Condition-Based Maintenance of Wind Turbine Systems Considering Different Turbine Types and Lead Times

Abeer Amayri

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By: Abeer Amayri

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__________ Dr. J. Bentaha __________ Chair

__________ Dr. S. L __________ CIIS Examiner

__________ Dr. C. Chen __________ External Examiner (MIE)

__________ Dr. Z. Tian __________ Supervisor

Approved by

______________________________ Chair of Department or Graduate Program Director

_____20_____ ____

Dr. Robin Drew

Faculty of Engineering and

Computer Science

Abstract

Condition-Based Maintenance of Wind Turbine Systems Considering Different Turbine Types and Lead Times

Abeer Amayri

Maintenance optimization is the main goal for wind power systems because it decreases the downtime and the total cost; therefore, the reliability and availability of the systems increase. The amount of maintenance and reliability research work and practices have increased significantly in recent years to achieve optimal maintenance strategies. Currently, the widely used maintenance strategy is Constant-Interval (CI) maintenance, which schedule maintenance actions at constant intervals based on historical failure and maintenance event data of the component population. Condition-Based maintenance (CBM) is used to optimize the maintenance actions based on the condition monitoring data, such as vibration data, acoustic emission data and oil analysis data. Thus, CBM can take advantage of the unit specific degradation information, maintain a component when it approaches failure, and thus has the potential to greatly lower cost and improve reliability.

The majority of previous work has focused on the farms that have one type of the wind turbines and constant lead times. In this thesis, we develop the CBM methods for wind farms with different types of wind turbines and different lead times, which is the case for

many wind farms. We consider that the wind farms contain several wind turbines, and each turbine has diverse components for instance gearbox, rotor, hub, tower, which are connected in a series system. CBM policies are developed, and simulation-based cost evaluation methods are proposed. In addition, the performance of the proposed CBM methods is compared with the currently used Constant-Interval methods. After extensive experiments, we conclude that the CBM methods are more effective in reducing the total maintenance cost. Furthermore, the CBM is affected by the total number of turbines and the types of the farms under roughly linear relation. The proposed CBM methods considering different turbine types and different lead times can more accurately model many wind farms, and will bring great benefit to the wind power industry.

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List of Acronyms

CBM	Condition -Based Maintenance
CI	Constant-Interval Maintenance
ANN	Artificial Neural Network
PM	Preventive Maintenance

List of Principal symbols

C_E	The total expected maintenance cost per unit time.
d_1^k	Level 1 failure probability threshold value for category *k*.
d_2^k	Level 2 failure probability threshold value for category *k*.
Pr_n^k	The failure probability of wind turbine *n* in category *k*.
k	The number of wind turbine categories in farm.
N	The number of wind turbines in each type.
M	The number of basic components in wind turbine.
α_m	Weibull distribution scale parameter for component *m*.
β_m	Weibull distribution shape parameter for component *m*.
$\mu_{k,p,m}$	Mean value of the ANN life percentage prediction error for component *m* in category *k*.
$\sigma_{k,p,m}$	Standard deviation of the ANN life percentage prediction error for component *m* in category *k*.
T_{max}	The maximum simulation time.
$TL_{k,n,m}$	The real failure time for component *m* in turbine *n* in category *k*.
$t_{k,n,m}$	The current age of component *m* in turbine *n* in category *k*.
$TP_{k,n,m}$	The predicted failure time for component *m* in turbine *n* in category *k*

using ANN.

$C_{k,t,f}$ The Failure replacement cost.

$IF_{k,n,m}$ Indicating whether a failure replacement being performed on component *m* in turbine *n* in category *k.*

$C_{f,k,m}$ The failure replacement cost for component *m.*

$C_{k,T,P}$ The Preventive replacement.

$IP_{k,n,m}$ Indicating whether a preventive replacement being performed on component *m* in turbine *n* in category *k.*

$C_{k,P,m}$ The variable preventive replacement cost for component *m* in turbine *n* in category *k.*

$C_{T,farm,k}$ The fixed cost of sending a maintenance team to the wind farm for category *k.*

t_{ABS} The current time in the simulation.

L The maintenance leads time.

$C_{f,k,n,m}^{CI}$ The failure replacement cost for component *m* in turbine *n* in category *k* in constant interval maintenance policy.

$C_{p,k,n,m}^{CI}$ The variable preventive replacement cost for component *m* in turbine *n* in category *k* in constant interval maintenance policy.

$C_{P,k,T}$ The fixed cost of maintaining a wind turbine *n* in category *k.*

C_{farm} The fixed cost of sending a maintenance team to the wind farm.

$C_{f,k,m}^{CI}$ The total cost of a preventive replacement for component *m* in the constant interval maintenance policy.

$H(T_{k,n,m})$ The expected number of failure for component *m* in category *k*

$f(t)$	Failure time distribution for component *m*.
T	The length of the time interval (time unit)
t_k^{CI}	The maintenance interval in constant interval maintenance policy for category *k*.
$C(t_k^{CI})$	The total excepted cost per unit time in constant interval maintenance policy for category *k*.

Chapter One

Introduction

In this thesis, we optimize the maintenance of wind power systems by Condition-Based maintenance. Condition-Based maintenance (CBM) is used to optimize the maintenance cost by reducing unnecessary maintenance actions and scheduling preventive maintenance. In particular, condition monitoring is the main resource for data during regular inspections which is used to determine the best time for the effective maintenance actions (Jin and Mechehoul, 2010). Moreover, sensors provide accurate data about the components and these data have shown to improve the reliability of systems. The CBM is used in many industries, for example aerospace industry, mining industry, petroleum industry (Jardine &M, 1990) and power industry (Tian et al., 2010). On the other hand, Time-Based maintenance is widely used to optimize maintenance by finding the optimal preventive replacement interval to minimize the total cost. Furthermore, it schedules the maintenance actions in two polices: Constant-Interval or Age-Based. In particular, the reliability of systems is increased by reducing the failure rate of components and selecting suitable maintenance policy. Moreover, the reliability is critical issue in some industries such as power industry since a small failure might destroy all system components (Jardine & Tsang, 2006).

In fact, many researchers have paid attention to the maintenance and reliability of wind power systems. For instance some of them have focused on the failure distribution and defined it (Tranver et al., 2006). Moreover, others have presented maintenance strategies to improve the reliability (Andrawus, 2006), while others have tried to optimize the maintenance by reducing the total cost (Tian et al. 2010).

Recently, the CBM and Constant-Interval maintenance were used to optimize the maintenance for wind farm during lead time by Tian et al. (2010). In particular, the authors defined two failure probabilities at turbine level. In addition, they considered that the farm has one type of turbines and constant lead time. Authors showed substantial results comparing to already exciting work as the CBM is reduced the total maintenance cost more than CI maintenance by 44.42%.

In this thesis, we will extended the work that has been done in (Tian et al. , 2010) by applying the CBM and CI maintenance for wind power farms, which have different types of wind turbines and different lead time of components. In other words, the farms may have more than one type of turbines or they can obtain the turbines from different suppliers, consequently the number of variable during maintenance is increased. Furthermore, we develop the CBM for the farms that have variable lead time for components, and study the consequence of different lead time of components on the total maintenance time and cost and failure thresholds. In addition, we use extensive experiments to clarify several wind farms cases.

In this chapter we introduce some maintenance and reliability for wind power systems, CI and CBM.

1.1.Related Work

In 3200 B.C., wind energy was used by Egyptians for the first time for sail boats on the Nile River. In the 1200s, Europeans begin to build windmills to grind grain. After that, Charles (1888) built the windmill which generated power for 350 electric lights in his home. Furthermore, Palmer Putman engineering tried to find a cheaper way to generate electrical power on large scale from wind by expert team in electricity, aerodynamics and weather (K. Bahrami-G et al, 2000). In addition, during the 1980s, wind farms were built in California, Denmark, Germany and other European countries.

Due to the improvements of the modern technology and the availability of the wind recourses in the world, the design of turbines has witnessed rapid development (Marsh, 2005). Therefore, the number of researchers who interested in a wind power increased, and hence the wind energy industry has shown a rapid development.

To improve the wind turbine productivity, researchers have to study the maintenance and reliability. In particular, the maintenance strategies used for wind power system are: corrective maintenance and preventive maintenance. Corrective maintenance is the traditional one, which repairs the failed components after failure occurring, while preventive maintenance tries to avoid failure and reduce unexpected failures.

In fact, several assumptions are used to define the preventive replacement. For instance, Bergman (1980) assumed that the life replacement costs are constant and discounted, while Jardine and Buzacott (1985) assumed that the failure cost replacement is higher than the preventive replacement cost and the failures rate is continuous and increasing with time. Also, preventive replacement is more effective for optimizing maintenance for large farms comparing with corrective maintenance and opportunity maintenance due to the fact it saves about 30% of the total maintenance cost (Ding, 2010). Many researchers have focused onthe preventive replacement scheduling and modeling more than corrective maintenance because the preventive replacement is the suitable maintenance strategy for the components which have high failure rate (Jardine, 1973). In general, the preventive replacement strategy is selected based on cost criteria (Barlow and Hunter, 1960). Yet, the frequent use of preventive replacement can increase the cost. Moreover, the preventive maintenance is used in two common strategies: Time-Based maintenance and Condition-Based maintenance.

Time-Based maintenance is one of the preventive replacement strategies, which has been implemented in two policies: Age-Based and Constant-Interval maintenance. The Age-Based maintenance is not suitable for the wind turbine system because it has high fixed cost, where this cost should be paid when the preventive replacement occurs for any component at certain age. In general, the Constant-Interval maintenance is used for the preventive replacement of wind turbine systems after a fixed interval of time. To improve Time-Based maintenance as optimization maintenance policy, the delay–time maintenance is added (Andrawus, 2007). In particular, the delay-time maintenance analyzed the failure of components which include: failure consequences, inspection time and cost. Figure 1 shows the delay-time maintenance for components as in Andrawus model. In this model the authors assumed that: the potential failure sets at P, the interval P-F is known and the components are monitored at intervals shorter than the P-F interval. Therefore, engineering judgement and experience are required to decide the P-F interval. Moubary (1991) suggested five ways to determine the P-F interval but he concluded ″it is impossible, impracticable or too expensive to try to determine P-F intervals on an empirical basis″.

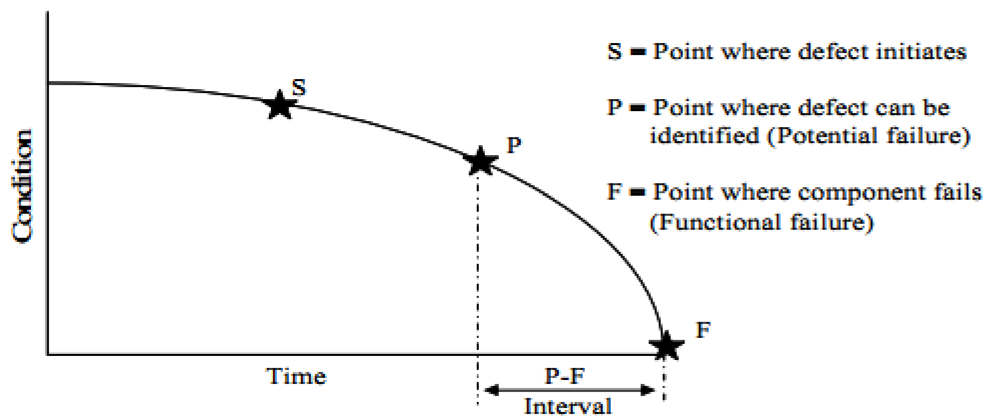


Figure 1: Potential-to-Functional Failure Intervals (Andrawus, 2006)

CBM is one of most effective preventive maintenance strategy. Mitchell (1998) defined it as″ Maintenance actions based on actual condition (objective evidence of need) obtained from in-situ, non-invasive tests, operating and condition measurement″, while Butcher (2000) defined the maintenance technology as ″CBM is a set of maintenance actions based on real-time or near real-time assessment of equipment condition, which is obtained from embedded sensors and/or external tests & measurements taken by portable equipment″. The CBM implementation goes through three steps: data acquisition, data processing and maintenance decision making. At data acquisitions, the operational data of equipments are collected through sensors. Next in data processing, the raw data is transferred into useful information for analysis and feature extraction. Finally in maintenance decision making, we decide whether sending maintenance team for the farm to replace components or not (Jardine et al., 2006).

Decision making by the CBM policy have been studied from different perspectives. For instance, Jardine (2003) reviewed and compared common uses of CBM decision making such as trend analysis expert system and neural networks. While Wang and Sharp (2002) talked about the CBM approach and the modern modeling in the CBM decision support. Furthermore, Starr (1997) mentioned that the set-up and operation costs are variable during CBM, which is important to decide which components benefit from a CBM strategy (Bengtsson, 2004).

Therefore, many researchers have tried to prove that CBM is suitable and very effective to use for maintenance of wind power systems. Andrawus (2006) evaluated the life cycle cost for a wind farm during 6 months scheduled maintenance; the CBM was one of these strategies. The authors concluded that CBM was the best investment strategy. Moreover, Nilsson (2007) repeated the experiment on a single wind turbine with different maintenance strategies and the CBM. The authors came up with the same conclusion in (Andrawus, 2006). Tian et al. (2010) developed the CBM strategy optimizing maintenance during lead time. Also, they compared between CBM and CI maintenance.

