice of delivering/consuming a specified amount of energy in future [25].

A bilateral electricity contract is a written agreement outside an organized marketplace between two parties, in which one party agrees to provide energy to the other party for a payment, and the items such as the source, amount, time period, and price can be defined. The length of the contract can be weeks, months or years [32]. The PPA is the most common form of a long-term bilateral contract.

1.2 Power Purchase Agreements (*PPA*)

Outcome-based contracts, also known as performance-based contracts, are contracts to allow the customers to pay the Original Equipment Manufacturers (OEMs) or the service providers only when the desired outcomes delivered, rather than pay for all activities and tasks [33], as the famous quote "the customer really doesn't want a drilling machine, he wants a hole in the wall" [34].

A power purchase agreement (PPA) is an outcome-based contract, for the purchase and sale of energy between a “buyer” who wants to purchase energy (e.g., a utility) and a “seller” who generates energy (e.g., a wind farm owner). The usage of PPAs is increasing globally for wind farms, for example, in the USA the total reported number of the signed or planned PPAs has reached 414, and the total capacity is 38,819 MW at the end of 2016 [35].

Wind farms are typically managed using PPAs for several reasons. First, although the wind energy can be sold into the local energy market (e.g., the “pool”), the revenue is uncertain due to the intermittence of wind resources, and the average local market prices that vary daily and hourly tend to be lower than the contract prices defined in PPAs [26]. Second, PPAs guarantee a revenue stream in which the energy generated and delivered will be paid for on the agreed price schedule. Third, the buyers typically don’t build and operate wind farms themselves; instead they prefer to buy energy from the sellers through PPAs [28].

The term of the agreement, the contracting price and the price schedule are generally defined in a PPA [36]. The contract term is typically 20 years [26]. The levelized cost of energy (LCOE) for a wind project represents the estimated cost to generate the wind energy, and is forecasted for the entire contract term. The price of energy in a PPA is negotiated based on the LCOE by accounting for the possible risks that could increase the actual LCOE [37]. The contract price can be either constant or escalated annually throughout the contract term [28].

In a PPA, the buyer may agree to pay for each unit of energy generated and delivered at a set price; in addition, the PPA may also define a maximum energy delivery limit, a minimum energy delivery limit, or both for a year. Once the energy delivered has exceeded the maximum delivery limit, the buyer may choose to buy the excess energy at a lower price, or not to buy at all, e.g., [38]–[40]. The buyer may also decrease the maximum energy delivery target for the next year by the amount of energy over-delivered in the current year, e.g., [41]–[44].

When a minimum delivery limit is defined in a PPA, the seller may have to compensate the buyer for the output shortfall at an agreed upon price if under-delivery happens, e.g., [41], [42], [45]. Or the buyer may increase the minimum energy delivery target for the next year to compensate for the under-delivered amount, e.g., [44].

1.3 Wind Turbine Reliability

PPAs only pay for the delivered energy. In this dissertation, all costs associated with operating and maintaining the wind farm are the responsibility of the wind farm owner. When the price of energy is negotiated for a PPA contract, the wind farm owner must account for the cost of maintaining the wind turbines. Over the past 30 years, wind turbines have grown from 50 kW to 6 MW, tower heights, rotor diameters and overall weights have also increased significantly, and wind turbine reliability has become a concern [9].

Wind turbine failure data in northern Germany were analyzed and the component failure rates were estimated by the Dutch offshore wind energy converter program (DOWEC). The average number of failures per turbine per year for onshore wind turbines was 2.20 in 2001, and the blades/pitch (average number of failures per turbine per year of 0.72), controller (average number of failures per turbine per year of 0.66) and the gearbox caused most failures [46], [47]. Also according to the downtime study by DOWEC, more than 85% of the downtime was caused by the blades, generator and gearbox [48]. In the Condition Monitoring for Offshore Wind Farms (CONMOW) project by Energy research Centre of the Netherlands (ECN), the electronics, controller and blades/pitch had the highest failure rate [49]. It was shown in a Sweden, Finland and Germany wind turbine failure data study that the average number of failures per turbine per year was 0.402. Failures of electrics, controller and blades/pitch were the most frequent, and the gearbox failures led to longest downtime due to difficulty to repair inside the nacelle, followed by blades/pitch [50], [51]. McMillan and Ault [52] demonstrated that the gearbox, generator, blades/pitch, rotor hub and drivetrain comprise around 67% of the total downtime in Germany. Spinato et al. [53] showed that the electronics had the highest failure rates, followed by blades/pitch and controller in Denmark and Germany, and gearboxes caused the longest downtime. To sum up, blades/pitch, controller and electronics are the components that failed most frequently, gearbox, generator and blades/pitch caused the longest downtime.

1.4 Prognostics and Health Management (PHM) for Wind Turbines

Prognostics and Health Management (PHM) is based on the Condition Monitoring (CM), which refers to the technologies and methods to monitor the operational and/or environmental parameters conditions of a system to evaluate its current operating state and to identify a developing fault if any [54]. PHM assesses the reliability of a system in its actual life-cycle conditions and determines its remaining useful life (RUL) [55].

RULs can be predicted for a single or multiple Line Replaceable Units (LRUs) within a system (e.g., an engine for an aircraft). After the data is collected from the sensors that monitor the health of the product continuously, the data is preprocessed with the outliers removed and feature extraction/construction is implemented. Then a diagnostic algorithm is carried out to identify the anomalies and root causes if there are any deviations from the healthy state. The next step is a prognostic algorithm to predict the RUL.

PHM approaches can be categorized as LRU-independent methodology (e.g., Life Consumption Monitoring (LCM) approach based on physics-of-failure (PoF) models) and LRU-dependent methodology (e.g., Health Monitoring (HM) approach based on failure mechanism specific fuses and HM approach based on precursor variable monitoring) [55]. As an example of the LRU-independent methodology, the LCM approach uses an environmental stresses history together with PoF models to cumulate and forecast RUL. HM approaches based on fuses or precursor variable monitoring are two examples of the LRU-dependent methodology, in which a fuse is manufactured with and coupled to a particular LRU or as a monitored precursor variable representing a non-reversible physical process. A unique RUL distribution is predicted for each instance of an LRU.

PHM triggers the transition from traditional time or cycle-based maintenance to predictive maintenance or known as condition-based maintenance (CBM), because RUL provides the maintenance decision-maker with the lead time to take appropriate actions prior to the failure to manage the health of the system. PHM also enables outcome-based contracts by creating the managerial flexibility to manage the impending failures.

CM and PHM technologies have been introduced into wind turbines to avoid premature failures, reduce secondary (collateral) damage to components, reduce maintenance costs, enable remote diagnosis, increase generation and optimize future design [56]. A significant body of work on CM and PHM for wind turbine subsystems exists. The key subsystems that the majority of this work focuses on includes: blades and rotor [56]–[60], gearbox and bearings [50], [51], [61]–[65], generator [56], [59], [66], tower [56], [59], [67]–[69] and other subsystems. These works use the data from the supervisory control and data acquisition (SCADA) and other sensors. Vibration analysis, acoustic emission and other methods are applied to monitor the subsystems of wind turbines to identify a developing fault if any. In some cases RULs are predicted using the prognostics approaches such as Mahalanobis distance and particle filtering.

1.5 *Maintenance Practices for Wind Farms*

1.5.1 Maintenance paradigms

Maintenance refers to the combination of all technical and associated administrative actions intended to repair the failed system to an operating state, or to refurbish and renew components/parts to prevent failure [70]. Maintenance can be generally divided into two categories as shown in Figure 1-7 [20]: proactive maintenance and corrective maintenance. The former is used to prevent the occurrence of a failure, while for the latter a problem already exists before the maintenance actions are taken [71].

The proactive maintenance is carried out at predetermined intervals or depending on prescribed criteria, to reduce the probability of failure or degradation. Using proactive maintenance, breakdowns are avoided or postponed. Typical maintenance activities include inspection, lubrication, parts replacement, cleaning and

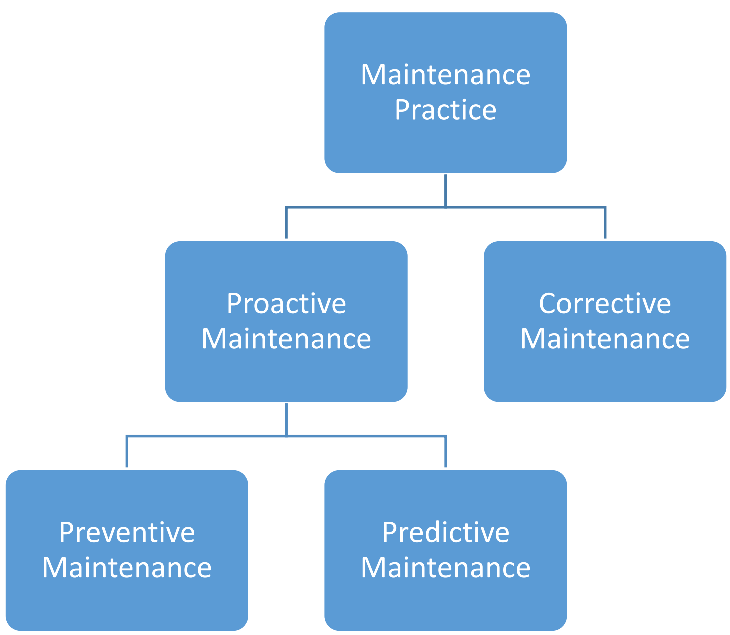

Figure 1-7: Maintenance practice categories [20]

adjustments. Proactive maintenance can be divided into preventive and predictive maintenance [71].

Preventive maintenance, also known as scheduled maintenance, involves the maintenance activities taken after a predetermined time interval or a specified percentage of system usage, to avoid invalidating the OEM warranty and/or to maintain systems that have known failure patterns [72], [73]. The preventive maintenance interval is determined based on the system reliability statistics; however a short interval may cause extra operational costs, wasting production time and unnecessary replacements of good components (throwing away significant remaining useful life), whereas a long interval may lead to frequent unexpected failures between intervals [72].

Predictive maintenance, also known as CBM, is initiated in response to the indicated deteriorated condition or performance of a component or system [72], [73]. Different from preventive maintenance, predictive maintenance is not performed after a fixed time or usage interval, but when there is an imminent need [74]. Maintenance decision-makers generally assign a time window for each predictive maintenance task, while the execution date can be decided based on the actual situations such as the schedule of the maintenance crew, the weather conditions and the production plan [21].

Despite the proactive maintenance, unanticipated failures may still occur resulting in significant downtime [7][75], and requiring corrective maintenance.

1.5.2 Maintenance practices for wind farms

The current mainstream maintenance practices for wind farms are preventive maintenance and corrective maintenance. The preventive maintenance interval depends on the manufacturer’s recommendations, weather conditions, accessibility, availability and reliability of wind turbines. If failures happen, corrective maintenance will be initiated immediately when conditions (e.g., the weather) are feasible [71], [76].

Maintenance tasks require skilled maintenance crew, spare parts, and special equipment. The maintenance crew usually works in teams of two people, dispatched to the wind farms according to the maintenance schedule. Although some spare parts are immediately available, others may need to be ordered. Some complex tasks may require special equipment such as cranes, vessels and helicopters that must be leased from their suppliers and have limited availability. Sometimes some turbines are connected in series to the grid, which means that a stoppage of one turbine for maintenance may also stop its posterior ones as well [21].

1.5.3 Predictive maintenance for wind farms

Operations and maintenance (O&M) refers to all actions, including the technical, administrative, and managerial and supervision actions, to retain or restore an item to a state in which it can perform its required function. As a major contributor to the levelized cost of energy (LCOE) of wind turbines, O&M costs accounts for 0.027 to 0.048 US dollars/kWh (10% to 15% for onshore and 25% to 30% for offshore) [4][7][24]. Historically O&M costs tend to be higher than they are anticipated to be in the project-planning phase, due to many reasons such as lack of statistics, poor assumptions, overestimations in the reliability and lifetime of the machines.

Generally, for onshore wind farms, the O&M costs are predictable during the first two to five years thanks to the operational experience available. After that, the maintenance costs become difficult to predict due to many uncertainties. For offshore wind farms, the O&M costs are much higher than for onshore due to the large size of the offshore wind turbines and farms, long distances from the shore, deep water and the severe marine environment [22].

Today's wind turbine emphasis is put to improve the productivity and economics of wind energy, and the net revenue of a wind farm is the revenue from the sale of generated electricity less the O&M costs [46]. Due to the fact that wind may cause the degradation patterns vary among turbines and with the trends toward larger wind farms and the longer distances from the operation and monitoring centers, wind farm maintenance decision-makers also want to avoid as many unnecessary visits as possible by detecting and fixing the problems before any failure occurs. For offshore wind farms, even small failures may lead to long downtime and high O&M costs due to the difficult access and repair at the offshore locations. Therefore the benefits of CM and PHM have been recognized, and most modern turbines are equipped with CM or PHM equipment [76]. Since a failure is a process rather than an event, the earlier the process is detected, the more the flexibility exists for managing the process. By giving a probabilistic forecast specific for each component or wind turbine, PHM enables the predictive maintenance strategy.

One major difference between CM and PHM is that the RULs can be predicted by PHM, which are useful to the predictive maintenance scheduling process; however RULs themselves cannot provide sufficient information for the decision to be made. At a certain time point, there can be multiple wind turbines or multiple components in a single turbine indicating RULs. The accuracy of the forecasted RULs, the future operational and environmental conditions, the maintenance opportunities, the damage accumulation/propagation, and the availability of equipment, spare parts and maintenance crew all have uncertainties [21]. Generally wind farms are not managed using an as-delivered payment model in which the market will buy whatever is produced, but using PPAs that are outcome-based contracts and define delivery schedules, penalties for under delivery, payment terms and so on. Considering all these factors, the maintenance decision-maker needs to decide if, when and on which turbines or components to perform the predictive maintenance, in order to minimize the risk of expensive corrective maintenance (which increases as the RUL is used up) while maximize the revenue earned during the RUL (which increases as the RUL is used up).

1.6 Problem Statement and Research Objectives

The problem addressed in this dissertation is how to schedule the predictive maintenance for multiple wind turbines with RUL predictions given by PHM in a wind farm managed using an outcome-based contract, i.e., a PPA. It is assumed that once the predictive maintenance opportunity is selected, predictive maintenance will be performed on all the wind turbines with RULs at that opportunity, or all the turbines with RULs continue to operate without predictive maintenance until their failures ("all or nothing"). In another word, at the selected predictive maintenance opportunity the model cannot maintain some turbines while leaving other turbines unmaintained. Once all the turbines with RULs fail, there will be a corrective maintenance event to restore these turbines to operation. The uncertainties in the forecasted RULs and the future wind speeds will be considered in the solution.

Assume the expected benefit of scheduling the predictive maintenance at time t is $E[v(t, x)]$, where x represents the all the other uncertain parameters (RUL and wind speed), and $v(t, x)$ is the stochastic function for the benefit of predictive maintenance at time t. The predictive maintenance scheduling problem can be formed as the following optimization form

$$\max_{t} E[v(t,x)] \quad (2)$$

A sample-path method (also referred to as sample average approximation method) based on Monte Carlo simulation can be applied to solve this maximization problem, which is a well-recognized simulation-based optimization approach [77]. This method assumes the expected benefit $E[v(t, X)]$ can be approximated by a averaged sample function in the following form

$$E[v(t,x)] \approx \frac{1}{M}\sum_{i=1}^{M} v(t,x_i) \quad (3)$$

where x_i is a sample of variable x, and M is the number of simulation samples.

So the corresponding approximation problem to Eq. (2) is as below, which is the problem to be solved in this dissertation. The term “expected” will be used interchangeable with the terms “average” and “mean” in the dissertation.

$$\max_{t} \frac{1}{M}\sum_{j=1}^{M} v(t,x_i) \quad (4)$$

In Chapter 3, the benefit of scheduling the predictive maintenance for a single wind turbine with an RUL indication at time t is defined as the predictive maintenance option value $OV_{PM}(t)$. The maximization problem in Eq. (4) is solved by selecting the predictive maintenance opportunity that leads to the highest expected predictive maintenance option value $EOV_{PM}(t)$ for the wind turbine based on Monte Carlo simulation. In Chapter 4 the influences of the PPA terms to the predictive maintenance option value are integrated into the approach developed in Chapter 3. The predictive maintenance option value $OV_{PM,K}(t)$ are defined for all K wind turbines in a wind farm with RUL indications, and the maximization problem is solved by selecting the predictive maintenance opportunity that leads to the highest expected predictive maintenance option value $EOV_{PM,K}(t)$ for all the K wind turbines.

The research objectives are:

- To enable the predictive maintenance scheduling for wind farms that are equipped with PHM and subject to PPAs, considering the uncertainties from multiple sources.
- To determine the impact of outcome-based contracts (specifically PPAs) on the predictive maintenance scheduling.
- To estimate the life-cycle benefit by applying the developed approach, compared with the state-of-art wind farm maintenance policies.

In this dissertation it is assumed that the wind farm is in a post-warranty period, and the wind farm owner has to pay the maintenance costs. It is also assumed that the wind farms are owned by the IPPs (e.g., renewable energy companies) who sell the generated electricity in the electricity wholesale market to the electric utilities under PPAs. All turbines are assumed to be equipped with PHM that is capable of predicting RULs.

The following research plan was followed:

- Task 1: Develop a methodology to simulate the predictive maintenance value by treating the PHM-based predictive maintenance opportunities for a single wind turbine managed using an "as-delivery" payment model. The predictive maintenance value will include the cumulative revenue loss and the avoided corrective maintenance cost, and the uncertainties in the RUL predictions given by PHM and the future wind speeds will be considered.

- Task 2: Develop a European-style Real Options Analysis (ROA) approach to schedule the predictive maintenance by maximizing the expected predictive maintenance option value. For comparison, a stochastic discount cash flow (DCF) approach will also be formulated to schedule the predictive maintenance by maximizing the expected predictive maintenance net present value (NPV).
- Task 3: Develop a PPA-based wind farm revenue earning model. The PPA features to be considered include the energy delivery target, contract price, excess (over-delivery) price and under-delivery penalties.
- Task 4: Extend the predictive maintenance value simulation method to a wind farm managed using a PPA with multiple turbines concurrently indicating RULs. The predictive maintenance value for each wind turbine with an RUL depends on the operational state of the other turbines, the amount of energy delivered and to be delivered by the whole wind farm.
- Task 5: Develop the wind farm level European-style ROA approach to schedule the predictive maintenance for all wind turbines with RULs. It is implicitly assumed that the decision-maker prefers to maintain multiple wind turbines during a single visit to the farm.
- Task 6: Implement a single wind turbine case study, both the as-delivered payment model and PPA will be considered, and both the European-style ROA and stochastic DCF approaches will be applied. The results will be compared and analyzed.

- Task 7: Implement a PPA-based wind farm case study with multiple wind turbines indicating RULs, both the European-style ROA and stochastic DCF approaches will be applied. The results will be compared and analyzed.
- Task 8: Apply the developed approach to the entire wind farm lifetime to estimate the life-cycle benefit and compare with the state-of-art maintenance policies.

Chapter 2: Review of Maintenance Modeling for Wind Farms

This chapter first reviews DCF based wind farm maintenance models, which can be categorized as Reliability-Center Maintenance (RCM) motivated models and simulation-based models. Then the Real Options Analysis (ROA) based maintenance models are reviewed. Finally, the gaps in the literature are identified.

2.1 Discounted Cash Flow (DCF) Based Models

DCF analysis is a method to value a project, company or asset using the concepts of the time value of money. All future cash flows are estimated and discounted to give their present values (PVs). The sum of all future incoming and outgoing cash flows is the Net Present Value (NPV). For example, in the valuation of a project, the project NPV is the summation of the PVs of all the cash inflows from the production phases (project payoff) and the cash outflows from the development phase (investment costs) [78]

$$\begin{aligned} Project\ NPV = {} & PV\ of\ project\ payoff\ in\ prodcution\ phase \\ & - PV\ of\ investment\ costs \end{aligned} \tag{5}$$

The discrete and continuous compound discounting relations are

$$PV = \frac{FV}{(1+r)^n} \tag{6}$$

$$PV = FVe^{-nr} \tag{7}$$

where FV is the future value, r is the discount rate per time period and n is the number of time periods.

Numerous DCF based maintenance models applicable to wind turbines and farms have been developed. These models can be broadly categorized as RCM motivated models and simulation-based models – the key differentiators are how maintenance event timing and reliability are modeled.

2.1.1 RCM motivated models

RCM motivated models are based on "counting" the number of failures and maintenance events for a wind turbine or farm during a period of time. These approaches usually model reliability with a constant failure rate from which the average number of failures in an analysis period (e.g., per year) are computed. In RCM motivated approaches, empirical models are typically used to formulate analytical expressions for the various contributions to the maintenance costs, including: inspection costs, maintenance costs, and failure costs (cost of resolving the failure, the business interrupt cost, and possibly collateral damage). In addition, these models may include various logistics costs, spare parts costs, labor costs, and the cost of money.