To assess the performance of reliability and maintenance some researcher went to apply synthetic data while others used real data. For instance, Windstats Newsletter is the most popular data in reliability research as it has failure data for turbine components. For example, Tranver et al. (2006) used the data to identify the failure rate as the number of failures per turbine per year. The authors defined the average failure rate during the study as the mean value for interval. Tranver assumed that the time between failures are independent and follows the exponential distribution (Tavner et al. , 2005). Moreover, Guo (2009) used Windstats for estimating Weibull distribution parameters by using Maximum Likelihood and Least-Squares methods.

On other hand, researchers have considered the real data. For example, in Germany farm Spinato and Tranver (2008) defined the failure rate functions for gearbox, generator and converter as the most important components in wind turbines, which are used to improve reliability by eliminating failure earlier and improving design. In the same vein, Echavarria et al. (2008) studied the failure rate for different Germany farms. In particular, they defined the failure rate as the number of failures per operational year. They focused on the main failure components in different designs and technologies and their effect on reliability.

1.2. Objective of this Thesis

In this thesis, we extend the work previously done by Tian et al. (2010). We will apply Condition-Based maintenance policy for wind farms considering more conditions for optimizing maintenance during lead time by defining two failure probabilities at turbine level. Furthermore, some farms have different types of turbines by obtaining turbines from different supplier which make the lead time variable or/and having different turbine capacities.

To support the CBM policy as maintenance policy for the wind farms, we will discuss different wind farms cases:

- Farms which have different number of wind turbines with constant lead time.
- Farms which have two, three and four types of farms with constant lead time.
- Farms which have different lead time and different number of wind turbines and different number of types.

Also, the CBM results will be compared with CI maintenance for the same farms.

1.3. Thesis Organization

This thesis is presented in 5 chapters. The rest of this thesis is organized as follows:

- In chapter 2, we review the maintenance and reliability theory, wind system, Time-Based and Condition-Based maintenance.
- In chapter 3, we discuss the CBM and CI maintenance methodologies of a heterogonous farm with constant lead time. Also, we add the numerical examples to show and compare different methodologies.
- In chapter 4, we discuss the effect of different number of turbines and different number of types on the total maintenance cost. After that, we will study different lead time of components affects on the total cost and failure thresholds in CBM policy.
- In chapter 5, we conclude and highlight the contributions of this thesis and suggest some future work.

Chapter Two

Literature Review on Wind Power System and Maintenance and Reliability Theory

In this chapter, we review existing wind energy systems and briefly introduce the reliability and maintenance for wind power systems.

2.1. Wind Energy

Wind energy has become one of the most important recourses for electrical energy due to its ability to reduce the greenhouse effect and it has the lowest price comparing to other methods as a renewable energy resource. Between 1995 -2010, the average capacity produced by wind energy has increased by 29.66% (based on statistical data published on *www.thewindpower.net*). Table 1 displays the statistical data.

Wind farm is a group of wind turbines to produce a large amount of electricity. The location of a wind farm is known as the sitting of the wind farm. Finding the perfect location takes one to three years because the winds speed and direction, the weather patterns and civil service in the area should be studied and measured before starting. Moreover, the best locations for wind farms are on hilltops, open plains, through mountain passes and near oceans or large lakes. In farms, the turbines are sorted in rows facing the prevailing wind. In particular, the distance between turbines should be measured carefully, where they should not be too far away from each other or so close.

Table 1: Statistical data for wind power production (1995-2010) (*www.thewindpower.net*).

Year	Capacity (MW)	Growth (MW)	Growth (%)
1995	4800	-	-
1996	6100	1300	27.1
1997	7480	1380	22.7
1998	9667	2187	29.3
1999	13701	4034	64.4
2000	18040	4339	31.7
2001	24319	6279	34.9
2002	31181	6862	28.3
2003	41343	10162	32.6
2004	49463	8121	19.7
2005	59137	9674	19.6
2006	74178	15041	25.5
2007	93952	19775	26.7
2008	121328	27376	29.2
2009	158008	36680	30.3
2010	194154	36147	22.9

There are several advantages of the wind energy:

- ✓ The fact that winds are free which makes producing electricity economical.
- ✓ Because the tower of wind turbines is very tall, the area in the farm can be used as farming areas.

- ✓ It is a clean source of energy.
- ✓ Due to the history and fancy look of wind energy, the farms can be used as tourism place.

The disadvantage of the wind energy:

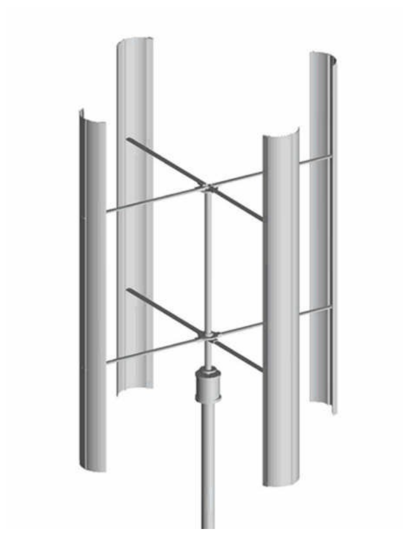
- ✓ It depends on the weather, which means if the wind is not strong enough; the turbines do not work efficiently.
- ✓ The price of farm land is very expensive because the price near the lacks or oceans and hilltops is expensive comparing with other places.
- ✓ Some people believe that the wind turbines are noisy and they affect their view of landscape.

2.2.Wind Turbine

A wind turbine is a tool used to transfer the kinetic energy of wind into mechanical energy. The rotor is the main component for converting kinetic energy into mechanical energy. In order to convert mechanical energy into electricity, there are many components have been used such as gearbox, generator and control system.

The average size of wind turbine starts from 100 kilowatts to several megawatts. Usually, large turbines are combined together in the wind farm to provide electrical network , while small turbines are used in home for telecommunication dishes or for water pumping.

Wind turbines are categorized based on the blades rotation, vertical-axis rotation and horizontal-axis rotation. In particular, the vertical-axis blades rotation is the oldest design for wind turbine. This type has simple design and it has low-tip speed ratio. While the horizontal-axis blades rotation is a modern design. In horizontal-axis rotation turbine, the speed of the rotor and the power production can be controlled by controlling the pitching of blades, also the blades are aerodynamic. Figure 2 shows the vertical-axis and horizontal-axis turbines.



A **B**

Figure 2: A. Vertical-axis rotational turbine (Greener website). B. Horizontal-axis rotational turbine (Small WindTips)

2.2.1. Wind Turbine Components

In this section, we present wind turbine components and the main function for each component as previously mentioned in (K. Bahrami-G et al., 2000). Figure 3 shows wind turbine components.

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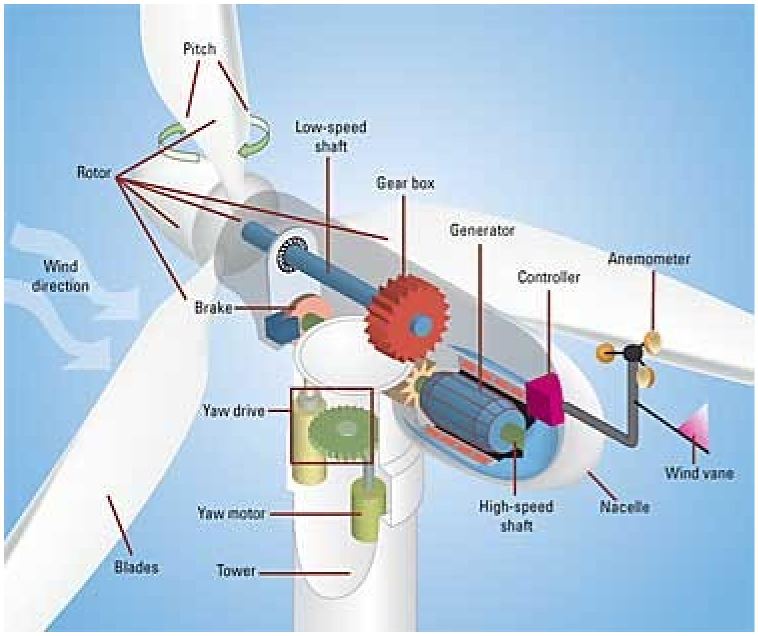


Figure 3: Wind Turbine Components (K. Bahrami-G et al., 2000)

- **The Rotor**

The rotor is the rotating part in the wind turbine. It includes four components; which are: rotor blades, pitch drive, extenders, and hub.

Description of rotor components:

✓ Most rotor blades are made of fiber glass, and sometime carbon fiber is added in order to make large turbines stronger. Rotor blades convert wind energy into mechanical energy. In fact, the number and the size of the blades affect the turbine performance.

✓ Pitch drive is required to control the pitch of the blades and to achieve maximum performance, optimum speed and rotation. When the wind has high speed the parallel pitch tries to reduce blades surface area and rotation speed. On the other hand, when the wind has low speed the perpendicular pitch increases the energy collected by the blades.

- ✓ Extenders are used to support the blades. Usually, extenders are made of steel.
- ✓ Hub is a base for blades and extenders. It binds to the nacelle by shaft and bearing

- **The Nacelle**

The nacelle is a frame (cover) used to protect or hold components. It has an outer surface to protect components from external environment and inner surface to support and distribute weight.

There are eleven subcomponents inside the nacelle for a wind turbine. The description for the nacelle's components is:

- ✓ Low speed shaft and high speed shaft are middle points between rotor hub and gearbox, gearbox and generator, respectively.
- ✓ Gearbox is used to transfer low speed rotation (low speed shaft is the input) to high speed rotation (high speed shaft is output).
- ✓ Coupling is used to connect the gearbox with the generator. By using flexible coupling the components damage will be reduced because the oscillating will be reduced.
- ✓ Bearing is required for shaft, gearbox, generator and rotating components.

- ✓ Mechanical brakes are one of the safety components. Furthermore, it is located between the gearbox and the generator. Mechanical brakes are used to stop blades rotations that give a chance for maintenance and inspection.
- ✓ The electrical generator converts high speed rotation produced from high speed shaft to electrical energy.
- ✓ Power electronics allow the generator to run at variable speeds and make reactive power possible.
- ✓ Cooling (large fan) is used to reduce the temperature of the generator and the gearbox.
- ✓ Yaw mechanism and four-point bearing. Rotors should face the best wind direction in order to generate maximum power. Yaw system has four sensors to find the best wind direction and move the rotor to face the best wind. Meanwhile, four-point bearing connect the nacelle to the tower.
- ✓ Electronic controllers are divided into three types depending on the place of the controller, which are: base controller for collecting performance data, nacelle controller and hub controller for monitoring rotor function.
- ✓ Sensors are used to calculate wind velocity, to collect the data for yaw system and to monitor the temperature inside the nacelle.

- **The Tower**

The tower is a large structure, and usually its height is more than its width. It is made of series of rolled steel tubes. In addition, it has three parts, which are: tower, base and flanges, and bolts.

Descriptions of tower components:

- ✓ Tower is the horizontal axis of the turbine. The length of the turbine tower affects the turbine performance. The range of tower heights is 60-100 m and the weights vary between 200 and 400 tons.
- ✓ The Base provides strong foundation to the turbine. It is used to support the tower and to transfer loads to foundation soil or bedrock.
- ✓ Flanges and bolts are used to join sections together.

- **The Balance System**

The balance system is important to achieve optimal results. In particular, the descriptions of balance system components are:

- ✓ Electrical collection system consists of:
  - o Transformers which are used to combine the voltage in collector line to usable electricity.
  - o Underground cables which are used to connect turbine to power lines.
  - o Power substations which are used to increase the voltage for long distance transmission.

- ✓ Communication systems authorize wind turbines to monitor themselves and to send report to controlling stations.
- ✓ Civil work includes roadway, parking, and cane and maintenance team.

2.3.The Reliability and Maintenance Theory

Throughout the years, the importance of maintenance and reliability has grown. Here we briefly mention the main fundamental knowledge of, reliability, Weibull distribution and maintenance optimization.

2.3.1. Reliability Theory

Reliability is the ″probability that an item will perform its intended function for a specific interval of time under stated conditions″ (Ramadumar, 1993). In particular, reliability is given by Jardine (2006):

$$R(t) = \int_{t}^{\infty} f(x)dx \tag{2-1}$$

where $R(t)$ is the reliability at time *t* and $f(x)$ is the failure probability density function.

The objectives of using reliability as part of optimization O&M are improving the maintenance strategy, reducing the failure rate and tolerance, and increasing the system availability.

Reliability has four elements including probability for success during the confidence interval, intended function (i.e. component functionality), stated condition (i.e.

component functionality) under specific operation condition, and functionality during specific period without failure.

In wind power system, reliability is an essential factor to ensure that the system works successfully which in turn affects the cost and the benefits of the system. . There are two modeling techniques for implementing reliability in the wind farm: reliability block diagram (RBD) and tree analysis. These two techniques are used the software packages Raptor and Pro-Opta; respectively. Raptor provides a simulation model while Pro-Opt imports data.

Bathtub curve is a common tool used to display the reliability of components (see Figure 4). According to the figure, it is clear that Bathtub shows the failure rate in three periods: decreasing failure (early failure), constant failure (random failure), and increasing failure (wear-out failure) (Davidson, 1941). Note that, in the last phase, the resistance for failures decreases while the failure rate increases.

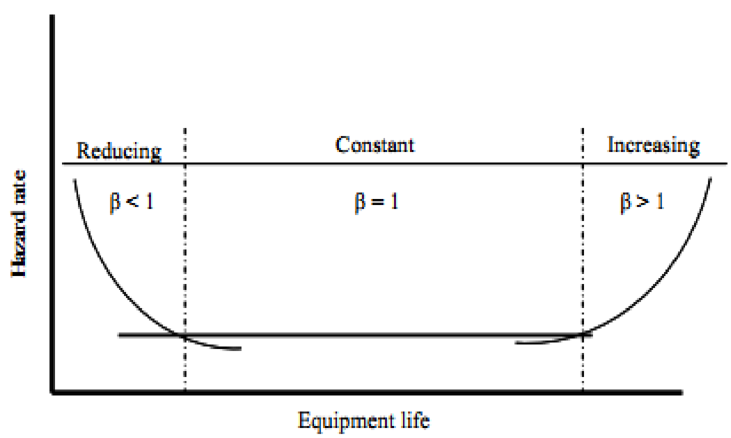


Figure 4: Bathtub Curve (Andrawus, 2007)

2.3.2. Weibull Distribution

Weibull distribution is a flexible and well known distribution that is used for lifetime data, and hence, it is used to determine the life time of wind turbine. This distribution can be written in three different ways based on the number of parameters, which can be one, two or three. Equation (2-2) and (2-3) display the probability density function (PDF) and cumulative distribution function (CDF) for Weibull distribution with two parameters (Andrawus, 2006).

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{2-2}$$

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{2-3}$$

where $f(t)$ is the probability density function at time *t*, $F(t)$ is the cumulative distribution at time *t*, α is the scale parameter and β is the shape parameter. All these parameters must be positive. The value of β affects the behaviour of failure component (i.e. increasing, decreasing or constant) based on following rules:

- $\beta < 1$: decreasing failure rate
- $\beta=1$: constant failure rate
- $\beta>1$: increasing failure rate
- $\beta=2$: linearly increasing failure rate.

2.3.3. Maintenance Theory

The objectives of maintenance can be summarized in as follows: checking system function by measuring availability, efficiency and product quality, ensuring system life, ensuring safety and seeing human well-being. Generally, there are two types of maintenance for components: corrective maintenance and preventive maintenance.

In corrective maintenance (also known as breakdown maintenance), the action is done after failure occurs and it is unscheduled and costly. In particular, the corrective replacement is done when unexpected failure occurs. Indeed, unexpected failures increase downtime, decrease production rate and increase the probability of damaged components.

On the other hand, preventive maintenance is used to avoid a failure, identify a failure in the beginning and find out a hidden failure. It has two types: Time-Based maintenance and Condition-Based Maintenance.

2.3.3.1. Time-Based Maintenance

Time-Based maintenance has two types of replacement: preventive replacement and failure replacement. The preventive replacement occurs after a specific period, while failure replacement occurs when a component fails. The Time-Based preventive maintenance can be divided into two types: Age-Based maintenance (AB) and Constant-Interval maintenance (CI). In AB maintenance, component is replaced when it achieves a specific age, and the data for each component is stored separately. On the other hand, using CI maintenance, the replacement is done after a specific time. Furthermore, in CI the system is considered as one unit, therefore there is a possibility of replacing a good component. In order to reduce the total cost, the number of replacements, failure and preventive, can be scheduled. Moreover, the balance is required between recourses and benefits. Figure 5 shows the total cost curve for Time-Based maintenance.

In some situations the Time-Based maintenance is considered as the best maintenance strategy because it has easy logistics, shorter downtime, higher availability, and maintenance activities are scheduled in good time line. However, it cannot be efficient because components are replaced before achieve the maximum lifetime.

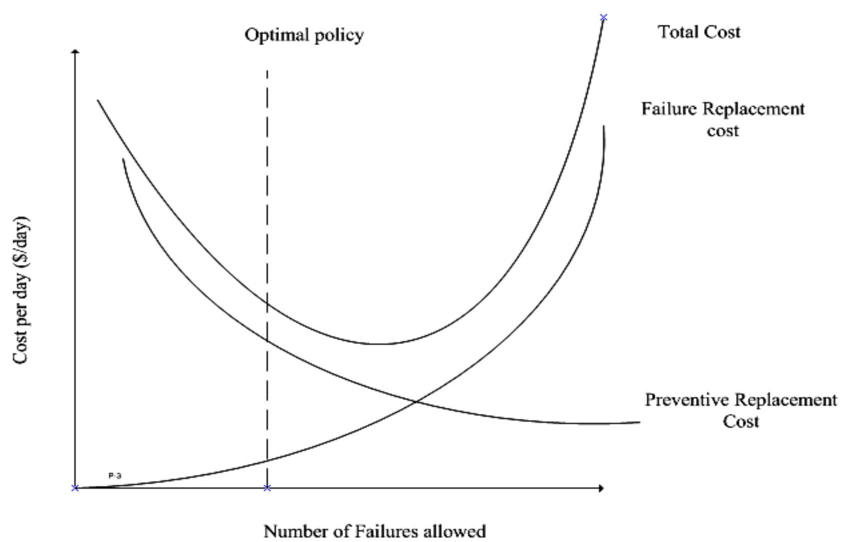


Figure 5: Optimal Replacement (Jardine, 2006)

2.3.3.2. Condition-Based Maintenance

Condition-based maintenance (CBM) is the type of maintenance that takes place when one or more sources of evidence show that the component almost is about fail or the performance has decreased. In particular, CBM is used to reduce preventive maintenance cost and unexpected failure. The effects of CBM on a system are: increasing the reliability while decreasing the maintenance costs, the number of maintenance operations causes and human error. On the other hand, the installation costs and the number of system components are increased because of checking and monitoring of the components.

CBM uses real data which are collected during condition monitoring. In particular, there are two types of the condition monitoring: continuous and periodic. The continuous monitoring uses sensors for monitoring components and taking actions when something happens. The periodic monitoring uses filtered and/or processed data. The common condition monitoring in CBM are:

- ✓ Vibration monitoring which is used to notice fatigue, wear, imbalance, misalignment, turbulence, etc. Moreover, vibration is measured by three parameters: amplitude, velocity and acceleration, which are measured using sensitive sensors.

- ✓ Processing parameters which are measured frequently during operation. These parameters indicate the health condition for the system such as, performance, efficiency, temperature, etc. Furthermore, such monitoring can be used for non-mechanical system such as exchangers and filtration.

- ✓ Thermography monitoring indicates infrared energy in a system. In other words, if there are any changes in the system temperature (colder or hotter), it will find the problems which would be either heat transfer or retention.

- ✓ Tribology monitoring is used in the CBM for interfacing sliding surface. This type is slow and expensive because it needs specific environments for testing and instrument (scanning electron microscope).

- ✓ Visual inspection is the simplest, but sometime not cheap or not accurate method for monitoring a system and it is used to indicate leaks, structural cracks, etc.

Diagnostic and prognostic are needed before CBM optimum. Diagnostics provide a map of information about the failure reasons and results during operation process under specific working condition. Furthermore, this map is known as pattern recognition. Usually, it is done manually by using graphical tools which need high training and personal skills. Also, there is automatic pattern recognition which works based on signals from the systems.

In prognostic, reaming useful life (RUL) determines the time left before failure by using the current age and condition and the past operation profile (Andrew et al, 2005). Usually, it is defined as conditional random variable:

$$T - t | T > t, Z(t)$$

where *T* is the random variable of failure time , *t* is the current age and *Z(t)* is the past condition profile. The prognostic approach fall into three categories: statistical approaches, artificial intelligent approaches and model-based approaches.

By using CBM, the components are used more efficiently, the maintenance action is well scheduled, the downtime is reduced, and it is easy to understand because the failure can be predicted. Meanwhile, it has high installation cost because of sensors, it is difficult to identify the critical or best condition for monitoring, and it is new in wind power industry.

2.4.Maintenance Optimization

The primary objective for maintenance optimization is finding the lower cost for maintenance with lower risk. In general, the optimization model should cover four points: description of the system function and importance, modeling of the decline in quality of the system and the consequences, description for available information and possible solutions, and the technique which helps to find the best balance (Rommert, 1996). Achieving maintenance optimization requires strong knowledge about a system, such as, historical data, the condition monitoring data and system event (failure event, suspension event, oil change, etc) related to the lifetime of the components.

2.5.Artificial Neural Network

Artificial Neural Network (ANN) is a model for describing the relationship between input and output. An ANN model consists of input, hidden layers and output. Each element is symbolizing by node and weight. The lines between the nodes indicate the flow of information between the nodes. In particular, the information flows only from the input to the output, which means the feed is forward in neural networks. The hidden and output layers are active, while the input layer cannot vary the data. The values in a hidden node are multiplied by weights. The weighted inputs are then added to produce single results. Before leaving the node, this result is passed through a nonlinear mathematical function called a transfer function. The active nodes of the output layer combine and modify the data to produce the output values of the neural network.

Figure 6 displays an ANN example (Tian, 2009). According to the figure, there are two condition monitoring measurements. The inputs for this model are: t_i is the age of the component at the current inspection point *i,* t_{i-1} is the age at the previous inspection point i *−1,* z_i^1 and z_{i-1}^1 are values of measurement 1 at the current and previous inspection points and z_i^2 and z_{i-1}^2 are values of measurement 2 at the current and previous inspection points. The output of the ANN model is the life percentage at current inspection time. For example, if the failure time of a component is 850 days and the age of the component at the current inspection point is 500 days, the life percentage value would be = 500/850×100%= 58.82% “ (Tian et al. ,2010) .

ANN widely is used in component health and life predication. For example, it is used in milling operation to determine how the cutting process is affected by surface roughness.

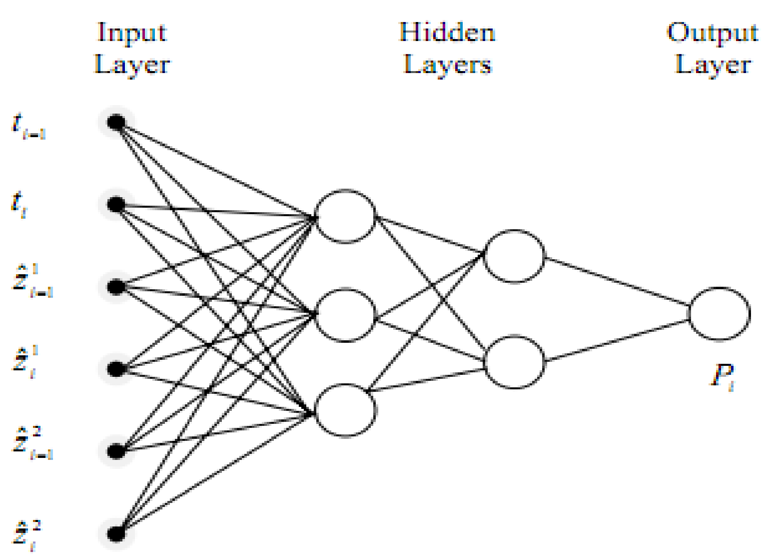


Figure 6: ANN Model (Tian, 2009)

For CBM purposes, all the pertaining information are fed to ANN as inputs and ANN produces a decision result as an output. Therefore, feeding of an appropriate data regarding the condition of data is important while using ANN and the rest of the job is performed automatically by ANN. The most common types of ANN are feed forward neural network and recurrent neural network. A feed forward neural network is that type of ANN in which connections between the units do not form a direct cycle. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes, to the output nodes. There are no cycles or loops for feedback within in the network. ANN can be used for health condition predication; also prognostic can be used for this purpose, such as model based predication methods.

Chapter Three

Condition-Based Maintenance Farms Considering Different Turbine Types

The objective of this chapter is to optimize maintenance of heterogeneous wind farm during the lead time. The lead time is defined as "the interval between the time maintenance decision is made and time when maintenance is performed" (Tian, 2010). There are two failure probability values for each turbine type: failure probability at component level ($Pr_{n,m}^{k}$) and failure probability at turbine level (Pr_{n}^{k}). The failure probability of turbine components is calculated by using equation (3-1) (Tian et al, 2010).

$$Pr = \frac{\int_{t}^{t+l} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-tp}{\sigma})^2}\, dx}{\int_{t}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-tp}{\sigma})^2}\, dx} \tag{3-1}$$

where l is the lead time, t is the age of the component at inspection point, t_p is the predicted failure time and σ is the standard deviation of prediction failure time.

The wind turbines are considered as series systems. If any component fails, the turbine will stop working even if other components work successfully. The failure of any turbines does not affect other turbines. The failure probability at turbine level is calculated by using equation (3-2) for turbine *n* with *m* components.

$$Pr_n = 1 - \prod_{m=1}^{M} (1 - Pr_{n.m}) \tag{3-2}$$

where Pr_n is the failure probability for turbine *n* and $Pr_{n.m}$ is the failure probability for component *m* in turbine *n*.

Sometimes, the farms have more than one power rate of turbine which makes the maintenance schedule more complicated. In this chapter, we display the methodologies of CBM and CI of heterogeneous wind farms. In both methodologies we are assume that the lead time is the same for all components.

3.1.Condition-Based Maintenance

In this section, we present The Condition-Based maintenance. The maintenance decision is chosen based on the failure threshold of the components at wind turbine between replacement and repair.

3.1.1. CBM Model

CBM methodology is used to determine failure probability values which minimize total maintenance cost per unit time, known as C_E, in wind the farm:

$$min \quad C_E \left(d_1^1, d_2^1, d_1^2, d_2^2, d_1^3, d_2^3, \dots, d_1^k, d_2^k \right)$$

$$s.t{:}\ 0 < d_2^k < d_1^k$$

where $d_1{}^k$ and $d_2{}^k$ represent two failure thresholds for each type in type *k*. The failure thresholds are discrete variables.