Numerous RCM motivated treatments exist; the remainder of this section reviews representative examples of these. In [79], the failure rate function is developed using published wind speed and turbine failure frequency distribution, and an annual O&M cost is estimated. In [80], existing real annual failure rate data are normalized to be constant through the lifetime of the turbine, and then the probability of a certain number of failures during lifetime for an offshore wind farm is estimated, to calculate the LCOE over lifetime. In [81] the life-cycle O&M cost of a wind farm is predicted by estimating the expected number of failures under different wind hazard levels based on structure/building life-cycle cost (LCC) estimation method. The analytical model with the most commercial traction is from ECN. The ECN O&M Tool [48], [82] focuses on estimating the wind farm's long-term annual average costs, downtime and revenue losses due to corrective maintenance, by determining the waiting time until weather conditions are acceptable for repair actions as a function of the maintenance activity, wind speed, wave height and workable weather window.

The preventive and corrective maintenance policy is considered in the models described in [48], [79]–[82]. Predictive maintenance has been included within some analytical models, aiming to estimate and compare the life-cycle maintenance costs among different maintenance strategies. For example, the failure rate is estimated from the historical data, and the failure consequences of critical components are expressed in financial terms to estimate the LCC of predictive maintenance policy for a wind farm [72]. A base model with constant failure frequency and an aging model with the frequency failure increasing exponentially are used to estimate the probability of failures through the lifetime of a wind turbine. It is assumed that the percentage of the failures to be predicted is constant, the CM can predict a failure three months in advance, and during that time the predictive maintenance is scheduled to happen at a fixed time point. The LCC for predictive maintenance policy is estimated in [20].

2.1.2 Simulation-based wind farm maintenance models

In the project valuation area, a stochastic DCF analysis can be implemented to simulate thousands of possible project scenarios, calculate the project NPV for each scenario, and analyze the probability distribution of all NPV results [78]. Similarly the simulation-based maintenance models use the discrete-event simulation (DES, which models the behavior of a complex system as an ordered sequence of events, each of which comprises a specific change in the system's state at a specific point in time) to simulate the failure and/or maintenance events by sampling from probability distributions, and is capable of estimating the long term maintenance costs. For instance, the CONTOFAX® model from TU Delft simulates the availability and the LCOE over a period of time, by following the state of each "component" in the wind farm with preventive and corrective maintenance. The failures of components are generated stochastically [75]. Another commercial analytical cost analysis is O2M® from Garrad-Hassan [83], which models the turbine failures and weather conditions as stochastic variables, and uses a Monte-Carlo simulation method. Nielsen and Sørensen [84] describe a model to evaluate the life-cycle maintenance costs of a single wind turbine with a single component. The damage to the component caused by wind and wave loads is simulated, the inspections are assumed to be scheduled periodically, and the predictive maintenance will be executed on the same day of the inspection if the detected damage level is larger than a predetermined limit.

There has been significant research on simulation-based predictive maintenance optimization for wind turbines and farms. Pazouki et al. [85] propose a CM-based predictive maintenance optimization model by choosing the failure probability threshold to trigger the predictive maintenance task and the periodical inspection interval as the two decision variables. A simulation-based optimization procedure is implemented to determine the optimum threshold and inspection interval by minimizing the maintenance cost per unit time for wind turbine system. Byon and Ding [86] develop a season-dependent dynamic model to schedule maintenance activities based on the deterioration status, failure modes, weather climates and maintenance lead time, assuming the wind farm operators make maintenance decisions on a weekly basis. Their aim is to decide the optimal actions to take for each week of a whole year to minimize the wind turbine life-cycle O&M cost. Tian et al. [87] develop an optimal predictive maintenance policy for a wind farm consists of multiple wind turbines by using the continuous PHM information. The inspection interval is assumed to be constant, and at each inspection point, the decision for the predictive maintenance can be made. The objective of the optimization is to find the optimal failure probability threshold values such that the total maintenance cost per unit time is minimized. Besnard and Bertling [88] present a simulation based predictive maintenance optimization approach applied to blades, by assuming that an inspection is carried out if blade deterioration is observed by online CM, and maintenance decision is made at the inspection. The decision variable to be optimized is the inspection interval by minimizing the maintenance costs per blade for the whole lifetime.

2.2 Real Options Analysis (*ROA*) *Based Models*

DCF models, whether analytical or simulation-based, don't account for the managerial flexibility that the decision-makers have to adapt to future uncertainties when they occur; rather DCF pre-determines the best future course of action at the present time and then assumes that that course of action will be followed no matter what the future uncertainties actually turn out to be. Alternatively, real options accounts for the flexibility that management has to change the course of action during the lifetime of a project based on what the actual future conditions turn out to be. A real option is the right but not the obligation to undertake certain business initiatives, such as deferring, abandoning, expanding, staging, or contracting a capital investment project [78]. Real options originate from financial options, and ROA refers to the valuation of the real options. ROA assumes managerial flexibility will allow value-maximizing decisions to be made at each decision point. DCF analysis only accounts for the downside of the future by using a risk-adjusted discount rate, while ROA captures the value of the upside potential by accounting for the proper managerial decisions. In fact, ROA is developed based on DCF analysis, and the option value equals the NPV found from DCF analysis plus the value added by the managerial flexibility [78].

Similar to financial options, real options can be categorized as the option to buy (called a "call" option) or the option to sell (called a "put" option). The call and put option value at expiration can be calculated as [78]

$$\begin{gathered} Call\ option\ value = max(option\ payoff - strike\ price, 0) \\ Put\ option\ value = max(strike\ price - option\ payoff, 0) \end{gathered} \tag{8}$$

where the strike price is the price to exercise the option. The payoff is the revenue after exercising the option (e.g., the net revenue from the production phase of the product). Real options can also be classified as the European options and the American options: the former has a fixed expiration date, whereas the latter can be exercised on or any time before the expiration date [78].

ROA has been applied to the maintenance modeling problems in many areas. Santa-Cruz and Heredia-Zavoni [89], [90] develop an ROA model for offshore platform life-cycle cost-benefit (LCCB) analysis by treating maintenance and decommissioning as real options. Uncertainties in hydrocarbon price, maintenance cost, environmental load, structural capacity and deterioration are considered. Their results show that the DCF approach will significantly underestimate the LCCB, while the ROA approach can account for the value of the managerial flexibility. Jin et al. [91] present an analytical ROA cost model to schedule joint production and preventive maintenance under uncertain demands. The real option is defined as the right to produce additional units at a lower price with the reliability and production efficiency improved by preventive maintenance. Compared with the traditional fixed-interval preventive maintenance strategy, the model proposed in [91] is found to reduce the risk of shortage or overage of stochastic demands. In [92], the maintenance and management costs of an existing bridge for thirty years is analyzed and minimized using ROA. The effects of repair cost, regular maintenance and management costs for inspection and painting and replacement cost are studied. A comparison is made between the ROA approach and the DCF approach. Goossens et al. [93] develop an Aircraft Maintenance Operations Performance Assessment Model to assess the differences in performance between different aircraft maintenance operations. The model is based on ROA, with identified key performance indicators (KPIs) capturing the maintenance operational and financial performance as inputs. A real-life case from the from the Royal Dutch Airlines aircraft maintenance department is presented.

For the wind farm maintenance optimization problem, Haddad et al. [94] were the first to apply the ROA to estimate the values of maintenance options created by the implementation of PHM in wind turbines. They demonstrate that the fundamental tradeoff in predictive maintenance problems with PHM is finding the point in time to perform predictive maintenance that minimizes the risk of expensive corrective maintenance (which increases as the RUL is used up), while maximizing the revenue earned during the RUL (which also increases as the RUL is used up).

2.3 Gaps in the Literature and Research Opportunities

The current RCM motivated wind farm maintenance models mainly formulate analytical expressions for the various contributions to the maintenance cost by assuming a constant failure rate. However predictive maintenance hasn't been considered in many existing models, and for the models that do include a predictive maintenance strategy, the predictive maintenance is assumed to happen in a fixed schedule: for example each failure is assumed to be predicted three months in advance, and the predictive maintenance is going to happen later at a fixed time point [27]. Exact time and sequences of failures and/or maintenance events are difficult to simulate using analytical models, and uncertainties from many sources such as the RUL predictions and maintenance opportunities haven't been integrated into the analytical expressions, let alone their interactions and correlations, which severely limits the applicability of analytical models to predictive maintenance optimization.

Existing simulation-based wind farm maintenance models can capture the uncertainties mentioned above and also the nonlinear effects, such as the combined occurrences of failures and accumulation during inaccessibility with respect to occupation of crew and equipment. Therefore predictive maintenance optimization methods have been developed based on the simulation method. However many of these optimization models are based on CM information without RUL predictions. Therefore they assume the maintenance decisions including the predictive maintenance are made on a periodic basis after an online or on-site inspection, and the predictive maintenance will be implemented immediately once decided. The decision variables to be optimized are mainly the threshold (e.g., the failure probability) to trigger the predictive maintenance and/or the inspection interval applicable for the whole life cycle, and the objective is to minimize the maintenance cost of the lifetime or unit time. Whereas given a specific time point at which the threshold is exceeded (e.g., a RUL is predicted by PHM), it is doubtful if carrying out the predictive maintenance immediately is a better choice than waiting for a longer time or even waiting for the corrective maintenance, especially when the wind farm is operated under an outcome-based contract defining performance requirements and penalties.

The existing simulation-based models don't consider the managerial flexibility that the maintenance decision-maker has to postpone the predictive maintenance, and fail to recognize the fact that predictive maintenance is a right but not an obligation; rather they assume the predictive maintenance will always be scheduled after the decision is made. When an RUL is predicted for a subsystem or turbine, there are multiple choices for the decision-maker including: performing predictive maintenance at the first maintenance opportunity, wait until closer to the end of the RUL to perform maintenance, or doing nothing, i.e., letting the turbine to run until failure. In order to accommodate these choices, the predictive maintenance opportunity triggered by a PHM prediction can be treated as a real option. When the value of the predictive maintenance option is determined, the maintenance decision-maker has a basis upon which to make a decision to perform the predictive maintenance or not and if the maintenance is to be done, when should it be done.

There have been ROA-based models developed for the maintenance modeling problem in other areas as described in [89]–[93], however none of these works have considered PHM based predictive maintenance, rather they model the preventive maintenance, predictive maintenance based on CM as real options.

Haddad et al. [94] first apply the ROA to the wind farm PHM based predictive maintenance optimization problem. However they haven't answered the question: when (amount of time) should the predictive maintenance be scheduled after the RUL indication? In [94] the wait-to-maintain-option is treated as an American-style option, therefore the model is actually suggesting a best maximum wait-to-maintenance date, and at each maintenance opportunity before that date, the decision-maker is expected to compare the predictive maintenance option value at that opportunity and the option value of waiting. If the former is higher than the latter, the predictive maintenance will be implemented at that opportunity; otherwise the decision-maker will wait until the next opportunity. When a simulation method (DCF or ROA) is used, each simulated scenario, which is called a "path" (each "path" represents one possible future that could happen), will use a different predictive maintenance date. The Haddad et al. solution [94] is correct for the assumption that each path will make an optimal decision on or before some maximum waiting duration and the solution delivered is the optimum maximum wait to date. However, maintenance decision-makers really face a different problem: given that the maintenance calendar is known when the RUL indication is obtained, at which opportunity should the predictive maintenance be done to get the maximum the option value, which is not the problem solved in [94]. This constraint makes the problem a series of European-style options, i.e., options that can only be exercised on a specific date rather than an American-style option.

Haddad et al. [94] also make the assumption that there are no uncertainties in the consumption of the remaining useful life (RUL). However, since the environmental conditions, primarily the wind speed, are uncertain, the lifetime consumption (the rate at which the RUL is actually used up) is subject to uncertainties. The RUL itself is also uncertain since the forecasting ability of PHM is also subject to uncertainties created by the sensor data collected, the data reduction methods, the failure models applied and the material parameters assumed in the models. The cumulative revenue rather than the revenue lost during RUL is simulated in Haddad et al. [94], while it is the latter that actually reflects value of the RUL thrown away due to predictive maintenance.

There have been maintenance modeling and optimization works for power systems other than wind turbines utilizing the Stochastic Dynamic Programming (SDP) approach, aiming at obtaining the optimal maintenance policy (a sequence of maintenance decisions) in a finite horizon [95], [96]. These models presume the maintenance decision has to be made periodically (e.g., once a week), and solve the optimization problem with a backward algorithm. However, in this dissertation the problem to be solved is somewhat different: given a specific RUL prediction, when should the predictive maintenance be scheduled? Furthermore, the timing of the future RUL predictions and maintenance decision time points will depend on the current predictive maintenance decision, the problem cannot be solved in a backward way like the SDP problems.

Chapter 3: PHM-Based Predictive Maintenance Scheduling for a Single Wind Turbine Managed Using an As-Delivered Payment Model (Tasks 1 & 2)

In this chapter the predictive maintenance option is defined, and future wind speed and the time to failure (TTF) simulation methods are introduced. Based on these models, the cumulative revenue and the predictive maintenance value are formulated. Finally the stochastic DCF and the European-style ROA approaches are used for scheduling the predictive maintenance opportunity for a single wind turbine managed using an as-delivered payment model are formulated.

Chapter 3, Chapter 4 and the Section 5.1 through 5.4 of Chapter 5 valuate the portion of the RUL thrown away due to predictive maintenance by the cumulative revenue loss. This analysis assumes the system life-cycle consists of a fixed number of maintenance cycles (e.g., a fixed number of spares defines the system lifetime), each of which may have different time lengths due to the uncertainties in the system/subsystem reliability and maintainability. An alternative interpretation of the RUL thrown away is to assume that it will cause extra predictive maintenance events in the life-cycle (e.g., a fixed length of time defines the system lifetime), which will be discussed in Section 5.5 of Chapter 5.

3.1 Predictive Maintenance Option

For a wind turbine, a predictive maintenance option is created by incorporating PHM into key subsystems to predict the RUL. When an RUL is predicted for a wind turbine using PHM, a predictive maintenance option is triggered that the decision-maker has the managerial flexibility to decide if and when to exercise before the turbine fails. Each possible predictive maintenance opportunity is a possible expiration time point for the predictive maintenance real option. When predictive maintenance is performed at an opportunity prior to the subsystem's or turbine's failure, the option is exercised. On the contrary, if predictive maintenance is not performed and the failure happens, the option expires and option value becomes zero (after which it is assumed that a corrective maintenance event will be performed to restore the failed turbine to operation, which "hedges" the risk of having a non-operational turbine because the predictive maintenance was either missed or not implemented). By implementing predictive maintenance, corrective maintenance cost can be avoided, which could be expensive. However, predictive maintenance results in a portion of the RUL of the subsystem being thrown away since maintenance is performed (and parts replaced) prior to their actual failure.

Assume a wind turbine is managed in isolation using an as-delivered payment model. Unlike a PPA, the as-delivered payment model only pays for the energy delivered and does not include an energy delivery target, excess or under-delivery price penalty. First the simulation time period is selected (e.g., a year). Assume at time t_0 of the simulation time period, the turbine is indicating an RUL for some subsystem (e.g., for the blade, main shaft and gearbox in cycles), and assume that subsystem will fail before the end of the simulation time period called T (e.g., end of the year) if the predictive maintenance is not implemented. Once the subsystem fails, the turbine will fail, therefore the predicted RUL is also for the turbine system. Wind turbine failures can be categorized as soft failures and hard failures: the former refer to the sub-critical failures that do not stop the turbine system from functioning (e.g., performance degradation), while the latter are the critical failures that cause the turbine system to stop working [97], [98]. In this dissertation it is assumed the RULs are predicted for turbine hard failures and soft failures are ignored. From time t_0 to T there are multiple predictive maintenance opportunities, and the decision-maker wants to decide which predictive maintenance opportunity should be scheduled. If the predictive maintenance is not implemented, there will be a corrective maintenance event at time t_c to fix the failed turbine and restore it to operation. The corrective maintenance will cause a downtime of *DT*, and will be finished before *T*.

3.2 Future Wind Speed Simulation

Assume that wind is the major environmental load causing damage to the key subsystems in the turbines (e.g., blade, main shaft and gearbox). A probability density function (PDF) is used to describe the historical wind speed data. Assume the historical wind speed *S* is recorded at height *B* with a sampling interval *l*, the probability function $f(\cdot)$ assuming a Weibull distribution is

$$f(S) = \frac{\beta}{\eta}\left(\frac{S}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{S}{\eta}\right)^{\beta}\right) \tag{9}$$

where β is the shape parameter and η is the scale parameter, which can be estimated as [11]

$$\beta = \left(\frac{\sigma}{\mu}\right)^{-1.086} (1 \le \beta < 10) \tag{10}$$

$$\eta = \mu \left(0.568 + \frac{0.433}{\beta}\right)^{-\frac{1}{\beta}} \tag{11}$$

where μ is the mean and σ is the standard deviation of recorded wind speed data.

After the Weibull distribution parameters are estimated, Monte Carlo simulation can be used to simulate a time series of wind speed $S_B(\tau)$ on height B, where τ is the time of the simulation time period with time period l per step (e.g., l = 1 hour, τ = 1, 2, ..., 8760 for a year). Then the Power Law [11] is used to convert to wind speed $S_H(\tau)$ on wind turbine hub height H

$$\frac{S_H(\tau)}{S_B(\tau)} = \left(\frac{H}{B}\right)^{\alpha} \tag{12}$$

where α is the Power Law exponent.

Using Monte Carlo simulation and the Power Law, M wind turbine hub height wind speed time series (called wind speed paths) can be simulated from t_0 to T, with each path representing a possible future wind speed over time.

3.3 Time to Failure Simulation

Assume an RUL is predicted in cycles caused by fatigue (RUL_F) at time t_0,[1] a probability distribution can be assumed to represent the uncertainties due to PHM

[1] The RUL can be represented as a time or any applicable lifetime usage measure depending on the particular failure mechanism(s) that are relevant and their primary life driver(s).

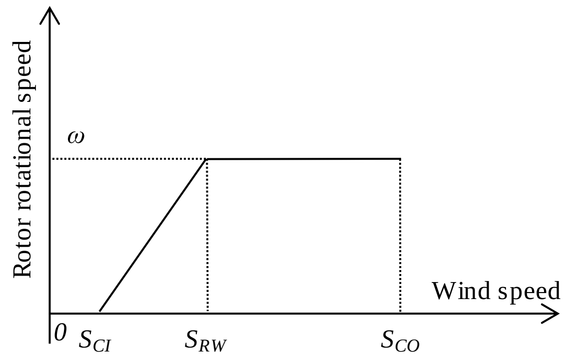

Figure 3-2: The relationship between the wind speed and the wind turbine rotor rotational speed.

sensor data, data reduction methods, failure models, damage accumulation models and material parameters [55]. For example, normal distribution has been used to represent the RUL estimations [99]–[101]. However, it should be noted that the model developed in this paper is generally applicable to any type of RUL distribution. RUL_F is assumed to be the mean of the distribution. For each of the M simulated wind speed paths, the distribution (depicted as normal for illustration purposes) in Figure 3-1 is sampled to obtain an actual RUL sample ($ARUL_F$, measured in cycles) from the distribution. Each combination of the $ARUL_F$ and the corresponding wind speed path represents a possible initial RUL and its future wind speeds.

The next step is to simulate the $ARUL_C$ (the actual RUL sample in calendar time) using the simulated wind speed paths. It is assumed that the RUL is consumed by rotor rotational cycles caused by the wind. When the wind speed is higher than the cut-in speed and lower than the rated speed, rotor rotational speed increases linearly with the wind speed until the rotor's nominal rotational speed. In this case the rotor rotational speed is constant at the nominal rotational speed; if the wind speed is higher than the cut-out speed, rotor stops rotating. Figure 3-2 shows this relationship, in which

ω is the rotor's nominal rotational speed, S_{CI}, S_{RW} and S_{CO} are the cut-in, rational and cut-out wind speed for the wind turbine respectively.

The RUL consumption (measured in cycles) caused to the turbine from time τ - 1 to τ, $D(\tau)$ can be calculated as

$$D(\tau) = \begin{cases} \frac{\omega l S_H(\tau)}{S_{RW}}, & S_{CI} \leq S_H(\tau) < S_{RW} \\ \omega l, & S_{RW} \leq S_H(\tau) \leq S_{CO} \\ 0, & 0 \leq S_H(\tau) < S_{CI} \text{ or } S_{CO} < S_H(\tau) \end{cases} \tag{13}$$

For each $ARUL_F$ and the corresponding wind speed path, by solving the following equation, an $ARUL_C$ is obtained as below, which represents the actual calendar time to failure

$$ARUL_F = \sum_{\tau=1}^{ARUL_C} D(\tau) \tag{14}$$

3.4 Cumulative Revenue Simulation

The next step is to develop a revenue calculation model. Assume that the wind turbine energy generation capacity will not degrade as damage accumulates in the subsystems, and the downtime for predictive maintenance is negligible. If the predictive maintenance is going to be implemented, the energy generated from time τ - 1 to τ, $E_{PM}(\tau)$ can be calculated as

$$E_{PM}(\tau) = \begin{cases} g(S_H(\tau)), & S_{CI} \leq S_H(\tau) < S_{RW} \\ E_R, & S_{RW} \leq S_H(\tau) \leq S_{CO} \\ 0, & 0 \leq S_H(\tau) < S_{CI} \text{ or } S_{CO} < S_H(\tau) \end{cases} \tag{15}$$

where $g(\cdot)$ is the power curve function, $g(S_H(\tau))$ is the wind energy generated from time τ - 1 to τ. E_R is the energy generated from time τ - 1 to τ with rated power.

The revenue earned from time τ - 1 to τ, $R_{PM}(\tau)$, can be calculated as

$$R_{PM}(\tau) = E_{PM}(\tau)P_C \tag{16}$$

where P_C is the energy price, assumed to be constant.

The cumulative revenue earned from time τ_1 to τ_2, $CR_{PM}(\tau_1, \tau_2)$, can be calculated as

$$CR_{PM}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{PM}(\tau) \tag{17}$$

Similarly, if the predictive maintenance is not performed, when the turbine fails at $ARUL_C$, it will be non-operational (i.e., down) waiting for a corrective maintenance event starting at time t_c, and finishing at time $t_c + DT$.

The energy generated from time τ - 1 to τ, $E_{CM}(\tau)$ can be calculated as

$$E_{CM}(\tau) = \begin{cases} E_{PM}(\tau), & t_0 < \tau \leq t_0 + ARUL_C \ or \ t_c + DT < \tau \leq T \\ 0, & t_0 + ARUL_C < \tau \leq t_c + DT \end{cases} \tag{18}$$

The revenue earned from time τ - 1 to τ, $R_{CM}(\tau)$, can be calculated as

$$R_{CM}(\tau) = E_{CM}(\tau)P_C \tag{19}$$

The cumulative revenue earn from time τ_1 to τ_2, $CR_{CM}(\tau_1, \tau_2)$, can be calculated as

$$CR_{CM}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{CM}(\tau) \tag{20}$$

3.5 Predictive Maintenance Value Simulation

If predictive maintenance is implemented at time t, where $t_0 < t < ARUL_C$, the cumulative revenue earned from t_0 to t is $CR_{PM}(t_0, t)$; if the wind turbine is run to failure for corrective maintenance at time t_c, the cumulative revenue earned from t_0 to $t_0 + ARUL_C$ is $CR_{CM}(t_0, t_0 + ARUL_C)$. The earlier the predictive maintenance is scheduled, the more revenue will be lost (more of the RUL will be wasted), so the cumulative revenue loss by implementing predictive maintenance at time t, $R_L(t)$, can be calculated as

$$R_L(t) = CR_{PM}(t_0, t) - CR_{CM}(t_0, t_0 + ARUL_C) \tag{21}$$

The avoided corrective maintenance cost by replacing corrective maintenance at time t_c after $ARUL_C$ with predictive maintenance at time t before $ARUL_C$, can be calculated as

$$C_A(t) = C_{CM} \tag{22}$$

where C_{CM} is the corrective maintenance parts, service and labor cost, which is assumed to be constant.[2]

The predictive maintenance value $V_{PM}(t)$ at time t, representing the extra value obtained by carrying out the predictive maintenance at time t rather than waiting for the corrective maintenance at time t_c, is defined as

$$V_{PM}(t) = R_L(t) + C_A(t) \tag{23}$$

[2] In reality, the predictive and/or corrective maintenance parts, service and labor cost may change over time as the damage propagates and/or the collateral damage occurs. In this dissertation these costs are assumed to be constant over time.

Figure 3-3 shows a graphical representation of Eq. (23). The cumulative revenue loss due to predictive maintenance, $R_L(t)$ is highest (absolute value) at the first maintenance opportunity after time t_0. This is because the most remaining life is disposed of if predictive mainenance is performed at this opportunity. As time advances, less RUL is thown away (and less revenue is lost) until the last predictive maintenance opportunity before time $t_0 + ARUL_C$. The avoided corrective maintenance cost, $C_A(t)$, is constant over time for each path. When $R_L(t)$ and $C_A(t)$ are summed, the predictive maintenance value, $V_{PM}(t)$, is obtained.

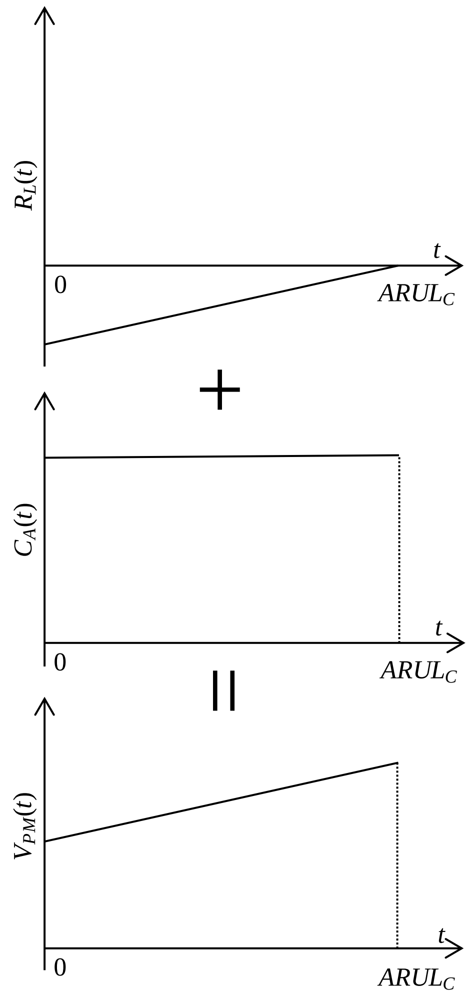

Figure 3-3: Simple predictive maintenance value formulation.

3.6 Predictive Maintenance Scheduling

3.6.1 Stochastic DCF approach

The fundamental tradeoff in the PHM based predictive maintenance scheduling problem is to minimize the risk of expensive corrective maintenance (which increases as the RUL is used up) while minimizing the value of the portion of the RUL thrown away (which decreases as the RUL is used up). If assume that the predictive maintenance will be implemented at some selected opportunity if the wind turbine hasn't failed yet, the predictive maintenance opportunity can be selected by choosing the one with the highest $NPV_{PM}(t)$ as

$$NPV_{PM}(t) = \begin{cases} V_{PM}(t) - C_{PM}, & t_0 < t < t_0 + ARUL_C \\ 0, & t_0 + ARUL_C \leq t \leq T \end{cases} \tag{24}$$

where $NPV_{PM}(t)$ is the NPV at time t_0 if the predictive maintenance implemented at t. C_{PM} is the predictive maintenance parts, service and labor cost, assumed to be constant (see footnote 2). The discount rate is ignored assuming the time period from time t_0 to t is short. When $t_0 < t < t_0 + ARUL_C$, $NPV_{PM}(t)$ can also be expressed as

$$NPV_{PM}(t) = (CR_{PM}(t_0, t) - C_{PM}) - (CR_{CM}(t_0, t_0 + ARUL_C) - C_{CM}) \tag{25}$$

where the first item in parentheses is the net revenue of predictive maintenance at time t, and the second item in parentheses is the net revenue of corrective maintenance at time t_c.

Eqs. (24) or (25) can be used to valuate the NPVs of all possible maintenance opportunities after t_0. At each predictive maintenance opportunity, the NPVs of all simulation trials are averaged to get the expected NPV curve, $ENPV_{PM}(t)$, and then the predictive maintenance opportunity can be selected that generates the highest expected NPV

$$ENPV_{PM}(t) = \frac{1}{M} \sum_{i=1}^{M} NPV_{PM_i}(t) \tag{26}$$

where the subscript i represents the ith Monte Carlo simulation trial, $i = 1$ to M.

3.6.2 European-style ROA approach

There is an implicit assumption in Eqs. (24) and (25) that the predictive maintenance will be implemented at the selected predictive maintenance opportunity if the wind turbine hasn't failed yet no matter the NPV is positive, zero or negative. However according to Eq. (25), if the net revenue of predictive maintenance is lower than corrective maintenance, a negative NPV will be generated. In other words, replacing corrective maintenance with predictive maintenance will not always be beneficial.

It is reasonable to assume that the wind turbine owner who is also the maintenance decision-maker is willing to schedule the predictive maintenance only if it is more beneficial than corrective maintenance (a positive NPV is generated from Eqs. (24) or (25), otherwise it is better to have the turbine run to failure for corrective maintenance. Therefore the predictive maintenance that follows PHM prediction for the wind turbine can be treated as real options, and at each possible predictive maintenance opportunity, a European-style ROA can be applied to valuate the predictive maintenance option as following

$$OV_{PM}(t) = \begin{cases} max(V_{PM}(t) - C_{PM}, 0), & t_0 < t < t_0 + ARUL_C \\ 0, & t_0 + ARUL_C \leq t \leq T \end{cases} \tag{27}$$

where $OV_{PM}(t)$ is the predictive maintenance option value at t_0 of the predictive maintenance implemented at time t. Similarly, the discount rate is ignored for the time period from time t_0 to t.

In Figure 3-4 an example V_{PM} path and three predictive maintenance opportunities t_1, t_2 and t_3 are shown. On the predictive maintenance opportunity before the t_0 + $ARUL_C$ (t_1 or t_2), if the predictive maintenance value is higher than the predictive maintenance cost, maintenance will be implemented (this is the case for t_2); otherwise, the turbine will be run to failure, and the option value is 0 (this is the case for t_1). After the t_0 + $ARUL_C$, the option expires and the option value is 0 (the case for t_3).

All predictive maintenance opportunities after time t_0 can be treated as a series of possible expiration time points of the European-style predictive maintenance option. At each predictive maintenance opportunity, the option values of all simulation trials are averaged to get the expected predictive maintenance option value, $EOV_{PM}(t)$, and then the predictive maintenance opportunity that generates the highest expected option value is selected. $EOV_{PM}(t)$ is given by,

$$EOV_{PM}(t) = \frac{1}{M}\sum_{i=1}^{M} OV_{PM_i}(t) \tag{28}$$

By applying the European-style ROA approach, assume before the wind turbine fails, at each predictive maintenance opportunity, if the predictive maintenance value is higher than the predictive maintenance cost, it will be implemented; otherwise, the

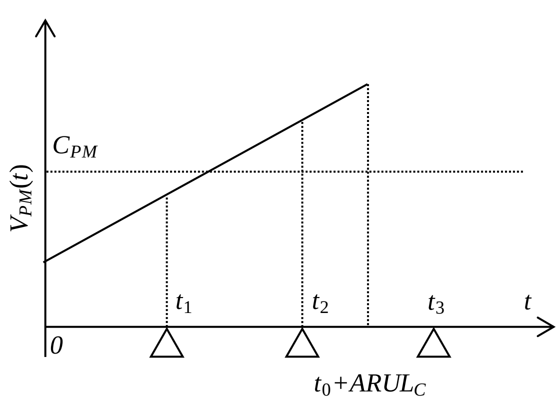

Figure 3-4: An example of the ROA valuation.

wind turbine will be run to failure, and the option value is 0. After the wind turbine fails, the option expires and the option value is 0. [3]

During the valuation process for each predictive maintenance opportunity, the stochastic DCF approach has to carry out the predictive maintenance, while the European-style ROA approach enables the managerial flexibility and may choose not to carry out the predictive maintenance if corrective maintenance is more beneficial.

[3] The ways to valuate real options include Black-Scholes, Binomial Lattice, Monte Carlo simulation etc., and this dissertation uses Monte Carlo simulation. Please see Section 6.4 for other valuation approaches.

Chapter 4: PHM-Based Predictive Maintenance Scheduling for Wind Farms Managed Using PPAs (Tasks 3, 4 and 5)

This chapter extends the European-style ROA approach for a single wind turbine developed in Chapter 3 to a wind farm with multiple turbines indicating RULs concurrently. The inclusion of PPA terms in the analysis is also addressed in this chapter. When there are multiple wind turbines with RUL predictions, different from the single turbine as-delivered payment model case, the operational state of all the other turbines in the farm, the amount of energy delivered, and the energy delivery target, prices and penalization mechanism for under-delivery defined in the PPA will all affect the value of the revenue earned, which will affect $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$. Therefore, it is necessary to develop the PPA-based cumulative revenue and under-delivery penalty calculation method.

4.1 PPA-Based Cumulative Revenue Modeling

Assume a wind farm is managed using a PPA. At time t_0, K turbines are indicating RULs (while J turbines operate normally without RUL indications and I turbines are down). It is assumed that all wind turbines in the farm are connected to the substation independently. These means that turbines that are not being maintained can continue generating energy (and revenue) when performing maintenance on the K turbines. From time t_0 to T there are multiple predictive maintenance opportunities, and the wind farm owner wants to decide which predictive maintenance opportunity should be scheduled for all K turbines. If the predictive maintenance is not implemented, there will be a corrective maintenance event at time t_c with a downtime DT to fix all failed turbines and restore them to operation.

By using Eqs. (9) through (12), M hub height wind speed paths can be simulated from time t_0 to T, with each path representing a possible future wind profile for the whole farm. By using Eqs. (13) through (14), M $ARUL_{C,k}$ samples can be calculated for each of the K turbines with RULs, k = 1 to K.

Assume in the PPA governing the wind farm, there is a constant energy delivery target ET set at the beginning of each simulation time period (called time 0), reflecting the wind energy buyer's energy demand. The energy generated before the target is met will be priced by a constant contract price P_C. A lower constant excess price P_E applies for all energy generated thereafter until T. If the target is not met at T, the buyer has to generate or purchase energy from other sources to fulfill the demand with a price P_R (called the replacement price). According to the PPA, the seller must compensate the buyer for the latter's overpaid energy cost, which is calculated as the shortfall energy amount priced by the difference between P_R and P_C.

For a wind farm with multiple wind turbines indicating RULs, the simplest predictive maintenance option implementation requires that all K turbines indicating RULs are maintained concurrently (i.e., during a single maintenance visit), and the downtime for maintenance is assume to be negligible. If the predictive maintenance is going to be implemented, the energy generated from τ - 1 to τ by the jth turbine operates normally without RUL (called turbine j) and the kth turbine indicating RUL (called turbine k), $E_j(\tau)$ and $E_{PM,k}(\tau)$ can be calculated as

$$E_j(\tau) = E_{PM,k}(\tau) = \begin{cases} g(S_H(\tau)), & S_{CI} \le S_H(\tau) < S_{RW} \\ E_R, & S_{RW} \le S_H(\tau) \le S_{CO} \\ 0, & 0 \le S_H(\tau) < S_{CI} \text{ or } S_{CO} < S_H(\tau) \end{cases} \quad (29)$$

If the predictive maintenance is going to be implemented on all *K* turbines at time *t*, the cumulative energy generated by the whole wind farm from time 0 to time *t*, $CE_{PM}(t)$ can be calculated as

$$CE_{PM}(t) = CE(t_0) + \sum_{\tau=t_0+1}^{t} \sum_{j=1}^{J} E_j(\tau) + \sum_{\tau=t_0+1}^{t} \sum_{k=1}^{K} E_{PM,k}(\tau) \quad (30)$$

where $CE(t_0)$ is the cumulative energy delivered by the whole wind farm from time 0 to t_0.

The revenue earned from time τ - 1 to τ by turbine *k*, $R_{PM,k}(\tau)$ can be calculated as

$$R_{PM,k}(\tau) = E_{PM,k}(\tau) P_{PM}(\tau) \quad (31)$$

where $P_{PM}(\tau)$ is the energy price with predictive maintenance implemented, defined as

$$P_{PM}(\tau) = \begin{cases} P_C, & CE_{PM}(\tau) \le ET \\ P_E, & CE_{PM}(\tau) > ET \end{cases} \quad (32)$$

The cumulative revenue earned from time τ_1 to τ_2 by turbine *k* $CR_{PM,k}(\tau_1, \tau_2)$ can be calculated as

$$CR_{PM,k}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{PM,k}(\tau) \quad (33)$$

Similarly, if the predictive maintenance is not going to be implemented on the *K* turbines, the corrective maintenance will fix all failed *K* turbines at time t_c. The cumulative energy generated by the whole wind farm from time 0 to *t*, $CE_{CM}(t)$ can be calculated as

$$CE_{CM}(t) = CE(t_0) + \sum_{\tau=t_0+1}^{t} \sum_{j=1}^{J} E_j(\tau) + \sum_{\tau=t_0+1}^{t} \sum_{k=1}^{K} E_{CM,k}(\tau) \tag{34}$$

where $E_{CM,k}(\tau)$ is the energy generated by turbine k from time τ - 1 to τ, calculated as

$$E_{CM,k}(\tau) = \begin{cases} E_{PM,k}(\tau), & t_0 < \tau \leq t_0 + ARUL_{C,k} \text{ or } t_c + DT < \tau \leq T \\ 0, & t_0 + ARUL_{C,k} < \tau \leq t_c + DT \end{cases} \tag{35}$$

When turbine k fails at t_0 + $ARUL_{C,k}$, it will be down for the corrective maintenance event starting at t_c.

The revenue earned from time τ - 1 to τ by turbine k $R_{CM,k}(\tau)$ can be calculated as

$$R_{CM,k}(\tau) = E_{CM,k}(\tau) P_{CM}(\tau) \tag{36}$$

where $P_{CM}(\tau)$ is the energy price at time τ with predictive maintenance not implemented, defined as

$$P_{CM}(\tau) = \begin{cases} P_C, & CE_{CM}(\tau) \leq ET \\ P_E, & CE_{CM}(\tau) > ET \end{cases} \tag{37}$$

The cumulative revenue earned from time τ_1 to τ_2 by turbine k $CR_{CM,k}(\tau_1, \tau_2)$ can be calculated as

$$CR_{CM,k}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{CM,k}(\tau) \tag{38}$$

4.2 Predictive Maintenance Value Simulation

To extend the approaches for a single wind turbine to a wind farm, the value paths associated with multiple turbines have to be accumulated in some fashion and there are several ways this can be approached. One possible way is to generate the predictive maintenance value paths for each of the K turbines with RULs independently, then do the stochastic DCF or the European-style ROA approach for each turbine, and finally add the expected predictive maintenance NPV curves or option value curves together to pick the maintenance opportunity with the peak value. By doing this there is an implicit assumption that the maintenance decision-maker is able to schedule predictive maintenance for each of the K turbines individually. However a potential problem with this method is that, the value paths for each of the K turbines also depend on the maintenance decisions for the other K - 1 turbines, which creates significant complexity. An alternative accumulation method is to generate the predictive maintenance value paths for each of the K turbines with RULs, add them, and then do the stochastic DCF or the European-style ROA analysis on the accumulated predictive maintenance paths. This accumulation approach assumes that the wind farm owner only wants to implement the predictive maintenance on all K turbines during a single visit ("all or nothing" assumption). Due to the harsh environment and limited availability of the maintenance resources, in reality the wind farm owner probably prefers to maintain multiple turbines during a single visit to the farm, as assumed in the presented model.

If predictive maintenance is implemented on all K turbines at time t, the cumulative revenue earned by turbine k from t_0 to t is $CR_{PM,k}(t_0, t)$; if corrective maintenance is implemented on all K turbines at time t_c, the cumulative revenue earned by turbine k from t_0 to $t_0 + ARUL_{C,k}$ is $CR_{CM,k}(t_0, t)$.

The cumulative revenue loss by implementing predictive maintenance on all K turbines at time t, $R_{L,K}(t)$, can be calculated as

$$R_{L,K}(t) = \sum_{k=1}^{K} CR_{PM,k}(t_0, t) - \sum_{k=1}^{K} CR_{CM,k}\left(t_0, t_0 + ARUL_{C,k}\right) \tag{39}$$

where $t_0 < t < ARUL_{C,min}$, $ARUL_{C,min}$ is the shortest $ARUL_{C,k}$ of all K turbines. It is assumed that all K turbines will be maintained predictively together before $ARUL_{C,min}$. Once the first turbine failure happens, the predictive maintenance option expires.

The avoided corrective maintenance cost by replacing corrective maintenance at time t_c with predictive maintenance at time t for all K turbines, can be calculated as

$$C_{A,K}(t) = C_{CM,K} + \left(UP_{CM,K} - UP_{PM,K}\right) \tag{40}$$

$C_{CM,K}$ is the sum of the corrective maintenance parts, service and labor costs for all K turbines

$$C_{CM,K} = \sum_{k=1}^{K} C_{CM,k} \tag{41}$$

where $C_{CM,k}$ is the corrective maintenance parts, service and labor cost for turbine k.

If the predictive maintenance is implemented at time t, the under-delivery compensation $UP_{PM,K}$ paid by the seller to the buyer allocated to the turbines with RULs (assume the penalty will be allocated to each turbine in the farm equally) can be calculated as

$$UP_{PM,K} = \begin{cases} \left(ET - CE_{PM}(T)\right)(P_R - P_C)\dfrac{K}{I+J+K}, & CE_{PM}(T) < ET \\ 0, & CE_{PM}(T) \geq ET \end{cases} \tag{42}$$

Similarly, if the predictive maintenance is not implemented, the under-delivery compensation $UP_{CM,K}$ can be calculated as

$$UP_{CM,K} = \begin{cases} \left(ET - CE_{CM}(T)\right)(P_R - P_C)\dfrac{K}{I+J+K}, & CE_{CM}(T) < ET \\ 0, & CE_{CM}(T) \geq ET \end{cases} \quad (43)$$

The predictive maintenance value $V_{PM,K}(t)$ at time t, representing the extra value obtained by carrying out the predictive maintenance on all K turbines at time t rather than waiting for the corrective maintenance at time t_c, is defined as

$$V_{PM,K}(t) = R_{L,K}(t) + C_{A,K}(t) \quad (44)$$

4.3 *Predictive Maintenance Scheduling*

If assume that the predictive maintenance will always be implemented at the selected opportunity, the predictive maintenance opportunity can be scheduled by choosing the one with the highest net profit of the predictive maintenance as

$$NPV_{PM,K}(t) = \begin{cases} V_{PM,K}(t) - C_{PM,K}, & t_0 < t < t_0 + ARUL_{C,min} \\ 0, & t_0 + ARUL_{C,min} \leq t \leq T \end{cases} \quad (45)$$

where $C_{PM,K}$ the sum of the predictive maintenance parts, service and labor costs for all K turbines, defined as

$$C_{PM,K} = \sum_{k=1}^{K} C_{PM,k} \quad (46)$$

$C_{PM,k}$ is the predictive maintenance parts, service and labor cost for turbine k.