3.1.2. CBM Policy

The CBM policy, considering *k* types of wind turbines in a wind farm, is described as follows:

1. The types of wind turbines in a farm depend on manufacturer power rate (*k* types).
2. Failure replacement: check failed components, and the maintenance team will change components based on a schedule.
3. When the conditional failure probability, denoted by Pr_n^k, is larger than $d_1^k(Pr_n^k>d_1^k)$, preventive maintenance will be performed. Pr_n^k is failure probability for wind turbine *n* in type *k* .d_1^k is pre-specified level 1 failure probability for turbine *n*.
4. Implementing preventive maintenance on *n* turbines will decrease failure probability d_2^k, and d_2^k is level 2 failure probability.
5. Repeat steps 3and 4 for other turbine types in the farm.

3.1.3. Methodology

The procedure of the proposed CBM approach is outlined in Figure 7. In particular, the detailed explanations are given as follows.

Step 1: The number of wind turbine types depends on the rated power and we suppose there are *k* types of turbines in a wind farm. We select type *X* from *k* types of wind turbine in farm.

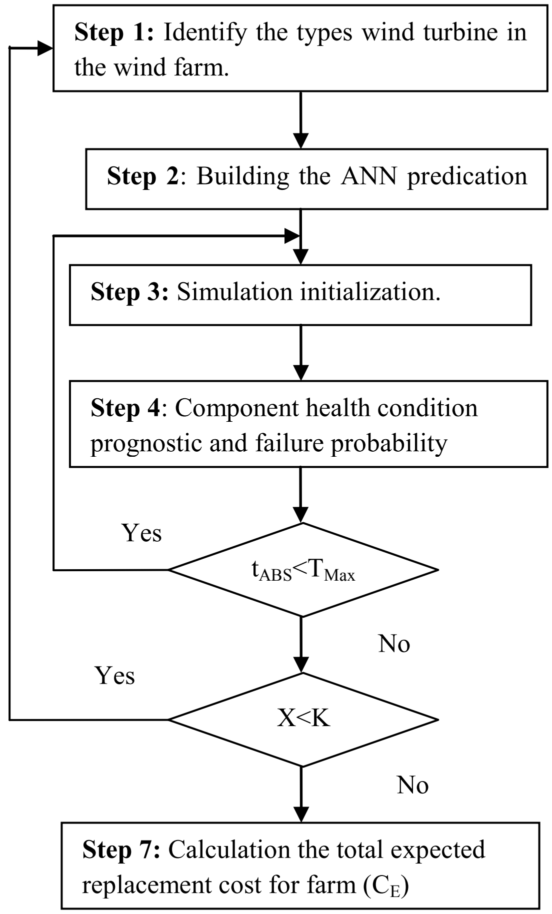


Figure 7: CBM methodology flow chart

Step 2: Artificial neural network (ANN) is used to predict failure time distribution before developing the CBM policy. The inputs for ANN are the historical age for components and condition monitoring data and the output is the life age of components. The Weibull distribution, in equation (3-3), is used as the life time distribution for the population of wind turbines. There are two parameters for this distribution for component *m*: scale parameter (α_m) and shape parameter (β_m).

$$f(m) = \frac{\beta_m}{{\alpha_m}^{\beta_m}} t^{\beta_m - 1} e^{-(\frac{t_m}{\alpha_m})^{\beta_m}} \quad (3\text{-}3)$$

where $f(m)$ is the life time for component m, β_m is the shape parameter for component m and α_m is the scale parameter for component m.

At each inspection point, ANN uses historical data in the form of normal distribution to predict the life percentage error for component m, by calculating mean ($\mu_{k,p,m}$) and standard deviation ($\sigma_{k,p,m}$).

Step 3: Simulation initialization. The overall objective of the simulation method for cost evaluation is to find the total excepted cost per unit time for the heterogeneous farm (k types) with *n* turbines of each type and *m* basic components per turbine because we do not have specific equations for CBM method. In this step, the maximum simulation iteration ($T_{\max}$) is selected in the step; the accuracy of the results is affected by the number of iterations. The total cost, current age and real failure time are set to zero before simulation starts. Weibull distribution parameters are used to generate real failure time ($TL_{\mathrm{k,n,m}}$) for each component.

Step 4: Component health condition prognostics and failure probability calculation. The failure probability for wind turbine adopts a normal distribution, based on the prediction failure distribution.

At a specific inspection point, the component *m* will have age ($t_{k,n,m}$), real failure time ($TL_{\mathrm{k,n,m}}$) and predicted failure time ($TP_{k,n,m}$). The failure probability will be calculated by (3-4):

$$Pr_{k,n,m} = \frac{\int_{t_{k,n,m}}^{t_{k,n,m}+l} \frac{1}{\sigma_{k,n,m}\, TP_{k,n,m}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-TP_{k,n,m}}{\sigma_{k,n,m} TP_{k,n,m}}\right)^2} dx}{\int_{t_{k,n,m}}^{\infty} \frac{1}{\sigma_p\, TP_{k,n,m}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-TP_{k,n,m}}{\sigma_{k,n,m} TP_{k,n,m}}\right)^2} dx} \tag{3-4}$$

where $Pr_{k,n,m}$ is the failure probability for component *m* in turbine *n* for type *k, L* is the lead time, $t_{k,n,m}$is the age of component *m* in turbine *n* for type *k,* $\sigma_{k,n,m}$ is the standard deviation for component *m* in turbine *n* for type *k* and $TP_{k,n,m}$ is the predicted failure time for component *m* in turbine *n* for type *k.*

Step 5: CBM decision making, cost update, and component age and real failure time value update:

- Failure replacement cost is performed for the components which have the current age for component *m* in turbine n is larger than the failure age for the component, it will fail. The cost is calculated if the failure occurs in any basic components by using (3-5).

$$\Delta C_{k,T,F} = \sum_{n=1}^{N} \sum_{m=1}^{M} IF_{k,n,m} C_{f,k,m} \tag{3-5}$$

  where $IF_{k,n,m}$ takes either one for failed component or zero for working component and $C_{f,k,m}$is the failure replacement cost for component *m* in turbine *n* in type *k*.

- Preventive replacement is performed for components which have a high failure probability and high failure replacement cost comparing with preventive replacement cost. The failure probability will be less than d_2^k by using preventive replacement, equation (3-6)

$$\Delta C_{k,T,P} = \sum_{n=1}^{N}(\sum_{m=1}^{M} IP_{k,n,m}c_{k,p,m} + IT_{k,n}c_{p,k,T}) \tag{3-6}$$

where $IP_{k,n,m}$ is either one for preventive replacement or zero if no preventive replacement is performed, $C_{k,p,m}$ is the preventive replacement cost for component m in turbine n under type k, $IT_{k,n}$ is equal to one when preventive replacement is performed without failure for component m in turbine n and $c_{p,k,T}$ is the fixed cost for the maintenance of the turbine.

- ❖ Fixed cost to the farm which is added to the total cost when either failure or preventive replacement occurs in farm (C_{farm}). Each type takes a certain percentage from fixed cost based on the number of turbines in this type to total number of turbine in the farm, equation (3-7).

$$\Delta C_{T,Farm,k} = I_{farm}C_{farm}\frac{n_k}{\sum_{k=1}^{K} n_k} \tag{3-7}$$

where I_{farm} is either one when any replacement is performed or zero when no replacement is performed in farm.

- ❖ The total cost for type k is calculated by summarizing failure, preventive and fixed costs for this type at specific inspection point, we have

$$\Delta C_{T,k} = \Delta C_{T,Farm,k} + \Delta C_{k,T,P} + \Delta C_{k,T,F} \tag{3-8}$$

If replacement (failure or preventive replacement) is performed on any component, the lead time should be added to t_{ABS}, equation (3-9), otherwise the inspection will be moved for next inspection point (see equation (3-10)) and repeat steps 1, 2 and 3.

$$t_{ABS} = t_{ABS} + L \tag{3-9}$$

$$t_{ABS} = t_{ABS} + T_i \quad (3\text{-}10)$$

Total replacement cost per unit time. Once the simulation program reaches the maximum iteration, the value of T_{max} for all type is obtained, since the value of T_{max} is equal to t_{ABS}.

$$C_{E,k} = \frac{\Delta C_{T,k}}{T_{max}} \quad (3\text{-}11)$$

Step 6: If this condition is true, step 4 and 5 will be repeated for the next type, until all turbines are checked.

Step 7: The total replacement cost per unit time in the farm is calculated by summation of variable and fixed costs per unit time, (3-12).

$$\Delta C_E = \sum_{k=1}^{K} min\ (C_{E,k}) \quad (3\text{-}12)$$

The total cost is measured by $/ day or $/ year based on the annual cost in engineering economics.

3.2. Time -Based maintenance

The main objective of time based maintenance policies is to determine the optimal interval for preventive replacement to minimize total expected cost per unit time. There are two types of Time-Based maintenance: Constant-Interval maintenance and Age-Based maintenance. The Constant-Interval maintenance is widely used for wind turbine system. In the following subsections, we display the methodology of Constant-Interval maintenance for heterogeneous wind farm. Figure 8 shows the methodology.

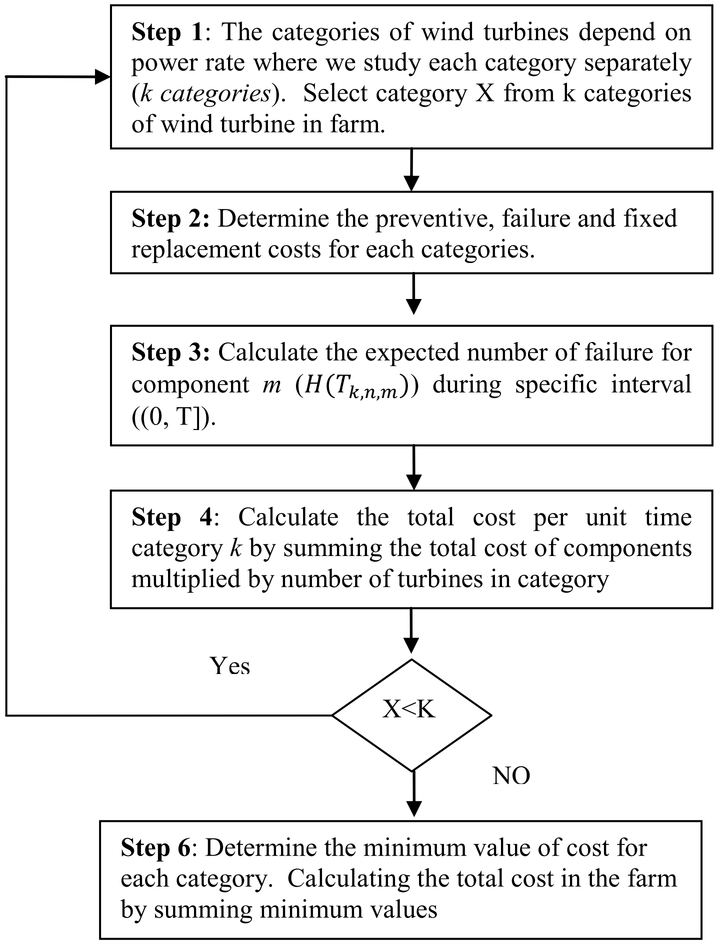


Figure 8: Flow chart for Constant-Interval maintenance policy

3.2.1. Methodology

Step 1: The number of wind turbine types depends on the rated power and we suppose there are *k* types of turbines in a wind farm. Select type *X* from *k* types of wind turbine in farm.

Step 2: we determine the preventive (see equation (3-13)), failure (see equation (3-14)), and fixed replacement costs for each category. Also, the Weibull distribution (see equation (3-3)) is used as failure time distribution for wind turbine with two parameters for each component with: scale parameter (α_m) and shape parameter (β_m).

$$C_{p,k,n,m}^{CI} = C_{p,k,n,m} + \frac{C_{p,k,T}}{M} + \frac{C_{farm}}{M \sum_{k=1}^{K} N_k} \quad (3\text{-}13)$$

$$C_{f,k,n,m}^{CI} = C_{f,k,m} + C_{farm} \frac{n_k}{\sum_{k=1}^{K} n_k} \quad (3\text{-}14)$$

where $C_{p,k,n,m}^{CI}$ is the variable preventive replacement cost for component *m* in turbine *n* in type *k* in constant interval maintenance policy, $C_{f,k,n,m}^{CI}$ is the failure replacement cost for component *m* in turbine *n* in category *k* in constant interval maintenance policy and $C_{p,k,T}$ is the fixed cost of maintaining a wind turbine *n* in category *k*.

Step 3: Calculating the expected number of failures for component *m* ($H(T_{k,n,m})$) during specific interval ((0, T]):

$$H\left(T_{k,n,m}\right) = \sum_{i=0}^{T-1} [1 + H(T - i - 1)] \int_{i}^{i+1} f(t)dt, T \geq 1 \quad (3\text{-}15)$$

T is the length of the time interval and $f(t)$ is the failure time distribution for component *m* in turbine *n* in type *k*.

From equation (3-15), the failure will occur in either first, second, third,….. or *T* operating time. For example, if the preventive replacement occur on five days, then by using equation (3-15) we find out the expected number of failures during 5 days, $H(5)$. That means $H(1), H(2), H(3)$ *and* $H(4)$ are calculated to get $H(5)$.