At each predictive maintenance opportunity, the NPVs of all simulation trials are averaged to get the expected NPV curve, $ENPV_{PM,K}(t)$, and then the predictive maintenance opportunity can be selected that generates the highest expected NPV.

If treat the predictive maintenance that follows PHM predictions for wind turbines as a real option, at each opportunity, a European-style ROA can be applied to valuate the predictive maintenance option

$$OV_{PM,K}(t) = \begin{cases} max\left(V_{PM,K}(t) - C_{PM,K}, 0\right), & t_0 < t < t_0 + ARUL_{C,min} \\ 0, & t_0 + ARUL_{C,min} \leq t \leq T \end{cases} \quad (47)$$

By applying the European-style ROA approach, assume before $ARUL_{C,min}$ at each predictive maintenance opportunity, if the predictive maintenance value is higher than the predictive maintenance cost, it will be implemented on all K turbines; otherwise, all K turbines will be run to failure, and the option value is 0. After $ARUL_{C,min}$, the option expires and the option value is 0.

At each predictive maintenance opportunity, the option values of all simulation trials are averaged to get the expected predictive maintenance option value, $EOV_{PM,K}(t)$, and then the predictive maintenance opportunity that generates the highest expected option value is selected.

Chapter 5: Case Studies (Tasks 6, 7 and 8)

This chapter first describes case studies for a single wind turbine with and without a PPA (Section 5.1 and 5.2), and then a multi-turbine wind farm with a PPA when multiple turbines are indicating RULs concurrently (Section 5.3). Sections 5.4 and 5.5 provide an interpretation of the cumulative revenue loss and quantify the life-cycle cost benefit of developed approach. Section 5.5 also discusses a modification to the model that assumes constant time length life cycles (as opposed to life cycles defined by the number of spares or maintenance events).

5.1 Single Wind Turbine Managed Using an As-Delivered Payment Model

Buoy height 10-year (2003 to 2012) 10-minute average (5 m above sea level) wind speed data are obtained from station 44009 of the National Data Buoy Center, which is the closest buoy to the Maryland Wind Energy Area [102][103]. The wind speed data is incomplete for 2013 to 2017, which is therefore not used. An offshore wind farm in this area with Vestas V-112 3.0 MW offshore wind turbines is assumed for the study [104]. The rated output power is 3 MW, cut-in, rational and cut-out speeds are 3 m/s, 12 m/s and 25 m/s respectively, nominal rotational speed is 14 RPM. The hub height is site specific [104], and it is assumed to be 100 m above sea level. The parameter α is determined empirically as 0.1 for the area [11]. The 10-minute average wind speed data was first converted into the 1-hour average wind speed date, and then the Weibull distribution parameters η and β of buoy height wind speed data were

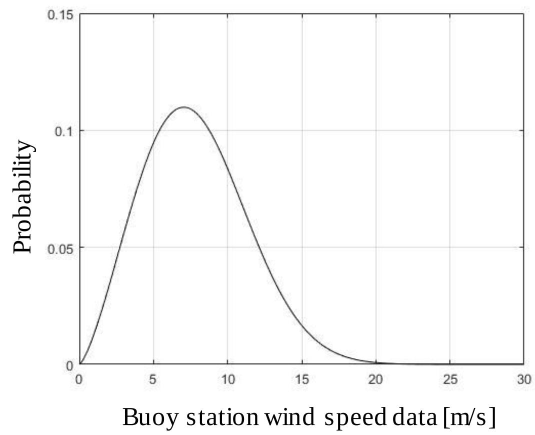

Figure 5-1: Weibull distribution for the buoy station wind speed data.

estimated to be 8.85 m/s and 2.38 respectively according to Eqs. (10) through (11). The obtained Weibull distribution probability density function is shown in Figure 5-1. Using Monte Carlo simulation and Eq. (12), 10,000 hub height wind speed paths can be simulated.

5.1.1 Simulation of the predictive maintenance value paths

Assume there is a single wind turbine managed using an as-delivered payment model. P_C is assumed to be \$50/MWh. At t_0 = 8,000 hours of a year, a PHM indication is triggered and a RUL of 100,000 cycles is predicted for a key subsystem (e.g., the main bearing). A triangular distribution is assumed to represent the RUL uncertainty with the mean of 100,000 cycles and the width of 200,000 cycles. Predictive and corrective maintenance parts, service and labor costs are assumed to be \$25,000 and \$14,000, respectively [85]. If the predictive maintenance is not implemented, there will be a corrective maintenance event starting at t_c = 8,500 hours, causing a downtime *DT* of 168 hours [86]. Using Monte Carlo simulation and Eqs. (13) through (14), 10,000

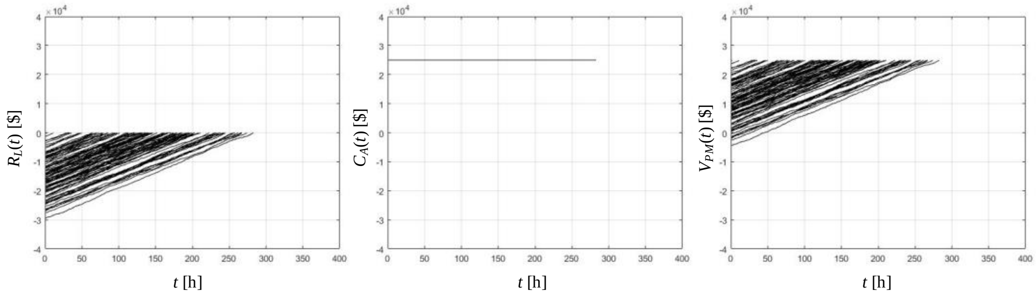

Figure 5-2: Left – $R_L(t)$ paths, middle – $C_A(t)$ paths, and right – $V_{PM}(t)$ paths for a single wind turbine managed using an as-delivered payment model (100 paths are shown).

$ARUL_F$ samples are obtained. By applying Eqs. (15) through (23), 10,000 $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ paths are simulated and shown in Figure 5-2.

As shown in the left plot in Figure 5-2, all the $R_L(t)$ paths start at different points on the vertical axis: the longer the $ARUL_C$ of a path is, the more cumulative revenue will be missed if one chooses to do predictive maintenance at the earliest opportunity, and therefore the lower the path's initial value. All paths are ascending over time, since the later the predictive maintenance is done, the smaller the cumulative revenue will be lost. Finally all the paths terminate at different time points when the $ARUL_C$ is used up, which represents the uncertainties in the predicted RUL and the wind speed. As can be seen in the middle plot in Figure 5-2, each $C_A(t)$ path is constant over time, and the combinations of the $R_L(t)$ and $C_A(t)$ paths according to Eq. (23), result in $V_{PM}(t)$ paths that are ascending (see the right plot in Figure 5-2).

5.1.2 Results from the Stochastic DCF approach

Assuming the predictive maintenance opportunity is once per hour, for the simulated 10,000 $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ paths, using Eq. (24), 10,000 NPV paths are obtained as shown in Figure 5-3. At each predictive maintenance opportunity, all NPVs

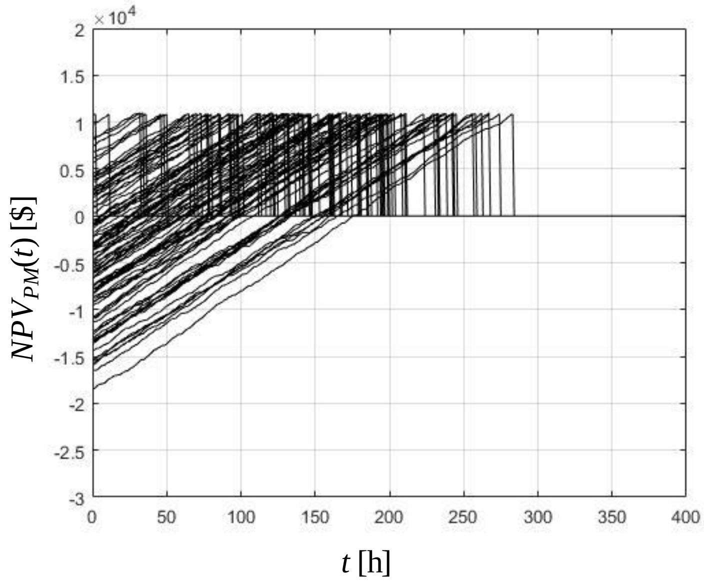

Figure 5-3: $NPV_{PM}(t)$ paths for a single wind turbine managed using an as-delivered payment model (100 paths are shown).

are averaged to get the expected predictive maintenance NPV as shown in Figure 5-5, in which the selected predictive maintenance opportunity is 6.0 days (145 hours) after time t_0 (pointed by the black dashed line), with the expected predictive maintenance NPV to be $3,078 which represents the expected net profit by replacing the corrective maintenance with the predictive maintenance. According to Figure 5-4, at the selected predictive maintenance opportunity, 57.1% of the paths will implement the predictive maintenance, because 42.9% of the paths have the turbine failed and the corrective maintenance will be implemented at the time t_c, which represents the tradeoff between the value of waiting to do predictive maintenance and the risk of ending up with corrective maintenance.

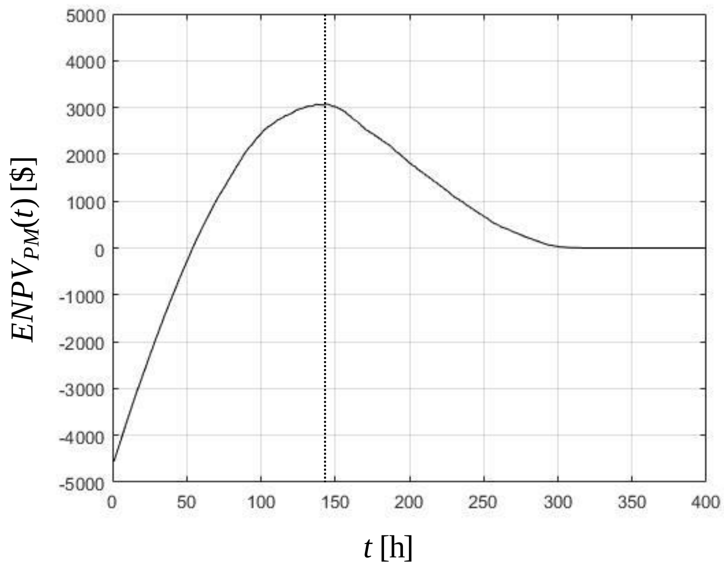

Figure 5-5: $ENPV_{PM}(t)$ curve for a single wind turbine managed using an as-delivered payment model (predictive maintenance opportunity is once every hour).

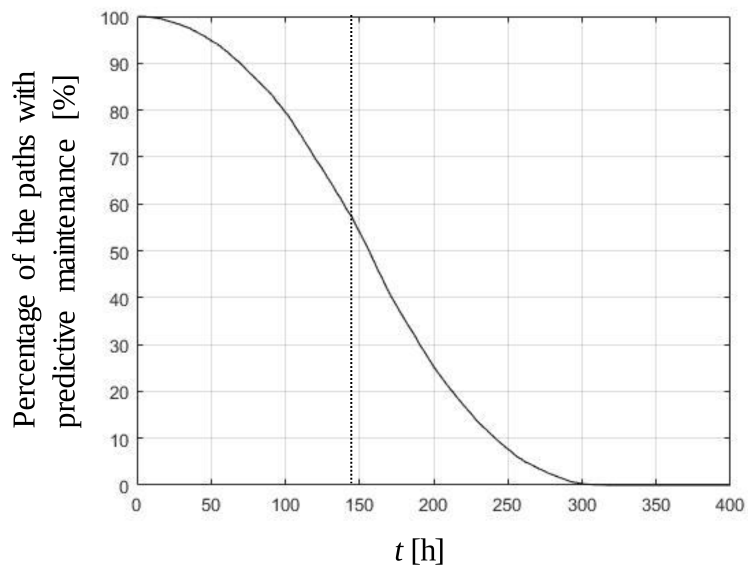

Figure 5-4: Percentage of the paths implementing predictive maintenance for a single wind turbine managed using an as-delivered payment model (predictive maintenance opportunity is once every hour).

5.1.3 Results from the European-style ROA approach

With the simulated 10,000 predictive maintenance value paths, using Eq. (27), 10,000 predictive maintenance option value paths are obtained in Figure 5-6, and the predictive maintenance NPV values are also shown in the left plot for comparison. It can be observed that predictive maintenance option present values are all non-negative. This is due to the nature of the real options to only capture the value of the upside potential by accounting for the proper managerial flexibility, which in this case means some paths choose not to implement the predictive maintenance given waiting for the corrective maintenance is more beneficial.

At each predictive maintenance opportunity, all option values are averaged to get the expected predictive maintenance option value as shown in Figure 5-7. The selected predictive maintenance opportunity is 5.2 days (124 hours) after t_0 (pointed by the blue dashed line), with the expected predictive maintenance option value to be \$3,281. At the selected predictive maintenance opportunity, besides the 32.0% of the paths have the turbine already failed, there are 12.5% of the paths choose not to implement the predictive maintenance but wait for the corrective maintenance at t_c as

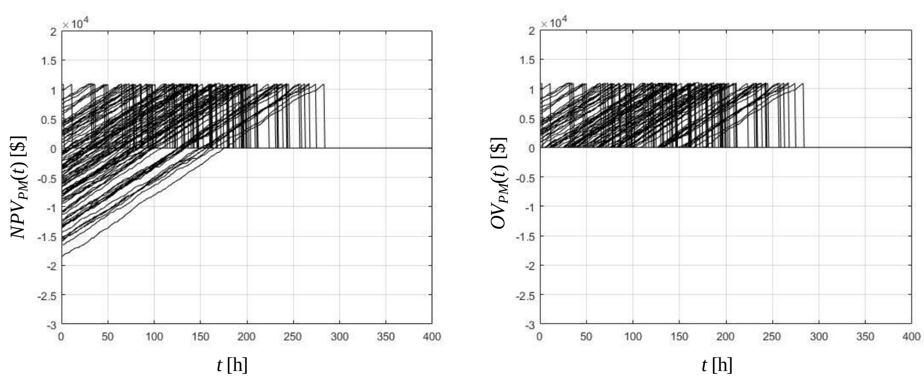

Figure 5-6: Left – $NPV_{PM}(t)$ paths, and right – $OV_{PM}(t)$ paths for a single wind turbine managed using an as-delivered payment model (100 paths are shown).

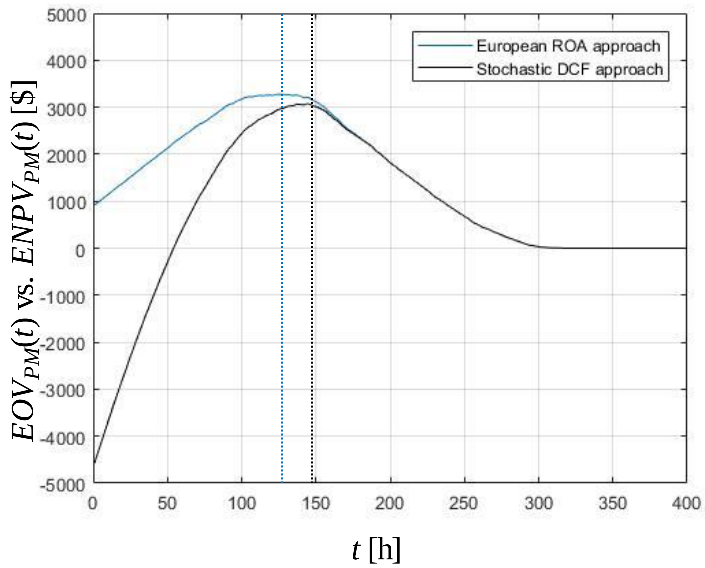

Figure 5-7: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single wind turbine managed under an as-delivered payment model (predictive maintenance opportunity is once every hour).

shown in Figure 5-8. The expected predictive maintenance NPV is also shown in the same plot. Both approaches suggest waiting for some time to implement the predictive maintenance, rather than implementing the predictive maintenance immediately after

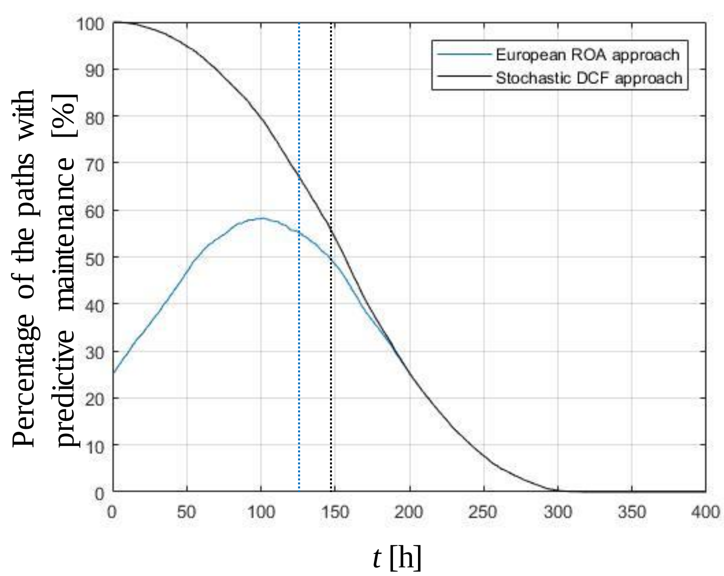

Figure 5-8: Percentage of the paths implementing predictive maintenance for a single wind turbine managed under an as-delivered payment model by two approaches (predictive maintenance opportunity is once every hour).

the PHM indication or waiting until closer to the end of the RUL, which represents the tradeoff to minimize the risk of corrective maintenance while minimize the value of the part of the RUL thrown away. The stochastic DCF approach suggests a later predictive maintenance opportunity with a lower expected NPV, because the European-style ROA approach is an asymmetric approach that only captures the upside value (when predictive maintenance is more beneficial) while limiting the downside risk (when corrective maintenance is more beneficial). In another word, because the stochastic DCF approach lacks the managerial flexibility to limit the downside risk, compared with the European-style ROA approach, it will suggest to wait longer for more increases in the predictive maintenance value, to increase the chance for the predictive maintenance to be more beneficial. Also, because of this asymmetric characteristic, at each maintenance opportunity, the expected option value from the European-style ROA approach is always greater than or equal to the expected NPV from the Stochastic DCF approach. The difference of the $211 is the additional value provided by the managerial flexibility that the real option approach correctly models.

As shown in Figure 5-10, when M is increased from 10,000 to 50,000, the European-style ROA approach still suggests gives the same predictive maintenance opportunity: 5.2 days (124 hours) after time t_0, and the expected predictive maintenance option value only varies within 0.3%.

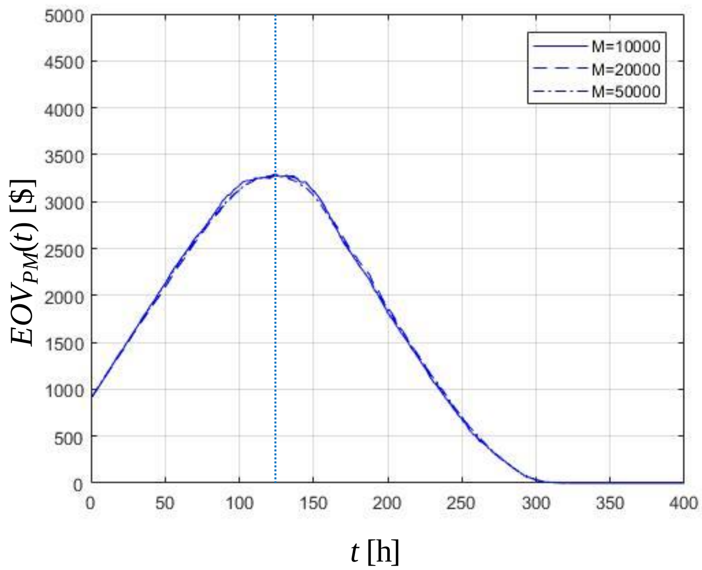

Figure 5-10: $ENPV_{PM}(t)$ curve for a single wind turbine managed under an as-delivered payment model when M is increased (predictive maintenance opportunity is once every hour).