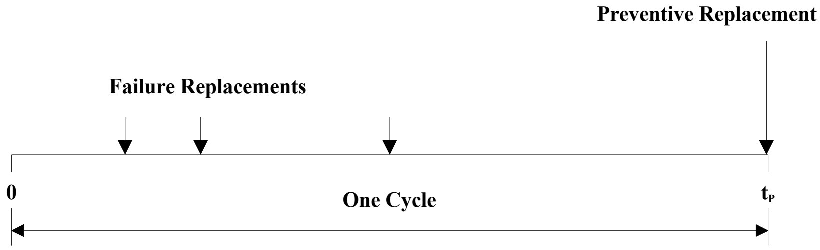


Figure 8: Replacement Cycle: Constant-Interval policy

Step 4: Calculate the total cost per unit time of type k by summing total cost for components, the multiply by number of turbines in category, equation (3-16).

$$C(t_k^{CI}) = N_k \; \frac{\sum_{m=1}^{M}(C_{f,k,n,m}^{CI} + C_{p,k,n,m}^{CI} \, H(t_{k,n,m}))}{t_k^{CI}} \tag{3-16}$$

$C_{f,k,n,m}^{CI}$ is the total cost of failure replacement for component m in type k during interval $(0, t_k^{CI}]$ and $C_{p,k,n,m}^{CI}$ is the total cost of a preventive replacement for component m in type k.

Step 5: Repeat step 3,4 and 5 for all categories.

Step 6: Determine the minimum value of cost for each type. Calculate the total cost in the farm by summing minimum values:

$$C_{T,farm}^{CI} = \sum_{k=1}^{K} \min(C(t_k)) \tag{3-17}$$

3.3.Numerical Examples

In this section, we present a numerical example. The mathematical model is programmed in MATLAB. The CBM and CI methodologies are applied on the same farm. Furthermore, MATLAB is used to the two policies based on the minimum total expected maintenance cost.

There are six turbines in the farm, among which three turbines belong to type 1, low capacity, and the others belong to type 2, high capacity. There are four key components for each turbine: rotor, main bearing, gearbox, and generator. The tables below display the reliability data for the turbines.

It is assumed that components from two different turbine types have different scale parameters, while they have the same shape parameters.

3.3.1. CBM Example

In this section we display an example for the CBM methodology in a wind farm. Weibull distribution is used to determine the components failure time. Table 2 displays the parameters of distribution: scale parameter (α) and shape parameter (β). The cost data, including the failure replacement cost, the variable preventive maintenance cost, the fixed preventive maintenance cost and fixed cost to wind farm are given in Table 3.

Table 2: Weibull failure time distribution for major components

Component	Scale Parameter α (Days)		Shape Parameter β
	Type 1	Type 2	
Rotor	3,000	6,000	3
Main Bearing	3,750	7,500	2
Gearbox	2,400	4,800	3
Generator	3,300	6,600	2

The ANN prediction is the first step. In the ANN step, failure time distribution is measured based on the parameters that indicate the failure. Standard deviation is presented as the error percentage for the turbine in Table 4. In addition, the lead time for maintenance is thirty days, with ten days for an inspection interval.

MATLAB software is used to develop the simulation program. 200,000 are used as the simulation iteration to guarantee more accurate results. The purpose of using CBM approach is to find the optimal CBM policy corresponding to the lowest cost. In other words, the lowest maintenance cost is the expected result.

Table 3: Failure replacement and preventive maintenance cost for major components

Component	Failure Replacement cost ($ 1000)		Variable Preventive maintenance Cost ($1000)		Fixed Preventive maintenance Cost ($1000)		Fixed Cost to wind farm	
	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2	Type1	Type2
Rotor	112	224	28	56	25	50	50	
Main Bearing	60	120	15	30				
Gearbox	152	304	38	76				
Generator	100	200	25	50				

The failure probability values vary with power rate for turbine. Optimal failure probability is linked with the optimal expected cost. The optimal failure probability values for type 1 are: $d_1^1 = 0.3981$ and $d_2^1 = 0.0009$ and the optimal cost is $ 293.0047 per day. For Type 2, the values of failure probability are: $d_1^2 = 0.0398$ and $d_2^2 = 0.0086$ and the optimal variable cost is $ 306.4844 per day. The total expected cost per unit time is $C_E =$ $ 599.4890 per day.

The figures below are used to show these results more clearly. Figure 9 shows the failure and preventive replacement cost versus failure probability for type 1 and Figure 10 shows the failure and preventive replacement cost versus failure probability for type 2.

Table 4: ANN life percentage predication error standard deviation value for major components

Component	Standard Deviation	
	Type 1	Type 2
Rotor	0.12	0.24
Main Bearing	0.10	0.20
Gearbox	0.12	0.24
Generator	0.10	0.20

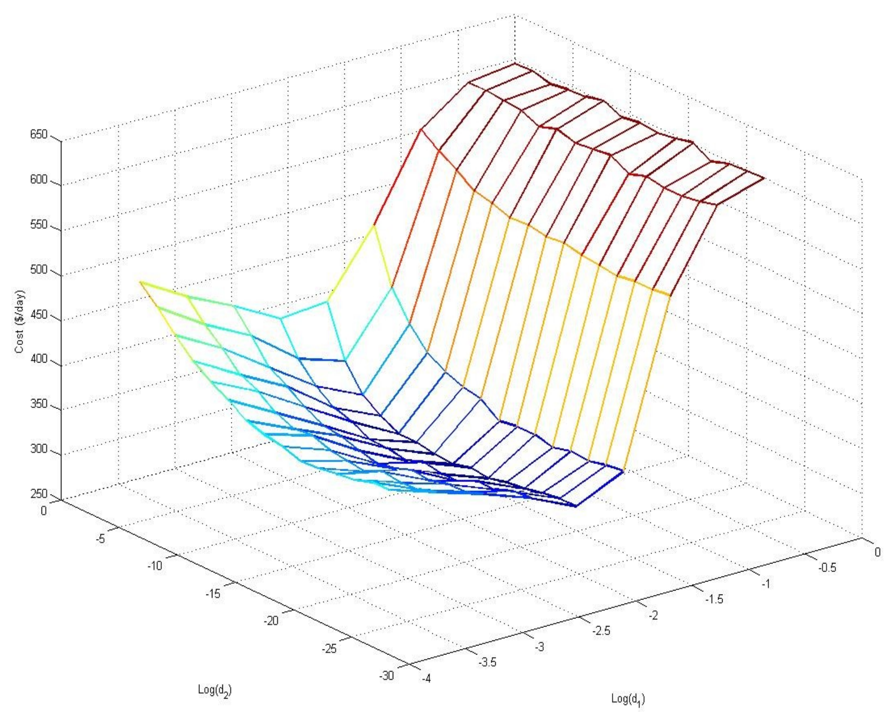


Figure 9: **Variable cost versus failure probability for type 1**

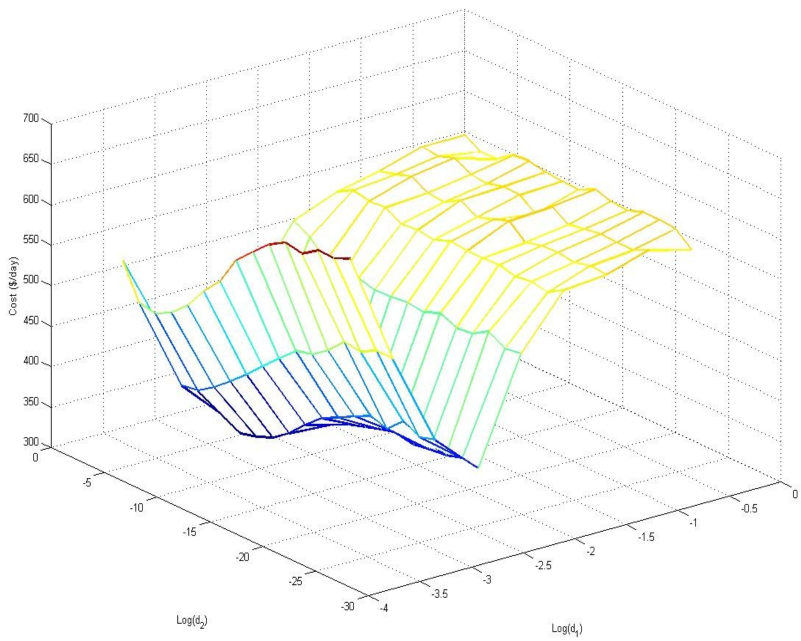
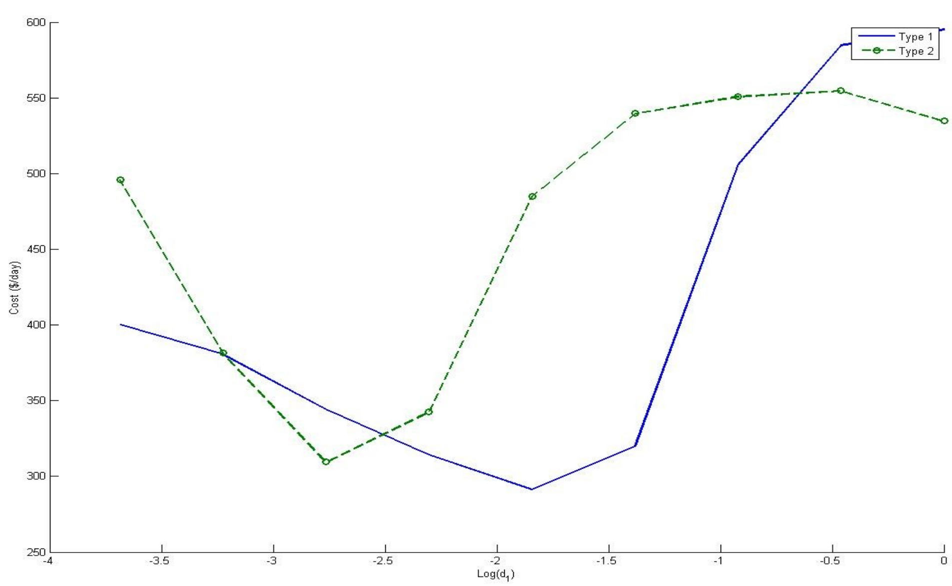
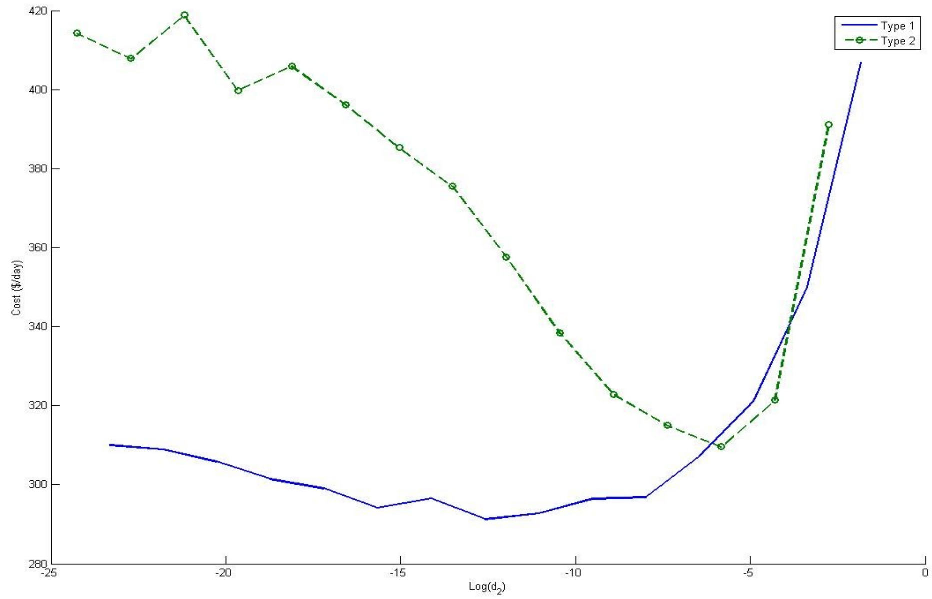


Figure 10: Variable cost versus failure probability for type 2

Figure 12.a. presents the change of d_1^k with the total maintenance cost, while Figure 12.b. shows the change of d_2^k with costs.



(a)



(b)

Figure 11: **(a) The total maintenance cost versus d_1^k in logarithm scale (b) The total maintenance cost versus d_2^k in logarithm scale**

3.3.2. Constant- Interval Example

This example uses the same date in the CBM example for comparing the two methodologies based on total expected cost per unit time. In this case, the failure replacement cost is equal to the fixed cost of the farm plus the failure replacement cost (see Table 5) and the preventive replacement cost is calculated by using equation (3-13). Table 5 displays the data.

The optimum cost for type 1 is \$ 462.3921 per day during (0, 1560] and the optimum cost for type 2 is \$ 435.7039 per day during (0, 3220]. The total expected cost for the farm is \$ 898.0960 per day. Figure 12 shows these results more clearly. The total expected cost is calculated by using a Time-Interval higher than the CBM.

Table 5: Cost data for the Constant-Interval maintenance policy

Components	Failure replacement cost ($ 1000)		Preventive replacement cost ($ 1000)	
	Type 1	Type 2	Type 1	Type 2
Rotor	137.00	249.00	36.33	64.33
Main bearing	85.00	145.00	23.33	38.33
Gearbox	177.00	327.00	46.33	84.33
Generator	125.00	225.00	33.33	58.33

Based on the results in section 3.3.1 and 3.3.2, CBM is better than CI based on the total expected cost per unit time for the same number of turbines in the farm and maintenance conditions. Furthermore, 33.36% of total cost is saved by using the CBM policy.