If the predictive maintenance value is higher than the predictive maintenance cost at all predictive maintenance opportunities due to high cumulative revenue loss or expensive corrective maintenance cost, then there will be no differences between the

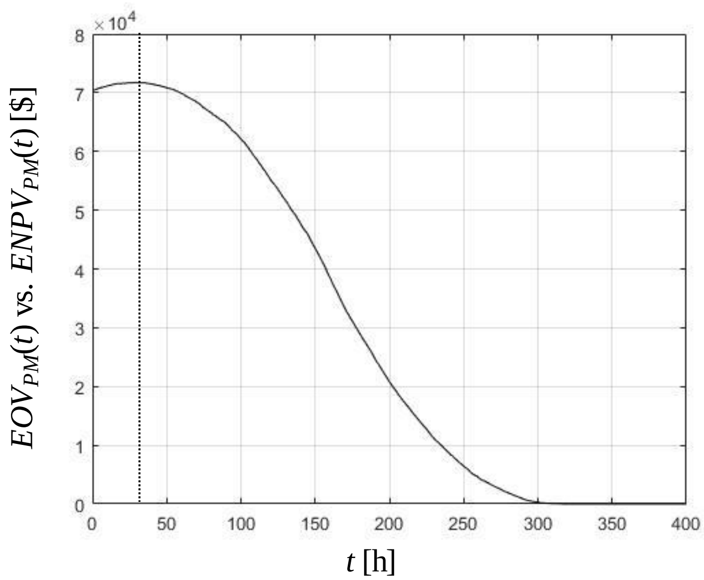

Figure 5-9: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single wind turbine managed using an as-delivered payment model (predictive maintenance opportunity is once every hour, corrective maintenance parts, service and labor cost of $100,000).

results from the European-style ROA and Stochastic DCF approaches. As it is shown in Figure 5-9, under the assumption of having a high corrective parts, service and labor maintenance cost of $100,000 and keeping all other parameters the same, both approaches suggest the same result of 29 hours (1.2 days) after t_0, with the expected predictive NPV and the expected predictive maintenance option value equaling to $71,753.

Therefore, unless the predictive maintenance value is much higher than the predictive maintenance cost, the European-style ROA approach offers a more conservative opportunity to schedule predictive maintenance. This means that when the maintenance crew arrives on the suggested maintenance date, the probability that the turbine has failed is lower, which also means a higher probability for the predictive maintenance to be implemented successfully. The European-style ROA approach also leads to an expected option value higher than the expected NPV from Stochastic DCF approach.

5.2 Single Wind Turbine Managed Using a PPA

5.2.1 Simulation of the predictive maintenance value paths

Now assume there is a single wind turbine managed using a PPA, *ET* is 10,500 MWh, which is estimated based on an assumed capacity factor of 0.4. P_C, P_E and P_R are $50/MWh, $30/MWh and $80/MWh respectively.[4] At t_0 = 8,000 hrs when $CE(t_0)$ is 10,000 MWh, RULs are predicted to be 100,000 cycles. A triangular distribution is

[4] When under-delivery happens under a PPA, to make up the difference, the seller can choose to purchase energy from the spot market in which the energy price is highly volatile, generate energy through some alternative means controlled by the seller, or purchase energy from a third party. In this dissertation it is assumed the seller and a third party have an agreement, which allows the former to purchase energy from the latter for any amount at any time with a fixed price P_R.

assumed to represent the RUL uncertainties with the mean of 100,000 cycles and the width of 200,000 cycles. Predictive and corrective maintenance parts, service and labor costs are assumed to be \$25,000 and \$14,000, respectively. There will be a corrective maintenance event starting at t_c = 8,500 hours, causing a downtime DT of 168 hours. By applying Eqs. (13) through (23), 10,000 $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ paths are simulated and shown in Figure 5-11. The change in slopes of some $R_L(t)$ paths indicates that ET is reached and then the P_E is applied. Some $C_A(t)$ paths are higher than \$25,000 corrective maintenance parts, service and labor cost, because for these paths under-delivery penalty will happen if the corrective maintenance is implemented. The earlier the failure happens, the longer that the turbine will have to wait for the corrective maintenance starting at time t_c, therefore the more the energy shortfall and the higher the under-delivery penalty will be.

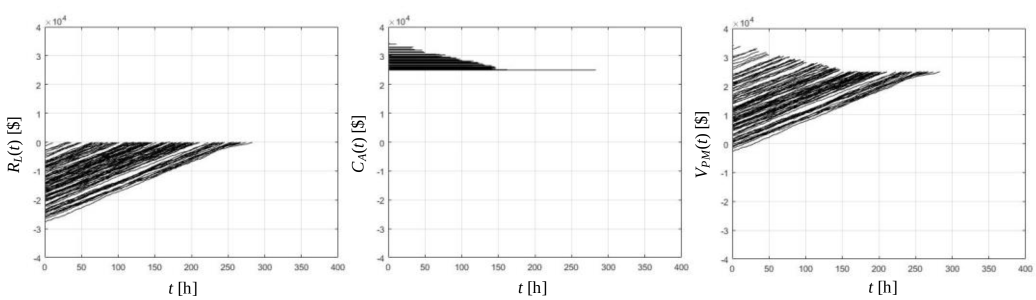

Figure 5-11: Left – $R_L(t)$ paths, middle – $C_A(t)$ paths, and right –$V_{PM}(t)$ paths for a single wind turbine managed using a PPA (100 paths are shown).

5.2.2 Results from the Stochastic DCF approach and the European-style ROA approach

If the predictive maintenance is available every hour, the expected predictive maintenance NPV curve and the expected predictive maintenance option value curve are shown in Figure 5-12. By the stochastic DCF approach, the selected predictive maintenance opportunity is 5.7 days (137 hours) after time t_0, with the expected predictive maintenance NPV of \$3,213. By the European-style ROA approach, the selected predictive maintenance opportunity is 3.8 days (92 hours) after time t_0, with the expected predictive maintenance option value of \$3,676. At the selected predictive maintenance opportunity, besides the 17.2% of the paths have the turbine already failed, there are 24.9% of the paths choose not to implement the predictive maintenance but wait for the corrective maintenance at t_c. The value difference between the two approaches of \$463 is the additional value provided by the managerial flexibility offered by the European-style ROA approach, which is 14.4% of the expected

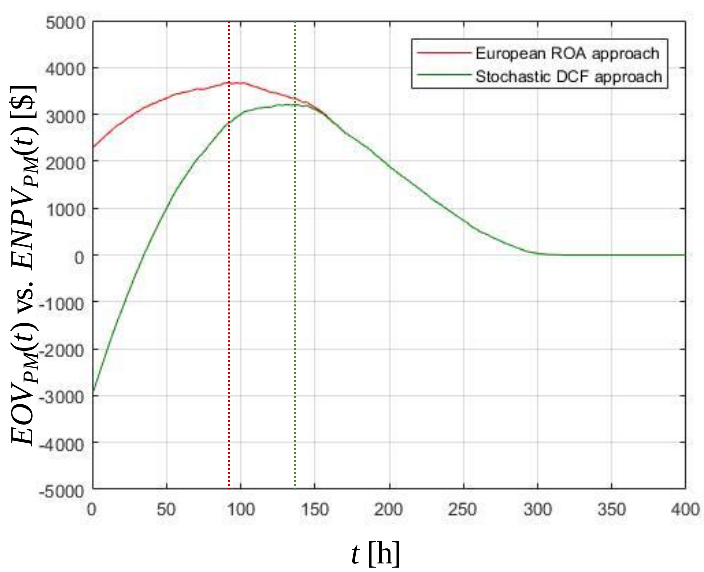

Figure 5-12: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single wind turbine managed using a PPA (predictive maintenance opportunity is once every hour).

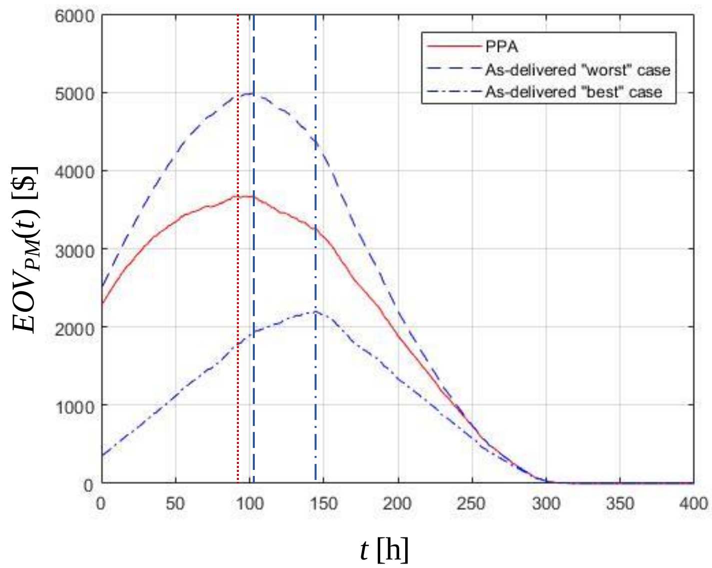

Figure 5-13: $EOV_{PM}(t)$ curves for a single wind turbine managed using a PPA vs. using as-delivered payment models (predictive maintenance opportunity is once every hour).

predictive maintenance NPV at its selected predictive maintenance opportunity in this example.

The results by the European-style ROA approach for the as-delivered payment model cases, and the result by the European-style ROA approach for the PPA case are shown in Figure 5-13 for comparison. Three as-delivered cases are assumed: the "worst" case only pays $30 for each MWh, which equals to the P_E of the PPA, and the "best" case, which pays $80 for each MWh which equals to the P_R of the PPA. According to Figure 5-13, the "worst" case suggests to schedule the predictive maintenance at 4.3 days (102 hours) after time t_0, the "best" case suggests 6.0 days (145 hours) after time t_0, while the PPA case suggest 3.8 days (92 hours) after time t_0. In the PPA case, some paths reach the ET and then a lower price P_E applies, which tend to shift the selected predictive maintenance opportunity to a later time. The longer waiting for predictive maintenance, the higher chance that the ET can be met, and then the fewer cumulative revenue could be lost compared with waiting for corrective maintenance (because a lower price P_E applies). In some other paths, the ET could not be met if waiting for corrective maintenance, therefore the under-delivery penalty tends to shift the selected predictive maintenance opportunity to an earlier time, to avoid the corrective maintenance leading to under-delivery penalty as much as possible. In this specific example, the effect of the under-delivery penalty dominates the over-delivery lower price, therefore compared with the as-delivered cases, which simply pay for constant energy prices and have no over-delivery lower price or under-delivery penalty, the PPA case suggests to do the predictive maintenance earlier. For comparison, the $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ paths for the as-delivered cases are shown in Figure 5-14. It is worth noticing that the "best" as-delivered case is suggesting a later predictive maintenance opportunity with a lower expected predictive maintenance option value

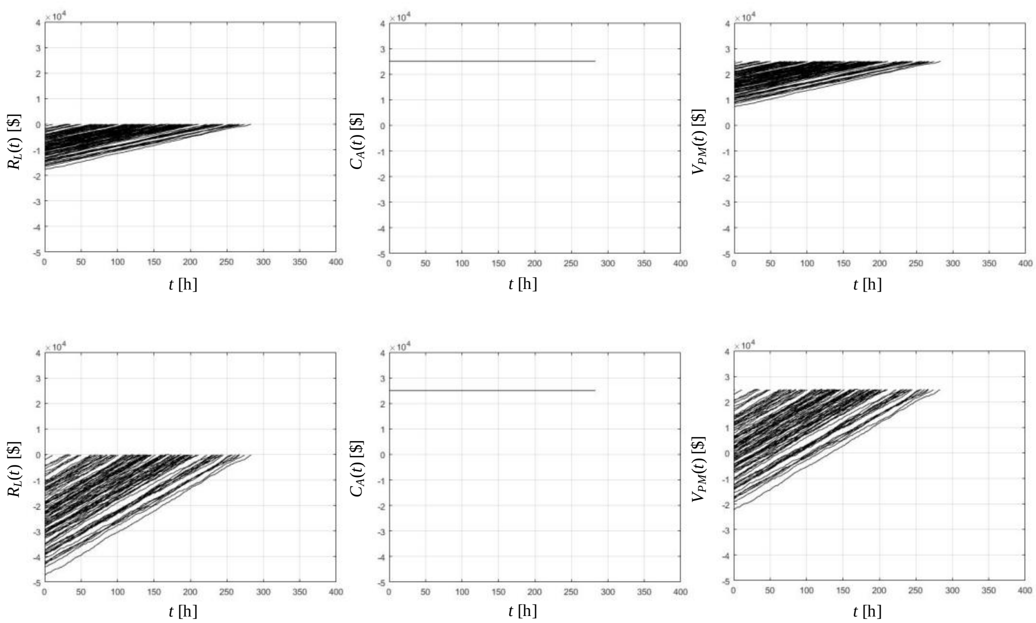

Figure 5-14: Upper left – $R_L(t)$ paths, upper middle – $C_A(t)$ paths, and upper right –$V_{PM}(t)$ paths for a single wind turbine managed using the "worst" as-delivered payment model; lower left – $R_L(t)$ paths, lower middle – $C_A(t)$ paths, and lower right –$V_{PM}(t)$ paths for a single wind turbine managed using the "best" as-delivered payment model (100 paths are shown).

than the “worst” as-delivered case. The “best” case has a much higher revenue rate than the “worst” case, so to maximize the revenue could be earned by waiting for predictive maintenance, the European-style ROA approach suggests to wait longer, which also increases the probability of ending up with a corrective maintenance that lowers the expected predictive maintenance option value.

Similar to the as-delivered case study, if the predictive maintenance value is higher than the predictive maintenance cost at all predictive maintenance opportunities due to high cumulative revenue loss or expensive corrective maintenance cost, then there will be no differences between the results from the European-style ROA approach and stochastic DCF approach. As it is shown in Figure 5-15, under the assumption of having a high corrective maintenance cost of $100,000 and keeping all other parameters the same, both approaches suggest the same result of 1.2 days (29 hours) after t_0, with

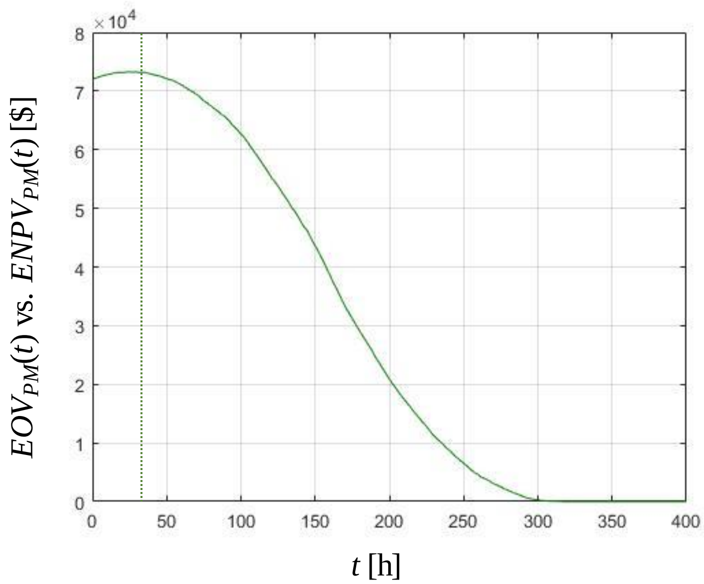

Figure 5-15: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single wind turbine managed using a PPA (predictive maintenance opportunity is once every hour, corrective maintenance parts, service and labor cost of $100,000).

the expected predictive NPV and the expected predictive maintenance option value equaling to 73,278.

5.2.3 Conclusions from the single wind turbine case study

- For both the as-delivered and PPA cases, both approaches suggest waiting for some time to implement the predictive maintenance, rather than implementing the predictive maintenance immediately after the PHM indication or waiting until closer to the end of the RUL.
- For both the as-delivered and PPA cases, the European-style ROA approach suggests an earlier predictive maintenance opportunity than the stochastic DCF approach, with the expected predictive maintenance option value higher than the expected predictive maintenance NPV. The difference represents the additional value provided by the managerial flexibility offered by the European-style ROA approach.
- For both the as-delivered and PPA cases, at each predictive maintenance opportunity, the expected option value from the European-style ROA approach is always greater than or equal to the expected NPV from the stochastic DCF approach. If the predictive maintenance value is higher than the predictive maintenance cost at all predictive maintenance opportunities, then there will be no differences between the results from the European-style ROA and stochastic DCF approach.
- For both the stochastic DCF and the European-style ROA approaches, the results are different between an as-delivered payment model and a PPA. In the PPA case, the over-delivery lower price tends to shift the selected predictive

maintenance opportunity to a later time, while the under-delivery penalty does the opposite – shifts the selected predictive maintenance opportunity to an earlier time.

5.3 *Wind Farm Managed Using a PPA*

5.3.1 Simulation of the predictive maintenance value paths

Assume there is an offshore wind farm with five turbines managed using a PPA with the *ET* of 52,500 MWh (5 times of the singe turbine case in Section 5.2), P_C, P_E and P_R are assumed to be the same as the singe wind turbine case. At t_0 = 7,500 hours when $CE(t_0)$ is 45,000 MWh, RULs are predicted for turbine 1 to be 200,000 cycles with 400,000 cycles as the width for a triangular distribution, (e.g. for the main bearing) and for turbine 2 to be 250,000 cycles with 400,000 cycles as the width for a triangular distribution (e.g., for the generator). There will be a corrective maintenance event starting at t_c = 8,500 hours, causing a downtime *DT* of 240 hours. Predictive and corrective maintenance parts, service and labor costs are assumed to be $25,000 and $14,000 for turbine 1, and $45,000 and $16,000 for turbine 2, respectively [85]. Assume at the same time, there is one turbine in the wind farm that is not operating.

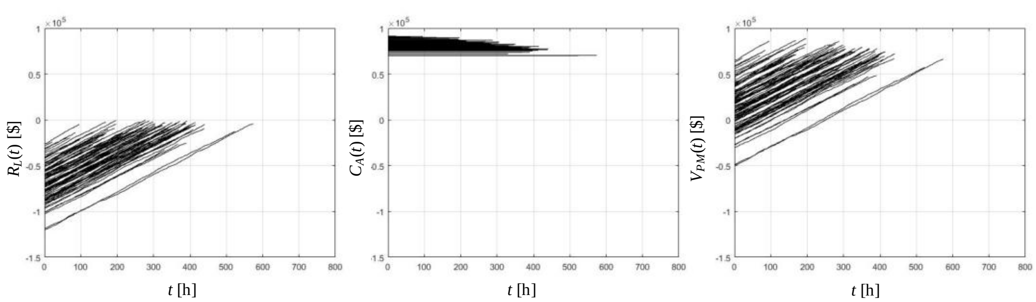

Figure 5-16: Left – $R_L(t)$ paths, middle – $C_A(t)$ paths, and right –$V_{PM}(t)$ paths for wind turbines 1 and 2 in a wind farm managed using a PPA (100 paths are shown).

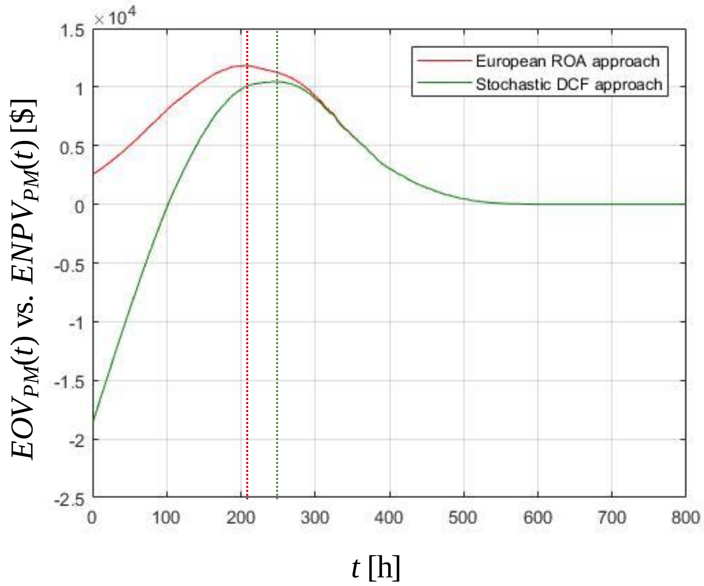

Figure 5-17: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for wind turbines 1 and 2 in a wind farm managed using a PPA (predictive maintenance opportunity is once every hour).

The predictive maintenance value paths can be generated for turbines 1 and 2 in Figure 5-16.

5.3.2 Results from the Stochastic DCF approach and the European-style ROA approach

Assuming the predictive maintenance opportunity is once every hour, the selected predictive maintenance opportunity can be determined as shown in Figure 5-17. The stochastic DCF suggests 10.2 days (245 hours) after time t_0, with the expected predictive maintenance NPV of $10,479, and the European-style ROA approach suggests 8.5 days (205 hours) after time t_0 with the expected predictive maintenance option value of $11,850. Again, the European-style ROA approach provides a more conservative opportunity with the expected option value higher than the expected NPV from Stochastic DCF approach for 13.1% which is $1,371 in value.

Assume at t_0 = 7,500 hours when $CE(t_0)$ is 40,000 MWh, the results by the European-style ROA approach for the "best" and "worst" as-delivered cases, and the

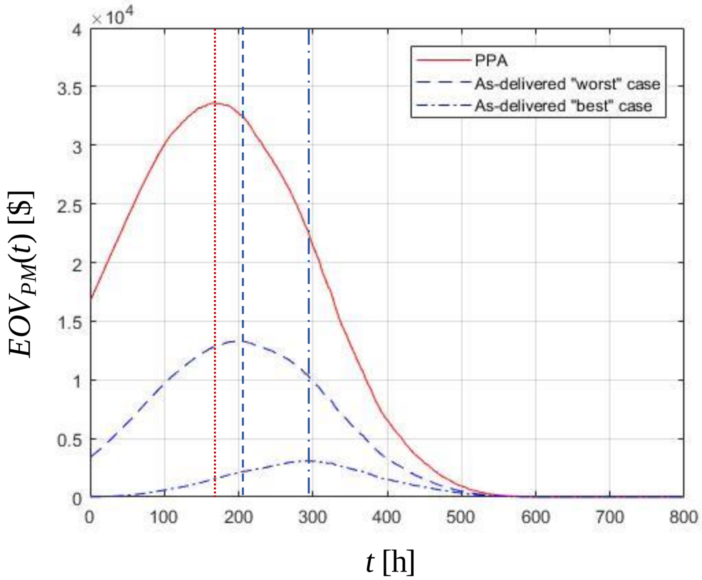

Figure 5-18: $EOV_{PM}(t)$ curves for wind turbines 1 and 2 in a wind farm managed using a PPA vs. using as-delivered payment models (predictive maintenance opportunity is once every hour).

result by the European-style ROA approach for the PPA case are shown in Figure 5-18 for comparison. The "worst" as-delivered case suggests to schedule the predictive maintenance at 8.5 days (205 hours) after time t_0, the "best" as-delivered case suggests 12.2 days (293 hours), while the PPA case suggests 6.9 days (165 hours). In the PPA case, at time t_0 the cumulative energy has been delivered by the whole farm is still far away from the annual target, besides there is one turbine not operating, therefore *ET* cannot be met (for many paths) if turbines 1 and 2 are run to failure for corrective maintenance, leading to under-delivery penalty. On the other hand, over-delivery is not going to happen if the predictive maintenance is implemented on turbines 1 and 2. Therefore in this specific example, because of the under-delivery penalty, compared with the as-delivered cases, the PPA case suggests to do the predictive maintenance earlier.

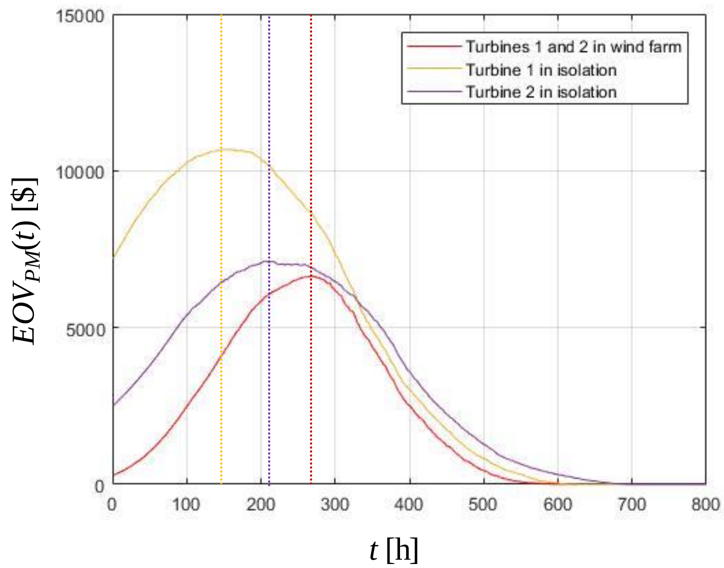

Figure 5-19: $EOV_{PM}(t)$ curves for wind turbines 1 and 2 in a wind farm managed using a PPA vs. wind turbines 1 and 2 managed in isolation using PPAs (predictive maintenance opportunity is once every hour).

Assume turbines 1 and 2 are managed in isolation using PPAs. The prices and *ET* are the same as previous single turbine farm case (1/5 of the wind farm case). At t_0 = 7,500 hrs of the year, $CE(t_0)$ = 9,000 MWh (1/5 of the wind farm case parameter given in Section 5.3.1), RULs are predicted for turbines 1 and 2. According to the European-style ROA approach, the selected predictive maintenance opportunity is 6.1 days (147 hours) after time t_0 for turbine 1 and 8.5 days (205 hours) after time t_0 for turbine 2, with the expected predictive maintenance option values to be $10,683 and $7,119 respectively as shown Figure 5-19. Alternatively, when the turbines are in a wind farm and there are no other wind turbines down, the European-style ROA approach suggests 11.2 days (269 hours) after time t_0 with the expected predictive maintenance option value of $6,647. In the wind farm case, the selected predictive maintenance opportunity is later, and the predictive maintenance option value is also lower than the two individual wind turbine cases. So the selected predictive

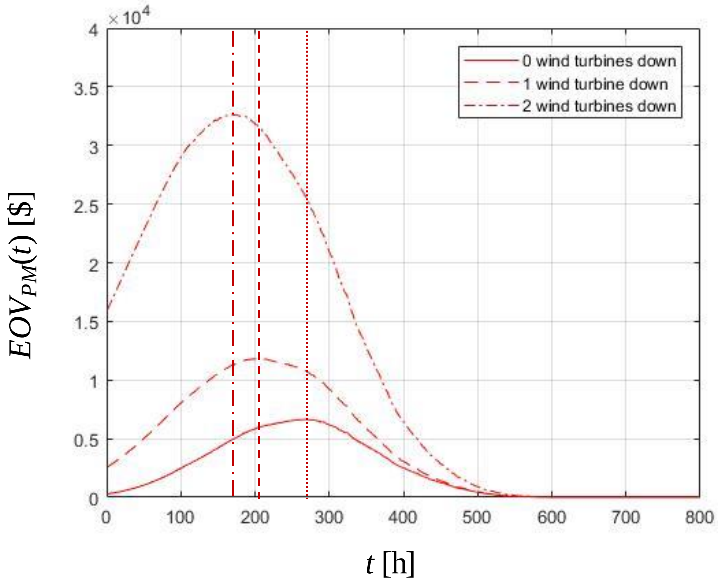

Figure 5-20: $EOV_{PM}(t)$ curves for wind turbines 1 and 2 in a wind farm managed using a PPA when there are other wind turbines down (predictive maintenance opportunity is once every hour).

maintenance opportunity can't be determined by simply treating those wind turbines with RULs as managed in isolation and adding up their results.

If there are different numbers of the turbines that are not operating at time t_0, the selected predictive maintenance opportunity by using the European-style ROA approach will also change as shown in Figure 5-20. In this specific example, the more non-operational turbines, the earlier that the selected predictive maintenance opportunity will be. The under-delivery will start to happen when one turbine is down, and when two turbines are down, considering the significant under-delivery penalty due to corrective maintenance, the selection of predictive maintenance opportunity will tend to be more conservative.

5.3.3 Conclusions from the wind farm case study

- For a wind farm under a PPA with multiple wind turbines indication RULs, the predictive maintenance value for each turbine depends on the operational state of the other turbines, the amount of energy delivered and to be delivered by the whole wind farm.
- The selected predictive maintenance opportunity for the multiple turbines indicating RULs in a farm managed using a PPA is not the same as the results for the individual turbines managed in isolation.
- The selected predictive maintenance opportunity for the turbines with RULs in a farm managed using a PPA may change when the number of the turbines down changes.

5.4 Interpreting the Cumulative Revenue Loss

This section constructs a simplified life-cycle scenario for a single wind turbine with no uncertainties, to interpret the cumulative revenue loss portion of the predictive maintenance value in the life-cycle.

Assume a single wind turbine life-cycle is a combination of multiple maintenance cycles (each maintenance cycle refers to the time period between two consecutive predictive or corrective maintenance events). Discount rate is ignored. PHM has been introduced to predict the system’s RUL, and there is only one predictive maintenance opportunity following each PHM indication (predictive maintenance downtime is ignored). If the predictive maintenance does not occur, after the system fails there will be a corrective maintenance event to restore the system to operation (corrective maintenance downtime is also ignored).

Assume the wind speed is constant during the life-cycle, therefore the rate at which the RUL is consumed is constant. Let t_{PHM} be the time from the maintenance event to the next RUL indication, t_{PM} be the time from the RUL indication to the predictive maintenance opportunity, and RUL_C be the predicted RUL in calendar time, which are all assumed to be constant, and $t_{PM} < RUL_C$.

Assume the revenue per unit time is u (the revenue rate), according to the definition of cumulative revenue loss, R_L for each predictive maintenance event can be calculated as

$$R_L = u(t_{PM} - RUL_C) \tag{48}$$

Assume both the predictive maintenance and corrective maintenance will be part replacement type that consume a spare part. Given a fixed number of maintenance cycles (e.g., fixed number of spare parts) N, if the predictive maintenance is always implemented, the life-cycle length is L_{PM}; if the corrective maintenance is implemented, the life-cycle length is L_{CM}. In this scenario $L_{PM} < L_{CM}$, because for each spare, a fixed portion of RUL will be thrown away. L_{PM} and L_{CM} can be calculated as

$$L_{PM} = N(t_{PHM} + t_{PM}) \tag{49}$$

$$L_{CM} = N(t_{PHM} + RUL_C) \tag{50}$$

The sum of the R_L in all N maintenance cycles is

$$NR_L = uN(t_{PM} - RUL_C) \tag{51}$$

which can also be represented as

$$NR_L = u(L_{PM} - L_{CM}) \tag{52}$$

If ignore all the other life-cycle cost components (e.g., preventive maintenance cost, installment cost, operation cost) except the predictive and corrective maintenance costs, the right-hand side of Eq. (52) is the difference between the life-cycle revenue earned by following the predictive maintenance policy and the life-cycle revenue earned by following the corrective maintenance policy. In other words, if the wind turbine is supported under either a predictive or corrective maintenance assumption with an identical number of spare parts, the corrective maintenance strategy allows the turbine to operate for an extra period of time L_{CM} - L_{PM}. This is graphically shown in Figure 5-21 (assume that both the last predictive and the last corrective maintenance event will still be implemented). Each arrow signifies an RUL indication, each triangular represents a predictive maintenance event and each diamond represents a corrective maintenance event.

5.5 Determination of the Life-Cycle Benefit

This section first applies a life-cycle benefit estimation to a single wind turbine with simplified assumptions and limited uncertainties considered, and then scales this model up to a wind farm level, to estimate the magnitude of the life-cycle benefit that

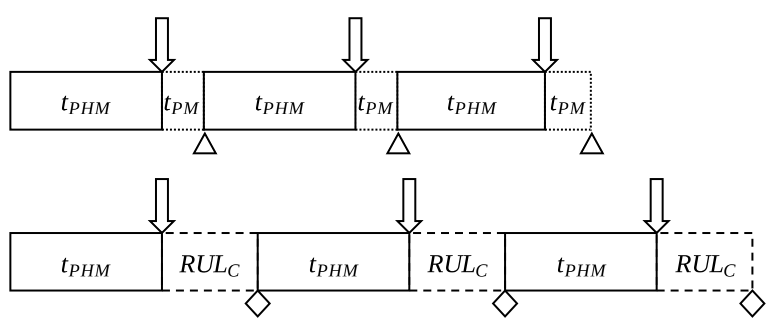

Figure 5-21: top: life-cycle of the predictive maintenance strategy, and bottom: life-cycle of the corrective maintenance strategy with same number of spare parts (e.g., N = 3).

the developed approach can bring to the wind farm owner compared with the state-of-art wind farm maintenance policies.

The previously developed approach valuates the portion of the RUL thrown away due to predictive maintenance as the cumulative revenue loss. It assumes the system life-cycle consists of a fixed number of maintenance cycles (e.g., a fixed number of spares), the length of each cycle may vary due to the uncertainties in the reliability and maintainability, therefore the system life-cycle length (in time) is also variable. Alternatively (more commonly) many existing wind farms managed using PPAs have a fixed time length of life-cycle (e.g., 20 years), which means the number of maintenance cycles (and spares) is not a constraint. Therefore in order to determine the life-cycle benefit, the construction of the predictive maintenance value of the developed approach needs to be adjusted. Similar to the approach described in Chapters 3 and 4, by implementing predictive maintenance prior to the end of RUL, corrective maintenance cost can be avoided, and the wind turbine can also earn revenue during the time period that the turbine would be down for corrective maintenance. However, predictive maintenance will result in a portion of the RUL thrown away and result in extra predictive maintenance events in the future.

Assume a single wind turbine is managed using an as-delivered payment model in an infinite horizon, therefore the influences of the installation and decommission phases of the life-cycle can be ignored. Time 0 is now defined as when the previous maintenance event was finished. Assume t_{PHM} (calendar time from time 0 to the RUL indication) is constant, and RUL_C (predicted system RUL in calendar time) follows a stationary distribution with the PDF as $h(\cdot)$ in the infinite horizon. Assume t_c (time from time 0 to the corrective maintenance opportunity) and DT (corrective maintenance downtime) are also constant in the infinite horizon.

If predictive maintenance is implemented at time t, where $t_{PHM} < t < ARUL_C$, the cumulative revenue earned from t to $t_c + DT$ is $CR_{PM}(t, t_c + DT)$; if the wind turbine is run to failure for corrective maintenance starting at time t_c, the cumulative revenue earned from t to $t_c + DT$ is $CR_{CM}(t, t_c + DT)$. So the cumulative revenue gained during the corrective maintenance downtime by implementing predictive maintenance at time t, $R_G(t)$, can be calculated as

$$R_G(t) = CR_{PM}(t, t_c + DT) - CR_{CM}(t, t_c + DT) \tag{53}$$

The avoided corrective maintenance cost by replacing corrective maintenance at time t_c after $ARUL_C$ with predictive maintenance at time t before $ARUL_C$, can be calculated as

$$C_A(t) = C_{CM} \tag{54}$$

The predictive maintenance value $V_{PM}(t)$ at time t, representing the extra value obtained by carrying out the predictive maintenance at time t rather than waiting for the corrective maintenance at time t_c, is defined as

$$V_{PM}(t) = R_G(t) + C_A(t) \tag{55}$$

The number of the extra predictive maintenance events as a result of the predictive maintenance at time t can be calculated as

$$EN_{PM}(t) = \frac{t_c + DT - t}{t} Probability(t_{PHM} + RUL_C > t) \tag{56}$$

The $Probability(\cdot)$ represents the probability that $t_{PHM} + RUL_C$ is longer than the predictive maintenance opportunity t, which can be calculated as

$$Probability(t_{PHM} + RUL_C > t) = \int_{t-t_{PHM}}^{\infty} h(\tau)d\tau \tag{57}$$

If assume that the predictive maintenance will always be implemented at some selected opportunity, by applying the stochastic DCF approach, the $NPV_{PM}(t)$ can be calculated as

$$NPV_{PM}(t) = \begin{cases} V_{PM}(t) - C_{PM}\left(1 + EN_{PM}(t)\right), & t_0 < t < t_0 + ARUL_C \\ 0, & t_0 + ARUL_C \leq t \leq t_c + DT \end{cases} \tag{58}$$

According to Eq. (26), at each predictive maintenance opportunity, the $ENPV_{PM}(t)$ can be obtained, and the predictive maintenance opportunity can be selected that generates the highest expected NPV.

A European-style ROA can also be applied to valuate the predictive maintenance option as

$$OV_{PM}(t) = \begin{cases} max\left(V_{PM}(t) - C_{PM}\left(1 + EN_{PM}(t)\right), 0\right), & t_0 < t < t_0 + ARUL_C \\ 0, & t_0 + ARUL_C \leq t \leq t_c + DT \end{cases} \tag{59}$$

Similarly, according to Eq. (28), at each predictive maintenance opportunity, the $EOV_{PM}(t)$ can be obtained, and the predictive maintenance opportunity can be selected that generates the highest expected option value.

After adjusting the developed stochastic DCF and the European-style option approaches for the PHM-based predictive maintenance scheduling for a single wind turbine managed using an as-delivered payment mode, now a case study is presented to estimate the magnitude of the life-cycle benefit.

For case study purposes, assume there is an offshore wind farm with two hundred Vestas V-164 8.0 MW offshore wind turbines [105] managed using an as-delivered payment model with the P_C of \$20/MWh in the Maryland Wind Energy Area

[102]. The hub height is assumed to be 100 m above sea level, and the Power Law parameter α is assumed to be 0.1 for the area [11]. The simulation step length is chosen to be 1-day. The 10-year (2003 to 2012) 10-minute average (5 m above sea level) wind speed data from station 44009 was converted into the daily average wind speed data, and the Weibull distribution parameters η and β of buoy height wind speed data were estimated to be 8.80 m/s and 3.10 respectively according to Eqs. (10) through (11). For simplicity, it is assumed the buoy height daily average wind speed is constant at the mean of the obtained Weibull distribution of 7.87 m/s. Then by using Eq. (12), the hub height daily average wind speed is constant at 10.62 m/s.

First, the case that a single wind turbine in the wind farm that predicts RUL in the infinite horizon is considered. In this case study it is assumed the mean of the Weibull time-to-failure distribution is 700 days (corresponding to a scale parameter of about 800 days if the shape parameter is 2),[5] t_{PHM} is assumed to be constant at 500 days, and RUL_C is predicted in a form of a stationary triangular distribution with the mean of 200 days and width of 380 days. There will be a corrective maintenance event starting at t_c = 893 days after time 0, causing a downtime DT of 7 days [86]. Corrective maintenance parts, service and labor cost is assumed to be $1,520,000, which is based on the data from [87] times a factor of 10, as the original cost data applies mainly for the 750 kW to 1 MW level wind turbines. Predictive maintenance parts, service and labor costs are assumed to be $1,368,000, which is 90% of the corrective maintenance

[5] The Weibull distribution has been widely used to model the modern wind turbine system field lifetime data [87][85][10], while due to the differences in the data sources, data processing procedures and so on, the Weibull distribution parameters vary significantly: the scale parameter for the Weibull distribution can vary from 100 days [85] up to 2,400 days [87].

parts, service and labor cost. 10,000 predictive maintenance value paths can be generated in Figure 5-22 according to Eqs. (53) to (55).

As shown in the left plot in Figure 5-22, all the $R_G(t)$ paths start at different points on the vertical axis: the shorter the $ARUL_C$ of the path is, the more extra cumulative revenue could be gained by implementing predictive maintenance rather than waiting for corrective maintenance, and therefore the higher the path's initial value. All the paths terminate at different time points when the $ARUL_C$ is used up, which represents the uncertainties in the predicted RUL. All the paths are also constant over time, since for each path the corrective maintenance downtime period is fixed. As can be seen in the middle plot in Figure 5-22, each $C_A(t)$ path is constant over time, and the combinations of the $R_G(t)$ and $C_A(t)$ paths according to Eq. (23), result in $V_{PM}(t)$ paths (see the right plot in Figure 5-22).

The selected predictive maintenance opportunities by both approaches are shown in Figure 5-23. According to the Stochastic DCF approach the suggested predictive maintenance opportunity is 183 days after time t_{PHM}, with the expected predictive maintenance NPV to be \$79,635. The European-style ROA approach suggests 167 days after time t_{PHM}, with the expected predictive maintenance option

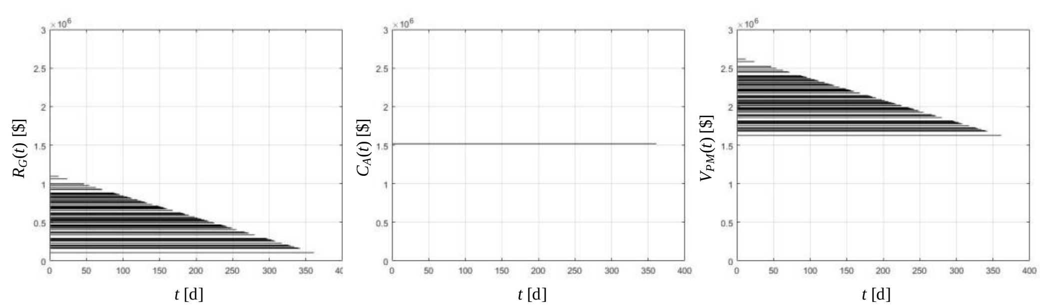

Figure 5-22: Left – $R_G(t)$ paths, middle – $C_A(t)$ paths, and right –$V_{PM}(t)$ paths for a single wind turbine managed using an as-delivered payment model (100 paths are shown).

value of \$90,511. Similar to the original approaches introduced in Chapter 3, the European-style ROA approach suggests an earlier predictive maintenance opportunity, with the expected predictive maintenance option value higher than the expected predictive maintenance NPV.

The next step is to estimate the life-cycle benefit brought by the developed approaches by comparing with other maintenance policies. Four maintenance policies are considered:

- Policy 1: corrective maintenance policy, which is purely "break-fix" type;
- Policy 2: predictive maintenance policy that applies the European-style ROA approach;
- Policy 3: predictive maintenance policy that applies the stochastic DCF approach;

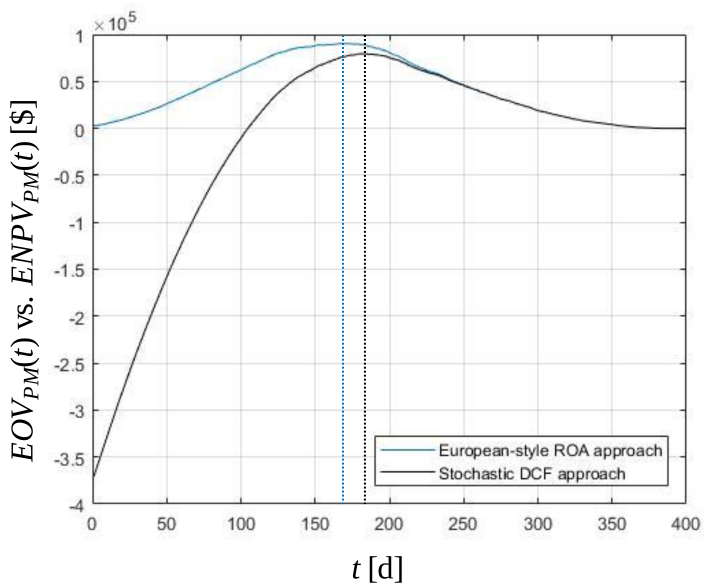

Figure 5-23: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single wind turbine managed using an as-delivered payment model (predictive maintenance opportunity is once every day).