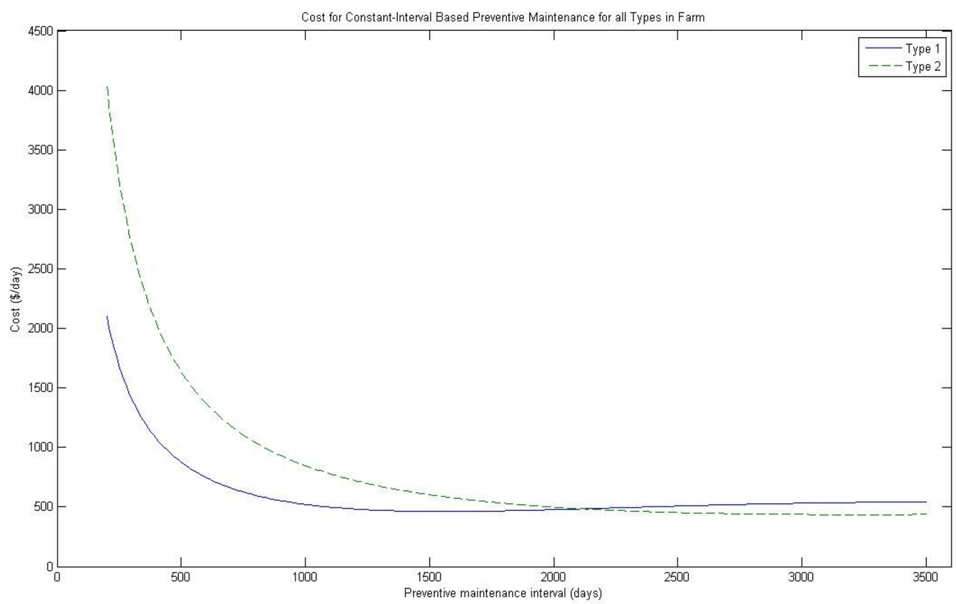


Figure 12: Cost plot for the Constant–Interval based preventive maintenance policy

Chapter Four

Condition-Based Maintenance for Wind Turbines with Different Numbers and Different Lead Times

CBM may be applied in several ways, such as farm with more than one type of turbines and the lead times of components are variable. In this chapter, we present some of these cases to show how the total maintenance cost and time are affected. Where the total maintenance time is the time required for run the model and get the optimum cost value. In more details, we will study farms that have different total number of turbines in different cases. We will apply the CBM methodology for the farms that have the different components lead time.

4.1. Different Total Number of Turbines in The Farms

In this section, we will present different total number of turbines in the farms. We study the relations between the maintenance time and cost and the number of turbines in the farm under the same condition through numerical examples. Furthermore, we will compare the time and cost required to complete maintenance in three farms. In each farm the number of turbines will be larger than previous one.

4.1.1. CBM Policy

In this case, we use MATLAB software to simulate the model with 200,000 iterations. We used the same data we previously study in section 3.3.1 in Table 2, 3 and 4. The results of the total maintenance cost and time for maintenance in the farm is displayed in Table 6 and Figure 13. Based on these results (Table 6 and Figure 13), the relationship between the number of turbines and maintenance time is roughly linear. In other words, the time required for completing maintenance for the farm with roughly twelve turbines is twice the time needed for a farm with six turbines.

Table 6: CBM Maintenance Time and Cost Results

Number of Turbines	Total cost ($)	Total time (Hour)
[3 3]	594.99	18.66
[6 6]	1184.20	37.96
[9 9]	1780.20	54.99

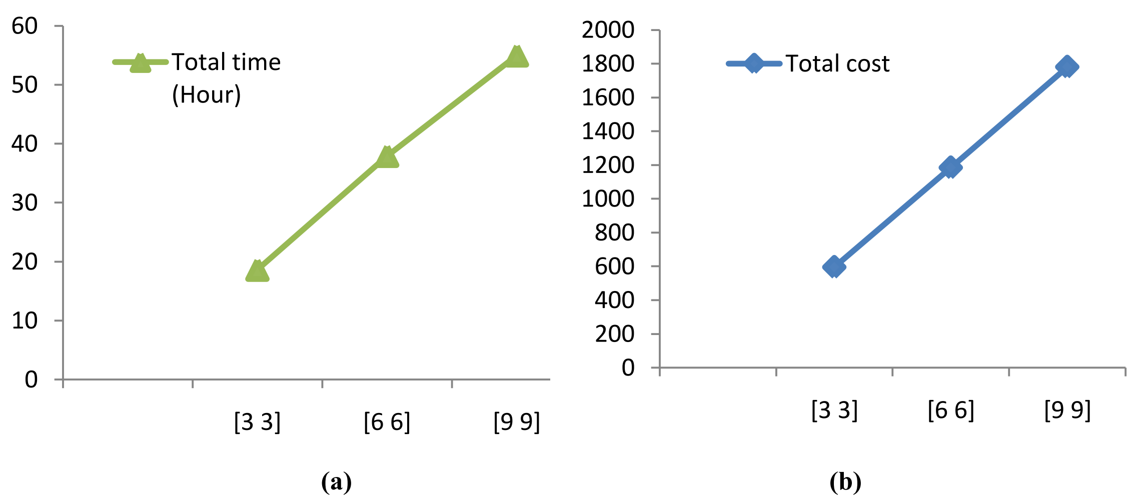
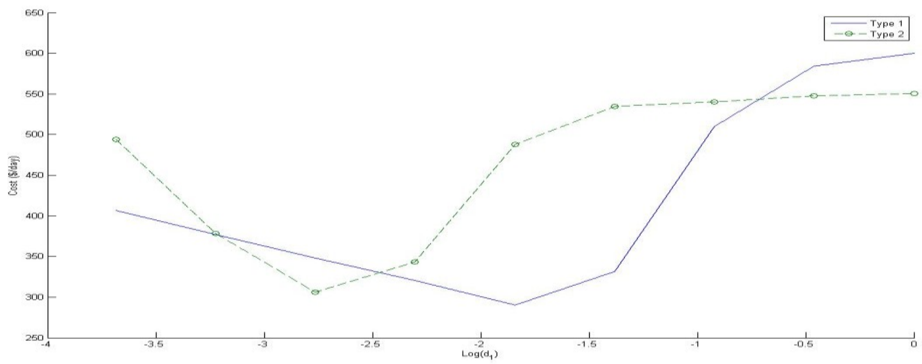
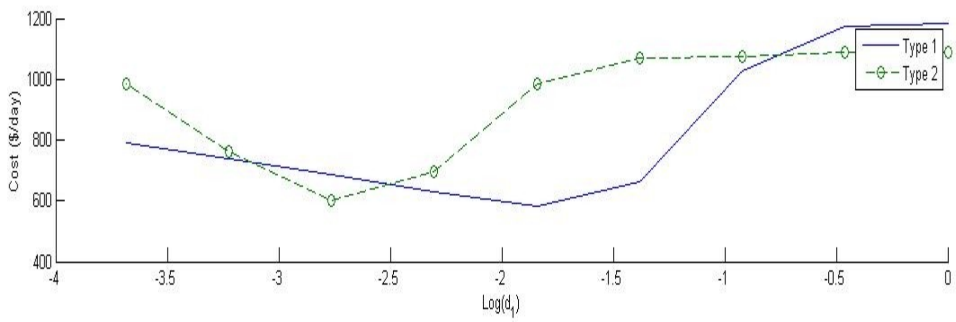


Figure 13: (a) Number of turbine in farm versus total time for maintenance. (b) The total cost versus number of turbines

The failure thresholds at turbine level are not affected by the number of turbines in the farm because they are affected by the number of variables in the model. For the type 1, the failure thresholds in all cases are: $d_1^1 = 0.3981$ and $d_2^1 = 0.0040$ and for type 2 the failure thresholds are: $d_1^2 = 0.0398$ and $d_2^2 = 0.0086$. According to Figure 14, the curve shape is the same for three cases but the total cost axis is different.



(a)



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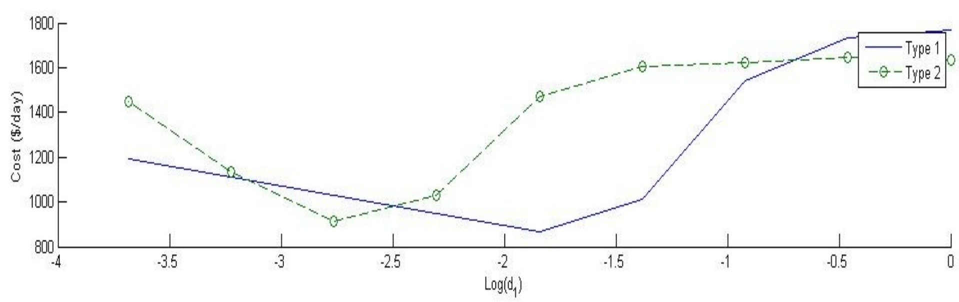
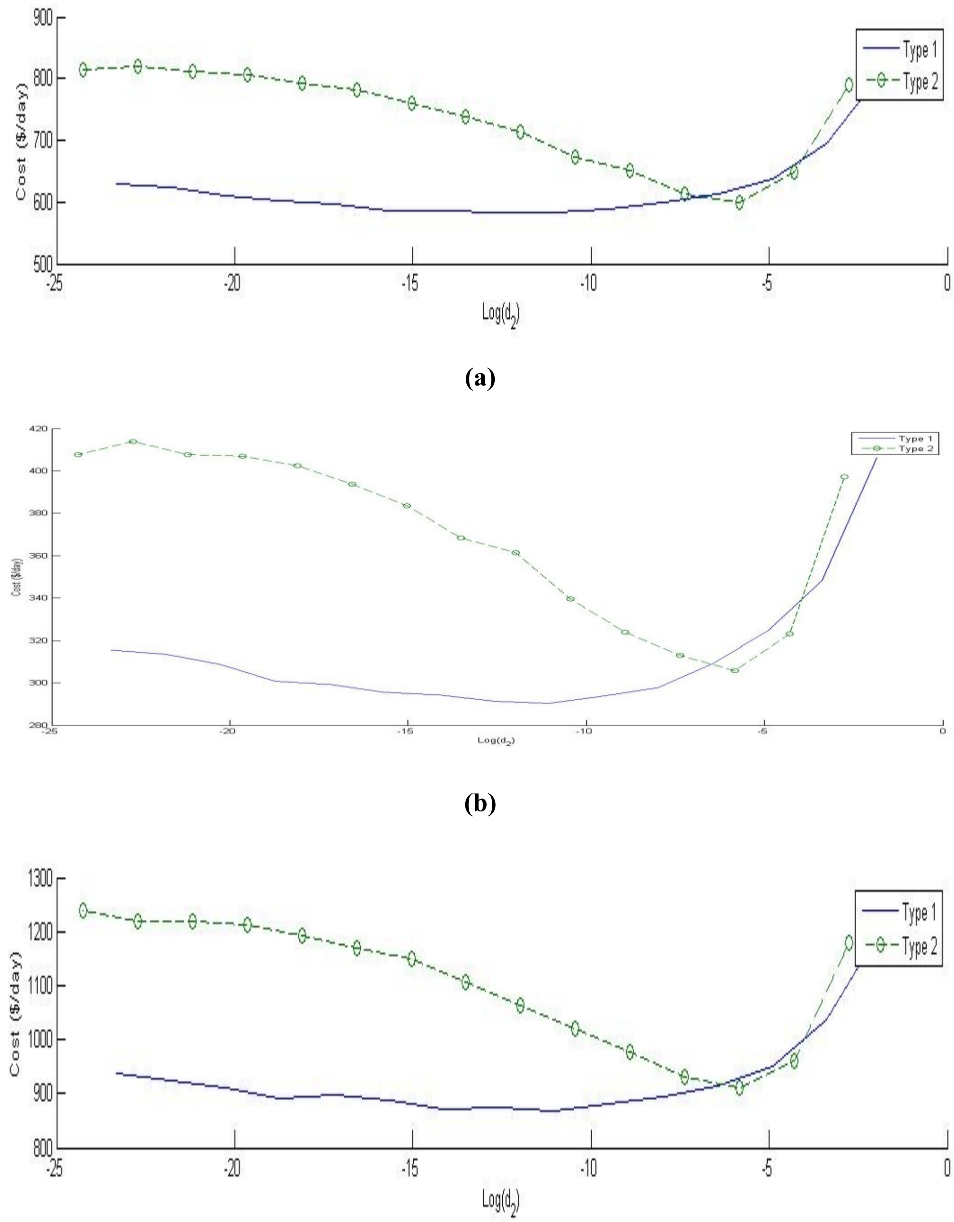


(c)

Figure 14: Total preventive and failure cost versus d_1^k in logarithm scale: (a). for farm has [3 3] (b) for the farm has [6 6] (c) for the farm has [9 9]



(a)

(b)

(c)

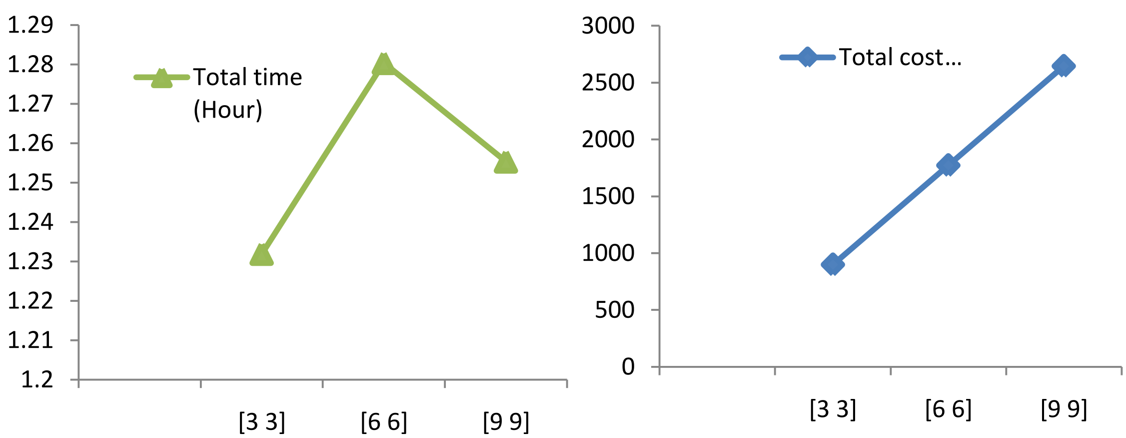
Figure 15: Total preventive and failure cost versus d_2^k in logarithm scale: (a) for the farm has [3 3] (b) for the farm ha [6 6] (c) for the farm has [9 9]

4.1.2. Constant –Interval Policy

In this section, we will use the same data we used in section 3.3.2 in Table 5. The number of turbines is the same as we used in section 4.1.1, which are 9, 12 and 18 turbines. According to Table 7 and Figure 16, the maintenance time for CI maintenance is not linear and it's almost the same in all cases. In CI, we found the total maintenance time and cost for each type separately. The time required for the farm with six turbines is almost the same as the farm which has twelve or eighteen turbines, while the total cost increases linearly with the total number of turbines in the farm.