- Policy 4: predictive maintenance policy that always chooses the earliest maintenance opportunity, which is common practice in most state-of-art wind farm maintenance modeling that consider predictive maintenance.

Preventive maintenance is assumed to happen on fixed time intervals for all the maintenance policies considered. Therefore, preventive maintenance practices are assumed to have an identical effect on the time-to-failure distribution or the predicted RUL equivalently for all the maintenance policies considered. The preventive maintenance cost is ignored in this analysis since it is a wash (same for all cases considered). Assume the wind farm is required to operate for 20 years and the length of each maintenance cycle in the corrective maintenance policy is constant at 900 days $t_{PHM} + tc + DT$ - to reach the 20-year life there will be 8 maintenance cycles. Following Policy 1, the expected net revenue for a single turbine in each maintenance cycle is \$462,630, which is the difference between the expected total wind energy revenue and the corrective maintenance parts, service and labor cost. The expected net revenues in each maintenance cycle following Policy 2 is \$553,141, which is the expected net revenue per maintenance cycle of Policy 1 plus the expected predictive maintenance option value \$90,511 at the suggested predictive maintenance opportunity by the European-style ROA approach. However, Policy 2 is expected to require an extra 2.8 predictive maintenance events in the 20-year life-cycle. Similarly, the expected net revenues per maintenance cycle by following Policy 3 is \$542,265, which is expected to require an extra 2.6 predictive maintenance events in the life-cycle. Finally, according to Figure 5-23, the black curve intercepts the vertical axis at -\$370,640, which implies that if one follows Policy 4, the expected net revenues per maintenance cycle will be \$91,990 = \$462,630 - \$370,640. Policy 4 is expected to result in 6.4 extra predictive maintenance events in the life-cycle. Assuming an annual discount rate of 7% [35], the discounted expected life-cycle net revenues of the four maintenance policies can be obtained as shown in Table 5-1.

Table 5-1: Single turbine discounted expected life-cycle net revenue of four maintenance policies.

Maintenance cycle	Policy 1 discounted expected net revenue [\$]	Policy 2 discounted expected net revenue [\$]	Policy 3 discounted expected net revenue [\$]	Policy 4 discounted expected net revenue [\$]
1st	377,644	451,528	442,650	75,091
2nd	329,849	394,382	386,627	65,588
3rd	269,255	321,933	315,603	53,539
4th	235,178	281,189	275,660	46,763
5th	191,975	229,534	225,021	38,173
6th	167,678	200,484	196,542	33,341
7th	136,876	163,654	160,437	27,217
8th	119,552	142,942	140,132	23,772
Discounted expected life-cycle net revenue [\$]	**1,828,006**	**2,185,646**	**2,142,671**	**363,483**

As can be seen from Table 5-1, Policy 2 leads to the highest discounted expected life-cycle net revenue as \$2,185,646, followed by Policy 3 with \$2,142,671. The former is \$357,639 (19.6%) higher than the Policy 1, while the latter is \$314,665 (17.2%) higher. The difference between Policy 2 and 3 is \$42,975, which is the value of the managerial flexibility. Policy 4 has the least discounted expected life-cycle net revenue, because it causes the most expected number of maintenance events in the life-cycle, and the predictive maintenance parts, service and labor cost is relatively expensive (90% of the corrective maintenance parts, service and labor cost).

The life-cycle benefit numbers estimated above are for a single turbine, based on which the life-cycle benefit for the whole wind farm with two hundred wind turbines can be estimated. Assume the wind turbine time to unexpected failure (e.g., the failure that cannot be predicted by the PHM) follows a Weibull distribution with a shape parameter of 3 and a scale parameter of 2,400 days [87]. The downtime for the corrective maintenance for the wind turbine fails unexpectedly is assumed to be fixed at 42 days [76]. Therefore, by applying the DES in a long horizon (e.g., 200 years), the average number of the wind turbines that are down unexpectedly in the infinite horizon can be roughly approximated to be 4. Therefore, for an offshore wind farm managed using an as-delivered payment model, a simple scaling (multiply by 196) is performed assuming that all the other operational turbines are identical. The expected life-cycle net revenues of the four maintenance policies for the entire wind farm are shown in Table 5-2. Policy 2 is $70,097,314 higher than Policy 1, while the Policy 3 is $61,674,267 higher than Policy 1. The difference between Policy 2 and 3 is $8,423,047, which is the value of the managerial flexibility.

Table 5-2: Wind farm discounted expected life-cycle net revenue of four maintenance policies.

	Discounted expected life-cycle net revenue [$]			
	Policy 1 **CM**	**Policy 2** **PM by ROA**	**Policy 3** **PM by DCF**	**Policy 4** **PM @ earliest opportunity**
Single turbine	1,828,006	2,185,646	2,142,671	363,483
Wind farm	358,289,274	428,386,588	419,963,541	71,242,743

If P_C is $131.93/MWh [106], which is the Maryland Offshore Renewable Energy Credit (OREC) energy price, the selected predictive maintenance opportunities

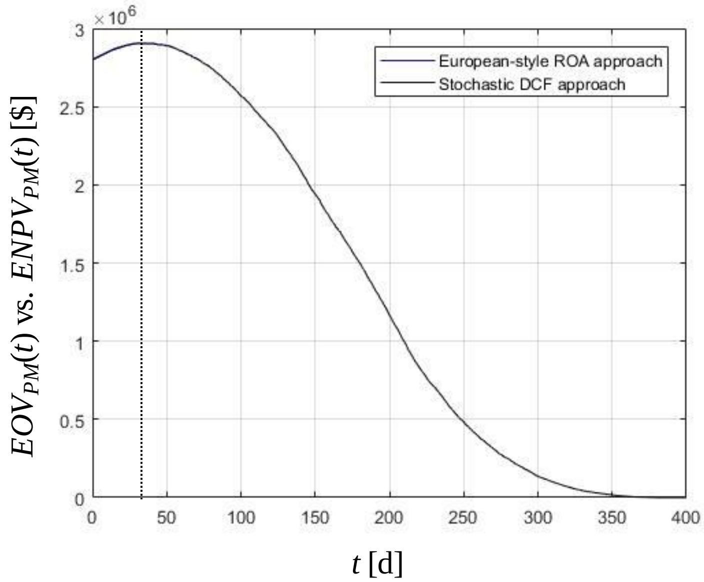

Figure 5-24: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single wind turbine managed using an as-delivered payment model with high P_C (predictive maintenance opportunity is once every day).

by both approaches are shown in Figure 5-24. The single turbine and the wind farm level life-cycle benefits can be estimated as shown in Table 5-3.

Table 5-3: Wind farm discounted expected life-cycle net revenue of four maintenance policies with high P_C.

	Discounted expected life-cycle net revenue [$]			
	Policy 1 CM	**Policy 2 PM by ROA**	**Policy 3 PM by DCF**	**Policy 4 PM @ earliest opportunity**
Single turbine	45,669,540	57,154,888	57,143,824	56,739,997
Wind farm	8,951,229,769	11,202,357,954	11,200,189,461	11,121,039,463

As can be seen from Table 5-3, Policy 2 still leads to the highest discounted expected life-cycle net revenue, followed by Policies 3 and 4. Because of the high earning rate, Policies 2 and 3 suggest the same predictive maintenance opportunity, and Policies 2, 3 and 4 all lead to similar discounted expected life-cycle net revenue about 25% higher than Policy 4.

In all the results presented in this section so far, the as-delivered payment model has been assumed, according to which the revenue earning for each wind turbine is independent and scaling by multiplying the number of all operational wind turbines provides a reasonable estimate of the wind farm level life-cycle benefit. When the whole farm is managed using a PPA, this simple scaling may not be correct. As has been discussed in Section 5.1 to 5.3, the over-delivery and under-delivery penalties brought by the PPA, and the operational status of all the other turbines in the farm will affect the selection of the predictive maintenance opportunities. For example according to Figure 5-20, if there will always be enough operational turbines in the farm to fulfill the annual energy delivery target (the case of the red solid line), the expected predictive maintenance option value at the selected may be relatively low. In this case, scaling by multiplying the single turbine's life-cycle benefit by the number of operational turbines (e.g., 196) may be an over-estimation. On the other hand, if it is common in the life-cycle that many turbines are down in the farm, and without restoring the turbines indicating RULs to operation, the annual energy delivery target cannot be met (the case of the dash-dot line in Figure 5-20), the expected predictive maintenance option value at the selected predictive maintenance opportunity may be quite high, and the simple scaling may lead to under-estimation of the value.

The objective of this section was to establish an estimate of the value of the approaches developed in this dissertation. Determination of the exact wind farm level value is complex and out of the scope of this dissertation, see Section 6.5.

Chapter 6: Summary, Expected Contributions, and Suggestions for Future Work

6.1 Summary

In this dissertation, a simulation-based methodology was developed to schedule the predictive maintenance for wind farms managed using PPAs when multiple turbines are indicating RULs from PHM. The target in the PHM-based predictive maintenance scheduling problem is to maximize the net revenue that could be earned in the maintenance cycle, which equals to the difference between the cumulative revenue and the maintenance cost. When a replacement-type predictive maintenance is implemented on a wind turbine system based on its RUL indication prior to the actual system failure, a portion of the RUL is thrown away that can be valuated as the cumulative revenue loss, representing the cumulative revenue shortage compared with waiting for corrective maintenance. However corrective maintenance, i.e., a break-fix type maintenance practice, is typically more expensive than the predictive maintenance. Therefore, to maximize the net revenue in the maintenance cycle, the fundamental tradeoff is to minimize the risk of ending up with the expensive corrective maintenance (which increases as the RUL is used up) while minimizing the value of the portion of the RUL thrown away (which decreases as the RUL is used up).

A European-style ROA approach was developed to schedule the PHM-based predictive maintenance, which identifies the maintenance decision-maker's managerial flexibility to only schedule the predictive maintenance if it is more beneficial (generates more net revenue in the maintenance cycle) than the corrective maintenance. The

European-style ROA approach valuates the European-style predictive maintenance option expiring at all the possible predictive maintenance opportunities, and selects the opportunity with the highest expected predictive maintenance option value. For comparison purpose, a stochastic DCF approach was also established that assumes the predictive maintenance has to be implemented at the selected opportunity even if it is less beneficial than waiting for corrective maintenance (no managerial flexibility). The over-delivery pricing and the under-delivery penalizing mechanisms in the PPA are modeled, and the uncertainties in the RUL predictions as well as the future wind speeds are considered in both approaches.

Case studies for a single wind turbine managed using a PPA, demonstrate that the developed European-style ROA approach suggests waiting for some time to implement the predictive maintenance, rather than implementing the predictive maintenance immediately after the PHM indication or waiting until closer to the end of the RUL. Because of the predictive maintenance option's flexibility to expire if implementing predictive maintenance is less beneficial than running the wind turbine to failure for corrective maintenance, the European-style ROA approach always has an expected option value that is greater than or equal to the expected NPV from the stochastic DCF approach. For the same reason, the ROA approach always suggests a maintenance opportunity that is no later than the stochastic DCF approach. When a PPA is used, the PPA over-delivery lower price tends to shift the selected predictive maintenance opportunity to a later time, while the PPA under-delivery penalty does the opposite – shifts the selected predictive maintenance opportunity to an earlier time.

When a wind farm managed using a PPA has multiple wind turbines indicating RULs concurrently, the predictive maintenance value for these turbines depends on the operational state of the other turbines, the amount of energy delivered and to be delivered by the whole wind farm. The selected predictive maintenance opportunity is not the same as the results for the individual turbines managed in isolation, and also differs when the number of the turbines down (not operational) changes. When there are many turbines not operating in the wind farm, the cumulative revenue loss and under-delivery penalty could be significant; therefore, the selection of the predictive maintenance opportunity tends to be more conservative.

Finally, a life-cycle benefit estimation on wind farm level is presented with simplified assumptions and limited uncertainties considered, to estimate the magnitude of the life-cycle benefit that the developed approaches can bring to the wind farm owner compared with the state-of-art wind farm maintenance policies. To accommodate the common fixed PPA term length requirement (e.g., 20-year), an adjustment has been made to the developed approaches by valuating the RUL thrown away as extra predictive maintenance events during the life-cycle. The expected benefits by applying the adjusted approaches are first estimated on a single wind turbine for a single maintenance cycle, which is then extended to an entire 20-year life-cycle, and finally scaled up to the whole wind farm. The wind farm 20-year life-cycle benefits are compared with the state-of-art wind farm maintenance policies, to demonstrate the capability of the developed PHM-based wind farm predictive maintenance scheduling approaches to improve the wind farm owners' profitability.

In this dissertation, when an RUL prediction is triggered, the developed approach is applied to select the predictive maintenance opportunity, then the predictive maintenance decision is made and the analysis ends. In reality the RUL prediction is dynamic and can be continuously updated as new information becomes available. When an updated RUL is obtained, the developed approach can be applied again to update the predictive maintenance opportunity selection as well. This process can continue until the minimum lead-time (prior to a maintenance opportunity) is reached.

Although an offshore wind farm is assumed and the offshore wind speed historical data is used in the case study, the methodology could easily be applied to an onshore wind farm as well.

It is assumed the wind farm owners have to pay for the maintenance, however they can also choose to purchase a contract from the manufacturer or a third party. Some wind turbine manufacturers claim that they can provide the "all-in-service" type Performance-Based Maintenance Contracts (PBMCs), which includes the availability or production-based guarantees.[6] If the performance guarantees are not met the manufacturer will pay compensations, and if the guarantees are exceeded the extra revenue will be shared between the wind farm owner and the manufacturer [107]. Therefore, by modeling the revenue share properly and making other necessary changes, the methodology can also be applied by the manufacturer to optimize the predictive maintenance opportunity.

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[6] PBMCs are not common. There are very few PBMCs in use today.

If the wind farm outputs are not managed under a PPA, but traded in a pool-based local market directly, the predictions of the variable hourly prices and production schedules from the market can to be used to simulate the predictive maintenance value, which are also subject to uncertainties.

6.2 Contributions

The contributions of this work include:

1. This dissertation is the first known wind farm predictive maintenance modeling work to integrate an outcome-based contract into the model.
2. This dissertation developed a new European-style ROA approach to valuate the PHM-based predictive maintenance option at a series of possible maintenance opportunities by considering the uncertainties in the RUL predictions and the future wind speeds.
3. This dissertation is the first known work to demonstrate scheduling of the predictive maintenance opportunity for multiple wind turbines with RULs in a wind farm by maximizing the expected PHM-based predictive maintenance option value.
4. This dissertation demonstrates that the optimum predictive maintenance timing for a system in isolation is NOT the same as the optimum predictive maintenance timing for a system that is a member of a population that is managed under an outcome-based contract.

6.3 Potential Broader Impacts

The proposed PHM-based predictive maintenance scheduling methodology based on European-style ROA enables the new capabilities to: a) combine the outcome-case contracts into the maintenance modeling problem as inputs; b) perform the real time PHM-based predictive maintenance scheduling decision support; c) select the predictive maintenance opportunity for a fleet of systems.

The outputs from the methodology (e.g., the life-cycle revenue and O&M costs) can be applied to select the appropriate maintenance policy in the wind farm planning phase, to improve the PHM design in the wind turbine design phase (e.g., to optimize the threshold to trigger the RUL prediction) and to optimize the outcome-based contract items (e.g., to adjust the over-delivery price). The methodology can also be extended to other industries that have a fleet of systems under an outcome-based contract and with PHM integrated. See Appendix A for preliminary work on extending the developed approach to the non-production systems managed using availability-based contracts.

6.4 Real Options Analysis Terminology

Real options analysis theory originates from financial options. While real options has been applied to a range of engineering problems, the fundamental options assumptions, listed in Table 6-1, are questionable, and approaches, such as the Black-Scholes and the Binomial Lattice, may not be applicable for solving real world engineering problems.

Table 6-1: Problems with the application of real options analysis assumptions to engineering problems.

Assumptions that real options "borrow" from financial options	**Problems with these assumptions when options are used to solve engineering problems**
Past events do not affect the future, e.g., random walk – Brownian motion	Past events may affect future, e.g., cycles and/or mean reversion
Path independence (recombing assumption in Binomial Lattice is based on it)	Path independence may not hold
Full information on the market exists with no arbitrage	No market exists, therefore the no-arbitrage assumption is dubious
Risk-neutral probability + risk-free discount rate	Objective probability + risk-adjusted discount rate (e.g., Weighed Average Capital Cost (WACC))

Researchers have realized these problems [108]–[110]. de Neuville developed a simulation-based decision-making methodology based on the managerial flexibility different from the "classic" real option analysis, and used the name "flexibility" [110].

The European-style ROA approach used in this dissertation is actually a simulation-based approach that samples from the objective probability and applies the risk-adjusted discount rate, therefore it does not rely on the "classic" real options analysis theory or depend on the assumptions in Table 6-1. The best description of the approach developed in this dissertation is a decision-tree analysis (DTA) type approach with European-style option valuation, which is consistent with the "flexibility" analysis defined in [110]. As there is an on-going debate about what actually defines "real options", this dissertation uses the term of "ROA" to reflect that it is based on the managerial flexibility.

6.5 Future Work

The current life-cycle benefit study is based on simplified assumptions and limited uncertainties considered, which are used for estimating the magnitude of the life-cycle benefit brought by the developed approaches compared with other state-of-art maintenance policies and models. Only the as-delivered payment model is considered, the situation that multiple wind turbines indicating RULs concurrently hasn't been considered. Besides, the choice of the discount rate (e.g., the WACC) hasn't been addressed, which may change over the time horizon. Therefore in order to estimate an accurate life-cycle benefit, in the future it is expected to integrate the PPA into the study, track the operational status of all wind turbines in the farm (the situation that more than one wind turbines indicate RULs at the same time may occur) through DES, and determine the proper discount rate to use.

There are also multiple ways for the developed approaches to be further improved:

- In the developed approach the expected predictive maintenance option values at all possible maintenance opportunities are compared. At each predictive maintenance opportunity, all simulated predictive maintenance option values form an asymmetric distribution. The impacts of different attitudes toward risks on the predictive maintenance opportunity selection can be studied. One possible way is to assume the maintenance decision maker is risk averse, and only willing to implement the predictive maintenance once the predictive maintenance value exceeds a pre-determined threshold higher than the predictive maintenance parts, service and labor cost. This will make the predictive maintenance option a "barrier" option type [78]. Another possibility is to compare the predictive maintenance opportunities based on the "worst cases” that lead to low or even zero predictive maintenance values through the Conditional Value At Risk.

- The dependencies among wind turbines in a farm caused by the layout of the farm can be considered. For example, in reality there can be multiple wind turbines connected in series to a substation, and performing maintenance on any of them results in the shut down of all the other turbines.
- For the future wind speed simulation, the wind speed spatial/time correlation models can be considered [111]. For example, seasonal differences can be integrated into the simulation of the wind speeds.
- The collateral damage on multiple subsystems, which may cause the wind turbine system to fail faster and the predictive and corrective maintenance costs to be higher, can also be modeled.
- The revenue earning model can consider the possible degradation in the power generation capacity caused by the damage accumulation.
- The uncertainties in the predictive maintenance opportunities caused by the weather (e.g., the wave height for offshore wind farm), the availability of the maintenance crew, equipment, spare parts etc., can also be considered.

The work to extend the developed approaches to the non-production systems managed using the availability-based contracts is expected to continue. For example, a contract model like the PPA model developed in Chapter 4 is needed to reflect the reasonable pricing, payment and penalizing mechanisms in the modern availability-based contracts. See the Appendix for preliminary analysis of non-production systems.

Appendix: PHM-Based Predictive Maintenance Scheduling for Non-Production Systems Managed Using Availability-Based Contracts

This appendix extends the PHM-based predictive maintenance scheduling approach for wind farms managed using PPAs developed in Chapter 3 and 4, to non-production systems managed using availability-based contracts. Availability-based contracts for non-production systems are used to manage fleets of system where the value delivered by the system is their operational availability, e.g., fleets of rental cars, bus systems, airlines, and military systems.

Introduction

Product service systems and outcome-based contracts

The impact of a contract oriented design processes on original equipment manufacturer (OEM) decision making for optimizing reliability in the post-production purchase period led to the development of integrated schemes with dynamic interdependencies of product and service, called product-service systems (PSSs) [112]. Product Service Systems (PSS) [112], [113] is a common product management approach that can include elements of performance contracting. PSS provides both the product and its service/support based on the customer's requirements, which could include an availability requirement. The product-service system (PSS) industry deals with complex systems with stochastic features that have significant influence throughout the life-cycle of the system, therefore the development and implementation of best-value, long-term, performance-based product-support strategies is required [114]. Hence, an effective combination of technical and monetary approaches that includes the inventory, maintenance, and operational decisions together to form a unified model that provides visibility into the effect of different parameters is required [115]. The PSSs are increasingly being provided and managed via outcome-based contracts in which the customer purchases the outcome of the product (rather than purchasing the product and/or purchasing specific product support activities).

Outcome-Based Contracts (also referred to in the literature as "Performance Contracting" [116], "Performance-Based Service Acquisition (PBSA)" [117], "Performance-Based Logistics (PBL)" [118], and "Performance-Based Contracting" [119]) refers to a group of strategies for system support that instead of contracting for goods and services/labor, a contractor delivers performance outcomes as defined by performance metric(s) for a system under contract.[7] The fundamental idea behind outcome-based contracting is reflected in a famous quote from Theodore Levitt [34]: "The customer doesn't want a drilling machine; he wants a hole-in-the-wall." Outcome-based contracts, pay for effectiveness (availability, readiness or other related performance measures) at a fixed rate, penalize performance shortcomings, and/or award gains beyond target goals.

Outcome-based contracts distinguish from other common contract mechanisms that are applied to the support of products and systems as shown in Table Appendix-1. Outcome-based contracts are not warranties [120], [121], lease agreements [122] or

[7] In this dissertation outcome-based will be used to infer general contracts that may or may not use availability as their key performance measure, and availability-based when the performance measure is actually an availability.

maintenance contracts [123], which are all break-fix guarantees. Rather outcome-based contracts are quantified "satisfaction guaranteed" contracts where "satisfaction" is a combination of outcomes received from the product, usually articulated as a time (e.g., operational availability, readiness), usage measure (e.g., miles), or an energy-based availability. In a common maintenance contract with a pay-per-replacement/repair agreement, an OEM has no incentive to change the system design to make the system more reliable or maintainable. In fact, the service operator might benefit from the system being less reliable. Alternatively, with an outcome-based contract mechanism where the customer only pays for the time that the system delivers the expected outcome (e.g., the system is operational), both the service provider and the OEM are motivated to improve the system reliability (and maintainability) [124]. Lease contracts [97] are use-oriented PSS where the ownership of the product is usually retained by the service provider. A lease contract may indicate not only the basic product and service provided; but also, other use and operation constraints such as the failure rate threshold. In leasing agreements, the customer has an implicit expectation of the outcome (e.g., a minimum availability), but not quantified contractually.

Table Appendix-1: Common contract mechanisms applied to the support of products and systems.

Contract mechanism	**Examples**	**Key Characteristics**	**Support Provider Commitment**
Break-fix guarantee	Common warranties Leases Maintenance contracts	Definition of, or threshold for, failure	Replace or repair on failure
Satisfaction guarantee	Warranties Leases	Satisfaction is not quantified	Replace or repair if not satisfied
Outcome guarantee	Outcome-based contracts	Carefully quantified "satisfaction"	Provider has autonomy to meet required outcomes any way they like

Availability-based contract (also referred to as "Availability Contracting", Contract for Availability (CfA) [125]), as a subset of outcome-based contracts, originated because in many cases customers with high availability requirements are interested in buying the availability of a system, instead of actually buying the system itself [33]. In this class of contract, the customer pays for the delivered availability, instead of paying for specific logistics activities, system reliability managements, or other tasks. Examples of availability-based contracts include the Availability Transformation: Tornado Aircraft Contract–ATTAC [125], which includes cost penalties that are evaluated for failing to fulfill a specified availability requirement in a defined time frame. Rolls-Royce introduced power-by-the-hour for its aircraft engines where maintenance, repair, and overhaul of the engines are all charged per hour of flight [125].

Besides the availability-based contracts, there are also other types of the outcome-based contracts, such as the PPAs which were introduced in Section 1.2. An alternative outcome-based contract mechanism called public-private partnerships (PPPs) has been used to fund and support civil infrastructure projects. Public-private partnerships (PPPs) have been used to fund and support civil infrastructure projects, most commonly highways [19]. Availability payment models for civil infrastructure PPPs require the private sector to take responsibility for designing, building, financing, operating, and maintaining an asset. Under the "availability payment" concept, once the asset is available for use, the private sector begins receiving an annual payment for a contracted number of years based on meeting performance requirements [20]. The challenge in PPPs is to determine a payment plan (cost and timeline) that protects the public interest, i.e., does not overpay the private sector; but also, minimizes the risk that the asset will become unsupported [21].

Production vs. non-production systems

Every contract has two sides: the customer who is the recipient of (and pays for) a specific level of outcome (e.g., availability) over the period of the contract, and the contractor who provides the outcome for the period of the contract. From the customer's viewpoint, there are revenue-earning systems from which the customer derives revenue (the outcome translates into customer revenue); and there are non-revenue-earning systems from which the customer does not derive revenue (the customer's value is mission completion). Revenue-earning and non-revenue-earning are customer distinctions, from the contractor's viewpoint, every contract is revenue earning (if it wasn't there would be no contract). Systems can also be distinguished based on the form of the outcome. For production systems the contractor's compensation is determined by a payment schedule that is based on the amount or quantity of outcome the system produces. For non-production systems, the contractor's compensation is determined by a payment schedule that is typically based on the availability of the system. Examples of the production vs. non-production systems are shown in Table Appendix-2

Table Appendix-2: Examples of production/non-production systems.

Example System	Contractor	Customer	Outcome for the Customer	Customer Value	Customer View	Contractor View
Wind farm	Wind farm owner	Utility company	Energy	Energy they can sell to their customers	Revenue earning	Production
Parking management	Towing company	Municipal government	Illegally parked cars removed	Managed parking	Non-revenue Earning	Production
Commercial aircraft engine	Engine manufacturer	Airline	Engine availability	Passengers they can fly or retain	Revenue earning	Non-production
Military aircraft engine	Engine manufacturer	Military	Engine availability	Successful mission completion	Non-revenue Earning	Non-production

Review of Maintenance Models Under Availability-Based Contracts

Researchers have studied planning and decision making under availability-based contracts in many different areas (e.g., maintenance, supply chain, logistics, and inventory management) and for many different applications (e.g., defense, avionics, railroads, infrastructure, and energy) [126]. Recently, there has been a significant amount of research that models and/or optimizes the maintenance for the systems managed under availability-based contracts. The inventory of a repairable system operating under an availability-based contract with an availability target is modeled as an M/M/m queue in [127]. Only the corrective maintenance strategy is considered, and the authors conclude that to improve the operational availability of the system, the contractor should improve the component reliability and the repair facility efficiency. In [128] a model is introduced to determine the optimal management of the spare parts inventory within the an availability-based contract which defines the availability as the expected outcome. Assuming an imperfect maintenance strategy within a finite horizon, the developed decision-making procedure maximizes the total expected profit for both the customer and the contractor, by optimizing the preventive maintenance interval together with the critical spares stock level. A game-theoretical approach for designing a availability-based contract by maximizing the customer's profitability, lowering the contractor's levelized cost, and ensuring the system availability is proposed in [129], by jointly optimizing the preventive maintenance interval, the spares inventory, and the repair capacity. The effects of the preventive maintenance cost functions on the optimal preventive maintenance policy for a leased product is investigated in [97], [122]. The optimal preventive maintenance schedule and the maintenance degrees are derived to minimize the contractor's expected total cost. The preventive maintenance cost is assumed to be either constant or linearly increasing.

Some models include the predictive maintenance strategy based on condition monitoring technologies indicating health degradations. In [130], the impact of the availability-based contracts on the condition-based maintenance decisions for repairable systems is examined. Periodic inspection is implemented for a system experiencing a stochastic health degradation process, and the system will be maintained predictively if the deterioration level is above the maintenance threshold. Contractor's rewards depends on the average availability according to the contract, and a profit-centric approach has been developed to maximize contractor's net revenue by optimizing the inspection interval together with the maintenance threshold. In [131] a condition-based maintenance policy for a single-component system operating under an availability-based contract is studied. Failures of this system can only be revealed by the periodic inspections, and the maintenance errors caused by imperfect repairs are considered. The objective of the developed model is to maximize the expected net revenue of the contractor by optimizing the inspection interval, and a case study on a wind turbine is provided. These models determine the number of condition monitoring based predictive maintenance events, but the actual timing of the predictive maintenance events cannot be modeled.

There have been maintenance optimization studies performed using simulation-based models considering outcome-based contracts. For example DES techniques have been used in an integrated model to optimize the payment and contract duration by incorporating the effects of condition changes, uncertainties, and required availability of infrastructure for PPPs [132]. This work resulted in obtaining an improved procurement and system acquisition model in which the system availability was chosen as the objective to meet contract requirements. However there are very few simulation-based maintenance models existing that consider the availability-based contracts, one example is [133] that investigates a DES-based approach to calculate the system availability considering four performance drivers: the lifetime distribution, the repair time distribution, the spare parts inventory and the repair facility. A preventive maintenance strategy is considered. By optimizing these four performance drivers, the total cost of the contractor under the outcome-based contract is minimized.

PHM-Based Predictive Maintenance Scheduling for Non-Production Systems Managed Using Availability-Based Contracts

Single system managed using an availability-based contract

To develop the PHM-based predictive maintenance scheduling approach, first a contractor revenue model under an availability-based contract is needed. One real availability-based contract example is the Integrated Merlin Operational Support (IMOS) contract signed by the Agusta Westland (AW) and the Ministry of Defence (MoD) in 2006 lasting for 25 years [125], for the through-life support for the entire MoD EH101 Merlin fleet with more than 40 helicopters. During the contract term, AW (the contractor) gets paid by the MoD (the customer) for each flying hour achieved by each member of the fleet at a fixed price. There is an annual fleet flying hour target set at the beginning of each year, which reflects the customer's requirement for the operational availability of the whole fleet. By the end of that year, if the annual fleet flying hour target is exceeded, the contractor will get bonus based on the amount of the excess flying hours provided; if the target is not met, the contractor will be penalized based on the shortfall amount. There is also a material availability target that requires a minimum number of operational helicopters, and if the actual number of operational helicopters becomes lower than the target anytime of the year, there will be a penalty to the contractor as well.

Assume a single system (e.g., a helicopter) with embedded PHM is managed using an availability-based contract between a contractor (e.g., the manufacturer of the helicopter) and a customer (e.g., the military), in which the availability is contracted as the measurable outcome, and the contractor is responsible for all the maintenance activities. The system will only operate in the missions assigned by the customer. In each mission, the customer only pays a fixed contract price P_C to the contractor for each unit of time that the system is operating (e.g., a flying hour). An operating time target FT is set in the contract for each of the outcome measurement window (e.g., an annual flying hour target for a year). By the end of the outcome measurement window, if the actual operating time provided by the contractor is lower than the target, a penalty on the contractor is calculated as the difference times P_C. If the target is exceeded during the window, a constant excess price P_E higher than P_C applies for all operating time provided thereafter till the end of the window. There is also a material availability penalization mechanism defined in the contract: for each unit of time during a mission, if the system is non-operational, the contractor has to compensate the customer for a fixed price of P_A.

Assume at time t_0 of the simulation time period, the system is indicating an RUL in calendar time (RUL_C) will fail before the end of the simulation time period T (e.g., end of the year) if the predictive maintenance is not implemented. A distribution is assumed to represent the RUL uncertainty, and RUL_F is assumed to be the mean of the distribution. The Monte Carlo simulation can be used to simulate M $ARUL_C$ samples.

From t_0 to T there are multiple predictive maintenance opportunities, and the decision-maker wants to decide which predictive maintenance opportunity should be scheduled. If the predictive maintenance is not implemented, there will be a corrective maintenance event at time t_c to fix the failed system and restore it to operational status. The corrective maintenance will cause a downtime of DT, and will be finished before

T. There is a mission starting at time $t_m > t_0$ which is known with no uncertainty, and will not end before T. The system can quite the mission for predictive or corrective maintenance, however there will be penalties. Assume outside the mission the RUL will not be consumed, therefore t_m - t_0 will be added to the simulated M $ARUL_C$ samples to represent the actual time to failure.

The next step is to develop a revenue calculation model. Assume the downtime for predictive maintenance is negligible. If the predictive maintenance is going to be implemented, the number of unit operating time (e.g., number of flying hours if simulation step is 1-hour) from time τ-1 to τ can be calculated as

$$F_{PM}(\tau) = \begin{cases} 1, & t_m < \tau \leq T \\ 0, & t_0 < \tau \leq t_m \end{cases} \tag{60}$$

The revenue generated from time τ-1 to τ, $R_{PM}(\tau)$ can be calculated as

$$R_{PM}(\tau) = F_{PM}(\tau)P_{PM}(\tau) \tag{61}$$

where $P_{PM}(\tau)$ is the price with predictive maintenance implemented, defined as

$$P_{PM}(\tau) = \begin{cases} P_C, & CF_{PM}(\tau) \leq FT \\ P_E, & CF_{PM}(\tau) > FT \end{cases} \tag{62}$$

$CF_{PM}(t)$ is the cumulative operating time from time 0 (the beginning of the outcome measurement window) to time t_0, can be calculated as

$$CF_{PM}(t) = CF(t_0) + \sum_{\tau=t_0+1}^{t} F_{PM}(\tau) \tag{63}$$

where $CF(t_0)$ is the cumulative operating time from time 0 to time t_0.

The cumulative revenue earned from time τ_1 to τ_2 $CR_{PM}(\tau_1, \tau_2)$ can be calculated as

$$CR_{PM}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{PM}(\tau) \tag{64}$$

Similarly, if the predictive maintenance is not performed, when the system fails at $ARUL_C$, it will be non-operational (i.e., down) for a corrective maintenance event starting at time t_c, and finishing at time t_c+DT. The number of unit operating time from time τ-1 to τ can be calculated as

$$F_{CM}(\tau) = \begin{cases} 1, & t_m < \tau \leq ARUL_C \\ 0, & t_0 < \tau \leq t_m \; or \; t_c + DT < \tau \leq T \end{cases} \tag{65}$$

The revenue generated from time τ-1 to τ, $R_{CM}(\tau)$ can be calculated as

$$R_{CM}(\tau) = F_{CM}(\tau) P_{CM}(\tau) \tag{66}$$

where $P_{CM}(\tau)$ is the price with predictive maintenance not implemented, defined as

$$P_{CM}(\tau) = \begin{cases} P_C, & CF_{CM}(\tau) \leq FT \\ P_E, & CF_{CM}(\tau) > FT \end{cases} \tag{67}$$

$CF_{CM}(t)$ is the cumulative operating time from time 0 (the beginning of the outcome measurement window) to time t_0, can be calculated as

$$CF_{CM}(t) = CF(t_0) + \sum_{\tau=t_0+1}^{t} F_{CM}(\tau) \tag{68}$$

The cumulative revenue earned from time τ_1 to τ_2 $CR_{CM}(\tau_1, \tau_2)$ can be calculated as

$$CR_{CM}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{CM}(\tau) \tag{69}$$

The cumulative revenue loss by implementing predictive maintenance at time t, $R_L(t)$, can be calculated as

$$R_L(t) = CR_{PM}(t_0, t) - CR_{CM}(t_0, t_0 + ARUL_C) \tag{70}$$

The avoided corrective maintenance cost by replacing corrective maintenance at time t_c after $ARUL_C$ with predictive maintenance at time t before $ARUL_C$, can be calculated as

$$C_A(t) = C_{CM} + (UP_{CM} - UP_{PM}) + AP_{CM} \tag{71}$$

where C_{CM} is the corrective maintenance parts, service and labor cost, which is assumed to be constant.

If the predictive maintenance is implemented at time t, the under-delivery compensation UP_{PM} paid by the contractor to the customer can be calculated as

$$UP_{PM} = \begin{cases} \big(FT - CF_{PM}(T)\big)P_C, & CF_{PM}(T) < FT \\ 0, & CF_{PM}(T) \geq FT \end{cases} \tag{72}$$

Similarly, if the predictive maintenance is not implemented, the under-delivery compensation UP_{CM} can be calculated as

$$UP_{CM} = \begin{cases} \big(FT - CF_{CM}(T)\big)P_C, & CF_{CM}(T) < FT \\ 0, & CF_{CM}(T) \geq FT \end{cases} \tag{73}$$

The material availability penalty AP_{CM} caused by corrective maintenance can be calculated as

$$AP_{CM} = (t_c + DT - t_0 - ARUL_C)P_A \tag{74}$$

The predictive maintenance value $V_{PM}(t)$ at time t is defined as

$$V_{PM}(t) = R_L(t) + C_A(t) \tag{75}$$

If assume that the predictive maintenance will always be implemented at some selected opportunity, by applying the stochastic DCF approach, the $NPV_{PM}(t)$ can be calculated as

$$NPV_{PM}(t) = \begin{cases} V_{PM}(t) - C_{PM}, & t_0 < t < t_0 + ARUL_C \\ 0, & t_0 + ARUL_C \leq t \leq t_c + DT \end{cases} \tag{76}$$

A European-style ROA can also be applied to valuate the predictive maintenance option as

$$OV_{PM}(t) = \begin{cases} max(V_{PM}(t) - C_{PM}, 0), & t_0 < t < t_0 + ARUL_C \\ 0, & t_0 + ARUL_C \leq t \leq t_c + DT \end{cases} \tag{77}$$

At each predictive maintenance opportunity, by applying the stochastic DCF or the European-style ROA approach, the $ENPV_{PM}(t)$ or the $EOV_{PM}(t)$ can be obtained, and the predictive maintenance opportunity can be selected that generates the highest expected NPV or the highest expected option value.

Case study

Assume there is a helicopter managed using an availability-based contract with the FT of 2,000 flying hours (fh), P_C, P_E and P_A are assumed to be \$30/fh, \$50/fh and \$15/fh respectively. At t_0 = 8,000 hours when $CF(t_0)$ is 1,600 fh, RUL is predicted to be 300 hours (with 600 hours as the width for a triangular distribution. The mission starts at t_m = 8,050 hours, and there will be a corrective maintenance event starting at t_c = 8,700 hours, causing a downtime DT of 48 hours. Predictive and corrective maintenance parts, service and labor costs are assumed to be \$10,000 and \$8,000. The predictive maintenance value paths can be generated in Figure Appendix-1.

As shown in the left plot in Figure Appendix-1, different from the wind turbine case studies, all the $R_L(t)$ paths are flat in the very beginning before the mission starts. Some paths change to a higher slope later because the annual flying hour target is met and then a higher price applies.

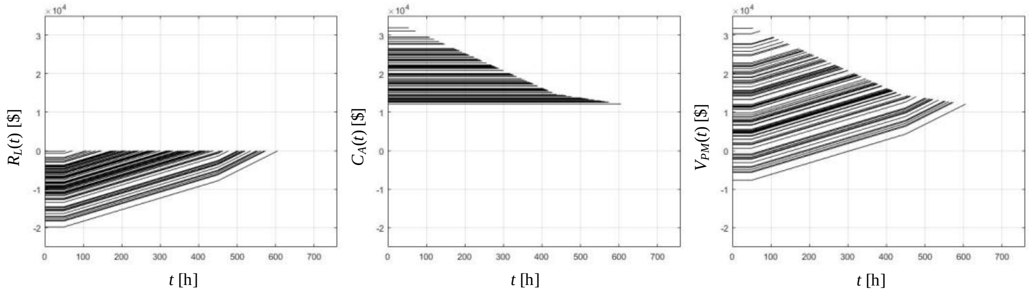

Figure Appendix-1: Left – $R_L(t)$ paths, middle – $C_A(t)$ paths, and right –$V_{PM}(t)$ paths for a single helicopter managed using an availability-based contract (100 paths are shown).

As shown in Figure Appendix-2, by the stochastic DCF approach, the selected predictive maintenance opportunity is 7.7 days (185 hours) after time t_0, with the expected predictive maintenance NPV of $3,762. By the European-style ROA approach, the selected predictive maintenance opportunity is 5.5 days (131 hours) after time t_0, with the expected predictive maintenance option value of $5,302. At the selected predictive maintenance opportunity, besides the 3.6% of the paths have the turbine already failed, there are 33.7% of the paths choose not to implement the

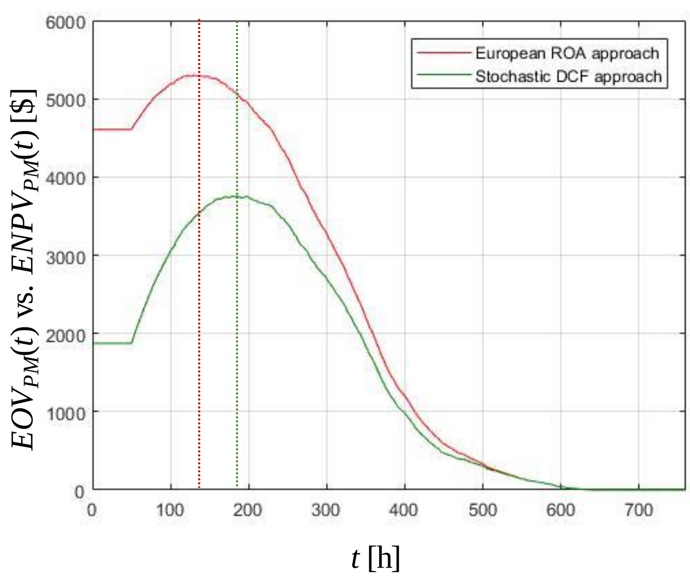

Figure Appendix-2: $ENPV_{PM}(t)$ and $EOV_{PM}(t)$ curves for a single helicopter managed using an availability-based contract (predictive maintenance opportunity is once every hour).

predictive maintenance but wait for the corrective maintenance at t_c. The value difference between the two approaches of $1,540 is the additional value provided by the managerial flexibility offered by the European-style ROA approach, which is 40.9% of the expected predictive maintenance NPV at its selected predictive maintenance opportunity in this example.

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