Table 7: Constant- Interval policy Time and Cost

Number of Turbines	Total cost ($)	Total time (Hour)
[3 3]	898.10	1.23
[6 6]	1772.30	1.28
[9 9]	2646.40	1.26



(a) (b)

Figure 16: (a). Number of turbines in farm versus the total time for maintenance (b) the total cost versus number of turbines

4.2. The Effect of the Wind Turbine Numbers in Different Types on Maintenance Cost and Time

In this section, we will discuss how the total cost and maintenance time are affected by increasing the number of turbines with increasing the number of turbine types. In this case, we will apply the CBM and Constant-Interval policies for three farms which have two, three and four types of turbines.

4.2.1. CBM policy

We used the same data we previously study in section 3.3.1 for type one and two. The new data will be added in the table for type three and four (assuming data). All the farm maintenance is conducted under the same conditions which include the lead time, the number of key components (i.e. four components), the inspection interval (ten days) and the number of iteration (200,000).

Table 8 displays the Weibull distribution parameters (α and β). The cost data are: failure replacement cost, variable preventive maintenance cost, fixed preventive maintenance cost and fixed cost are given in Table 9. The standard deviation data are displayed in Table 10. Based on the data in pervious tables, experiments have been conducted twice, the first run where the farm has three types of turbines and the second run where the farm has four types of turbines. In Table 11, the total expected cost and total maintenance cost for three cases (two types, three types and four types) are displayed. In all cases the number of turbines for each type is three. Figure 17.a displays the number of types versus the total maintenance time and Figure 17.b displays the total cost versus the number of types in the farm.

Table 8: Weibull failure time distribution for major components for four types

Component	Scale Parameter α (Days)				Shape Parameter
	Type 1	Type 2	Type 3	Type 4	β
Rotor	3,000	6,000	3000	6,250	3
Main Bearing	3,750	7,500	3750	6,250	2
Gearbox	2,400	4,800	2400	4,000	3
Generator	3,300	6,600	3300	5,500	2

Table 9: ANN life percentage predication error standard deviation value for major components for four types

Component	Standard Deviation			
	Type 1	Type 2	Type 3	Type 4
Rotor	0.12	0.24	0.18	0.3
Main Bearing	0.10	0.20	0.15	0.25
Gearbox	0.12	0.24	0.15	0.25
Generator	0.10	0.20	0.18	0.3

Table 10: Failure replacement and preventive maintenance cost for major components for four types

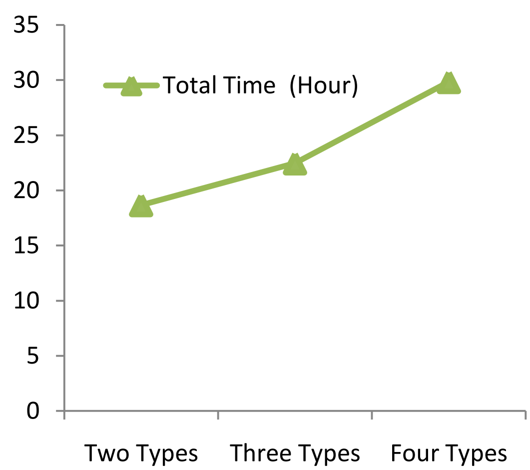
Component	Failure Replacement cost ($ 1000)		Variable Preventive maintenance Cost ($1000)		Fixed Preventive maintenance Cost ($1000)		Fixed Cost to wind farm	
	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2	Type1	Type2
Rotor	112	224	28	56	25	50	50	
Main Bearing	60	120	15	30				
Gearbox	152	304	38	76				
Generator	100	200	25	50				
Component	Failure Replacement cost ($ 1000)		Variable Preventive maintenance Cost ($1000)		Fixed Preventive maintenance Cost ($1000)		Fixed Cost to wind farm	
	Type 3	Type 4	Type 3	Type 4	Type 3	Type 4	Type 3	Type 4
Rotor	168	280	42	70	37.5	62.5	50	
Main Bearing	90	150	22.5	37.5				
Gearbox	228	380	57	57				
Generator	150	250	37.5	62.5				

According to these results, it is clear that the relationship between the numbers of turbine and maintenance time is linear. Thus, we can forecast the maintenance cost and time for farms with more than 4 types under the same conditions.

The farm that has three types of turbines, the failure thresholds are: Type 1: d_1^1 = 0.1585 and d_2^1 = 0.000. Type 2: d_1^2 =0.0631 and d_2^2 = 0.0029. Type 3: d_1^3 = 0.1000 and d_2^3 = 0.0002. These values are different than the value we got when we have two types. For the farm that has four types of turbines: Type 1: d_1^1 = 0.1585 and d_2^1 = 0.000. Type 2: d_1^2 =0.0631 and d_2^2 = 0.0029. Type 3: d_1^3 = 0.1000 and d_2^3 = 0.0010. Type 4: d_1^4 = 0.0631 and d_2^4 = 0.0029. It is clear that the value of failure thresholds are affected by increasing the number of turbines with increasing the number of turbine types in the farm because the number of variable in the model is increased. According to Figure 18 and 19, the curve of each type is similar.

Table 11: CBM results for the farms have two, three and four types of turbines

Number of Types	Total Cost ($)	Total Time (Hour)
Two Types	594.99	18.66
Three Types	833.71	22.60
Four Types	1072.90	30.07



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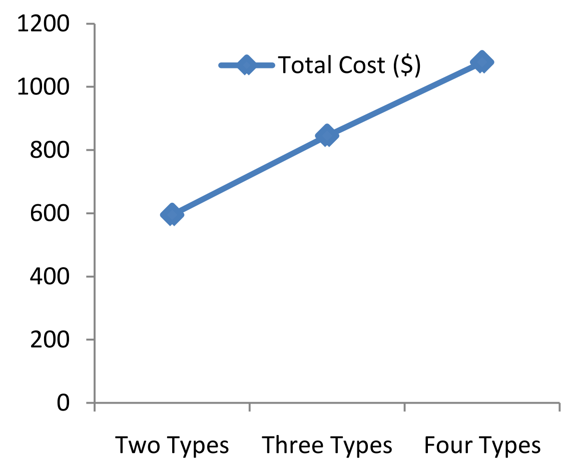
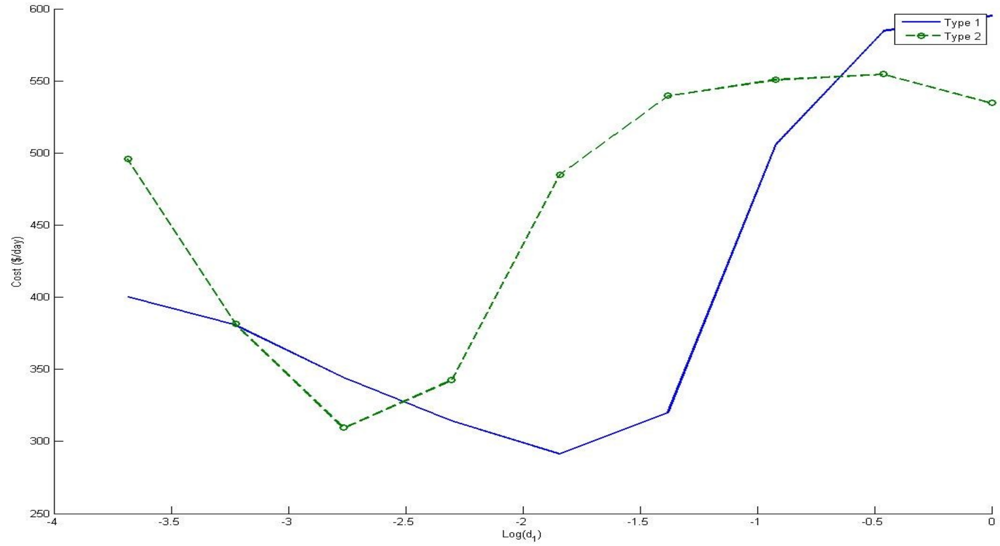


(b)

Figure 17: (a) Number of turbine types in the farm versus total time for maintenance. (b) The total cost versus number of turbine types



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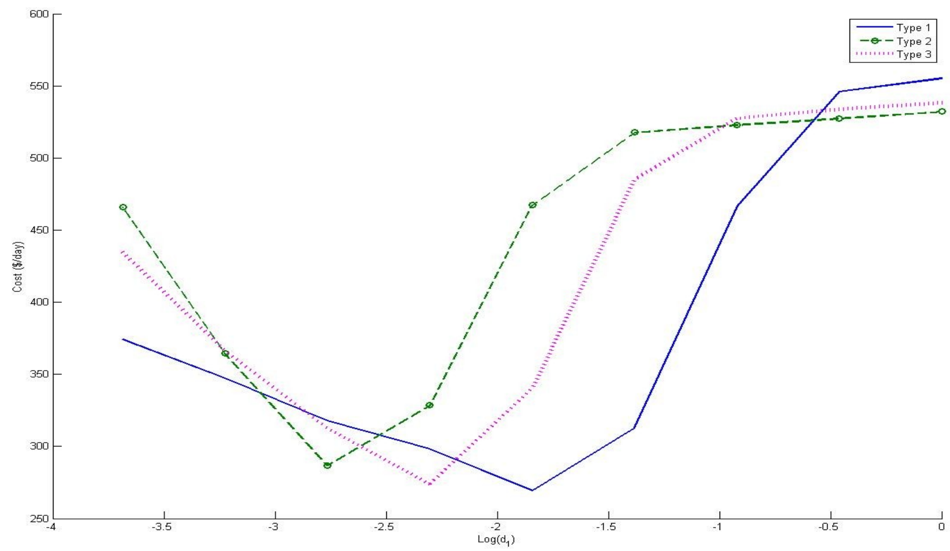

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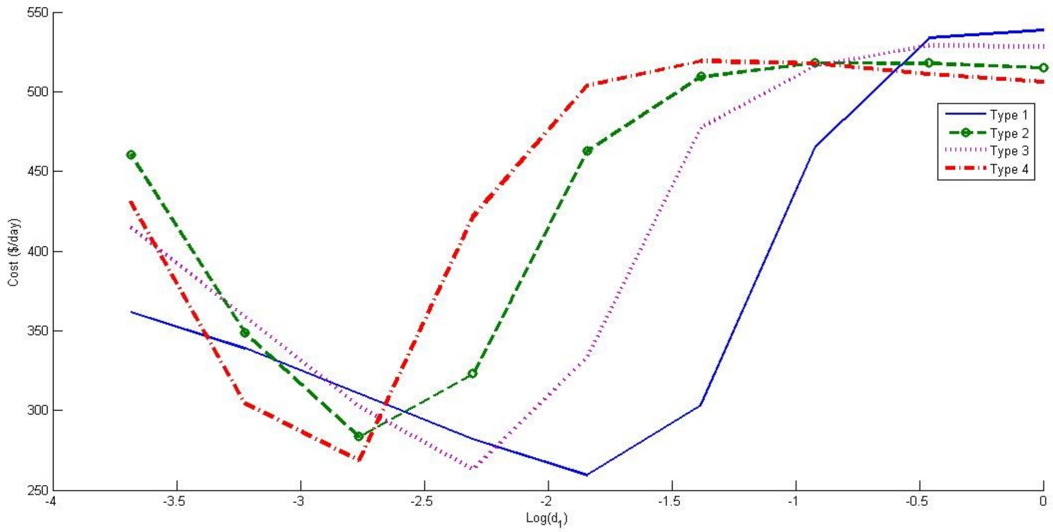
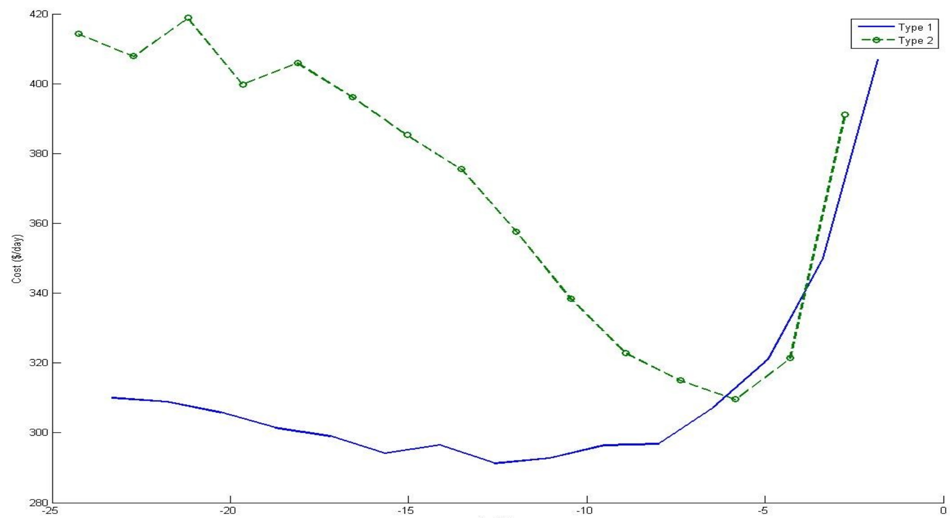
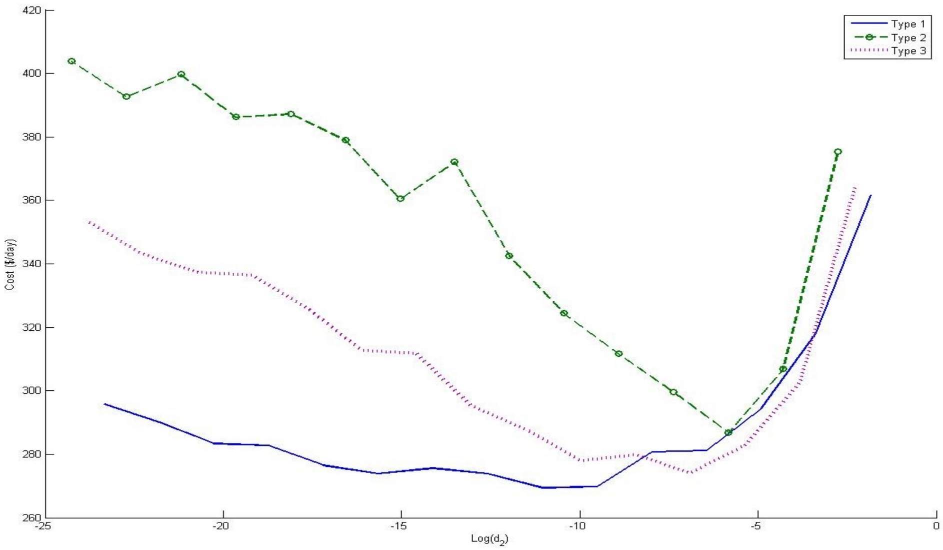


(c)

Figure 18: Total Preventive and failure cost versus d_1^k in logarithm scale: (a) the farm has two types (b) the farm has three types (c) the farm has four types



(a)



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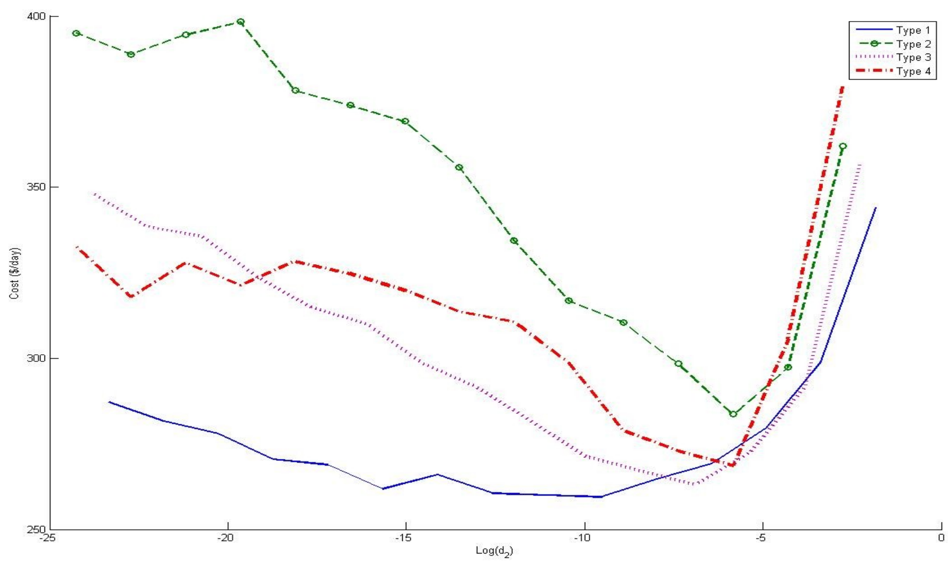


(c)

Figure 19: Total preventive and failure cost versus d_2^k in logarithm scale: (a) the farm has two types (b) the farm has three types (c) the farm has four types

4.2.2. Constant-Interval Policy

We used the same data we previously study in section 3.3.2. The new data will be added for the table for the type three and four. All the farm maintenance has the same conditions, which include the lead time, the number of basic components (four components), and the inspection interval (ten days).

Table 12: Cost data for the Constant-Interval maintenance policy for three types

Components	Failure replacement cost ($ 1000)			Preventive replacement cost ($ 1000)		
	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
Rotor	128.67	240.67	184.67	35.64	63.64	49.64
Main bearing	76.67	136.67	106.67	22.64	37.64	30.14
Gearbox	168.67	318.67	244.67	45.64	83.64	64.64
Generator	116.67	216.67	166.67	32.64	57.64	45.14

Table 13: Cost data for the Constant-Interval maintenance policy for four types

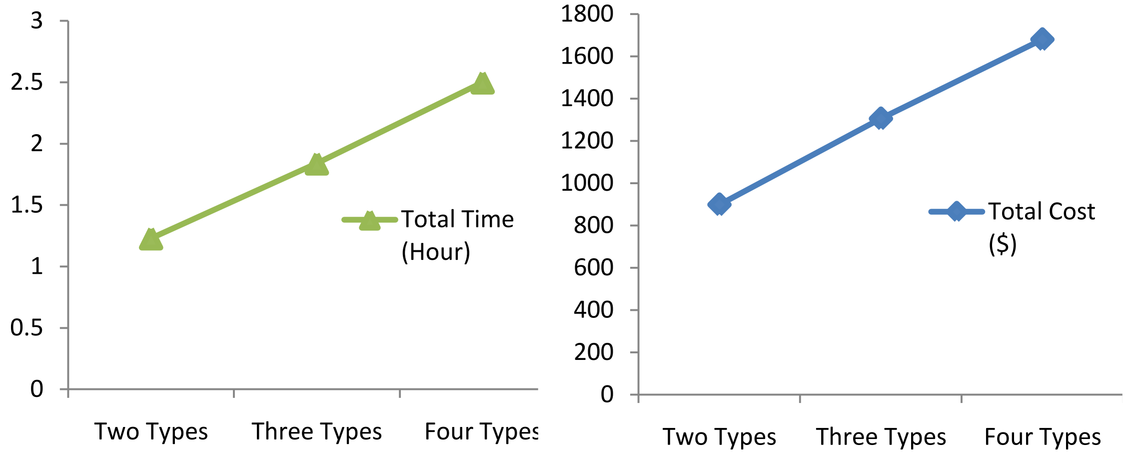
Components	Failure replacement cost ($ 1000)				Preventive replacement cost ($ 1000)			
	Type 1	Type 2	Type 3	Type 4	Type 1	Type 2	Type 3	Type 4
Rotor	124.5	336.5	180.5	292.5	35.29	69.54	52.42	86.67
Main bearing	72.5	132.5	102.5	162.5	22.29	43.54	32.92	54.17
Gearbox	164.5	314.5	240.5	392.5	45.29	89.54	67.42	111.67
Generator	112.5	212.5	162.5	362.5	32.29	63.54	47.92	79.17

Experiments have been conducted twice (the first has three types of turbines and the second has four types of turbines) in Table 14 and Figure 20.

Table 14: Constant-Interval results for the farms have two, three and four types of turbines

Number of Types	Total Cost ($)	Total Time (Hour)
Two Types	898.10	1.23
Three Types	1305.00	1.84
Four Types	1679.9	2.50

The total maintenance cost and time for Constant-Interval policy are affected by the number of turbines in the farm.



(a) **(b)**

Figure 20: (a) Number of turbine types in the farm versus total time for maintenance (b) The total cost versus number of turbine types

Based on the results in section 4.2.1 and 4.2.2, the CBM and CI maintenance are affected by increasing the numbers of turbine by adding more turbines types in the farm with roughly linear relationship.

4.3.CBM Considering Different Lead Times

Sometimes the lead times for the wind turbine components are not the same because of different suppliers; production rate; shipping distance; component size, etc. In this section, we analyze the effect of lead time on the total failure probability of the wind turbines.

The production process for wind turbine affects the lead time. It is adopted by the layout of factory, the availability of raw materials, the production method, the labour, etc. Transportation is critical issues in the wind turbine production, especially when the size increases. It is affected by transportation method, number of components, load height and seasonal transportation. The transportation methods of the wind turbines include: tractor-trailer, railroad, steerable dolly, barge, and chartered ocean or lake vessels. The transportation methods are selected based on the location of the farms and its access to the transportation methods (Wei, 2010). The transportation load is limited during some seasons, such as frozen road. In some area the load is also limited during rush hours or seasons.

4.3.1. Failure Probability with Different Lead Time

The failure probability at component level is calculated using equation (3-4), when the lead time is constant. The following equation is used to calculate the failure probability, with l_m rather than l, for the components with different lead times:

$$Pr_{k,n,m} = \frac{\int_{t_{k,n,m}}^{t_{k,n,m}+l_m} \frac{1}{\sigma_{k,n,m}\, TP_{k,n,m}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-TP_{k,n,m}}{\sigma_{k.n.m} TP_{k,n,m}}\right)^2} dx}{\int_{t_{k,n,m}}^{\infty} \frac{1}{\sigma_p\, TP_{k,n,m}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-TP_{k,n,m}}{\sigma_{k,n,m} TP_{k,n,m}}\right)^2} dx} \tag{4-1}$$

In equation (4-1), the failure probability ($Pr_{k,n,m}$) for each component depends on: lead time (l_m), current age ($t_{k,n,m}$) and standard deviation ($\sigma_{k,n,m}$). $TP_{k,n,m}$is the predicted failure time for component *m* in turbine *n* in category *k* using ANN. The failure probability at turbines level is calculated by equation (3-2), because the components are connected in series.

A numerical example is used to show the effect of different components lead time on the total maintenance cost and time and the failure probabilities for different scenarios of the farms.

The numerical example for wind farms considers that the components have different lead time. Also, we considered that we have different numbers of turbines in the farms. We will use the same data we used in section 3.3 for Weibull distribution parameters, standard divination errors and costs with different lead times for the components. Table 6 displays the lead time data. The lead time is assumed based on the scale parameter of Weibull distribution, while for the constant lead time case we use 30 days. The value of lead time is the maximum value for the type 1 lead times and the average lead times for type 2. After that, the results are compared with results for turbine with constant lead time.

Table 15: The lead time data

Components	Lead Time			
	Type 1	Type 2	Type 3	Type 4
Rotor	30	45	38	48
Main bearing	14	16	15	17
Gearbox	25	38	32	40
Generator	15	23	19	24

4.3.2. Failure Probability at Turbine Level with Different Lead Time

In this part, we discuss the effect of different lead time of components on the failure probability at turbine level. There are six turbines in the farm, among which three turbines belong to type 1 and the others belong to three turbines of type 2. There are four key components for each turbine: rotor; main bearing; gearbox; and generator.

We calculate the failure probability for components by using equation (4-1), after that we use equation (3-2) to calculate the failure probability at turbine level by using MATLAB code with iteration 200,000, after that we take the average value for results. We obtain that the failures probability for type 1 is: $0.1392 \times 10^{-9}, 0.1198 \times 10^{-9}$ and *0.2508*$\times 10^{-9}$. For type 2 are: $0.5300\times 10^{-4}, 0.5806 \times 10^{-4}$and 0.4907×10^{-4} when lead time is variable. For constant lead time, 30 days, the failures probabilities for type 1 are: $0.0803\times 10^{-8}, 0.0727 \times 10^{-8}$and 0.1610×10^{-8} and type 2 are: 0.1576×10^{-3} , 0.951×10^{-3} and 0.1044×10^{-3}.

Based on previous results, the failure probability at turbine level is affected by the lead time of components. Since we have components with lead time shorter than constant leas time case, the failure probability is reduced. In other words, the short lead time reduces the failure probability and the risk of downtime. On the other hand, if the lead time for components is larger than constant lead time case, the failure probability will be increased.

4.3.3. CBM Policy

In this section, we show the effect of different lead time of components on the maintenance cost and time and the failure probabilities for different farms. The farms cases are the same as pervious section with new data for lead time. The results are displayed in Table 16 and 17.

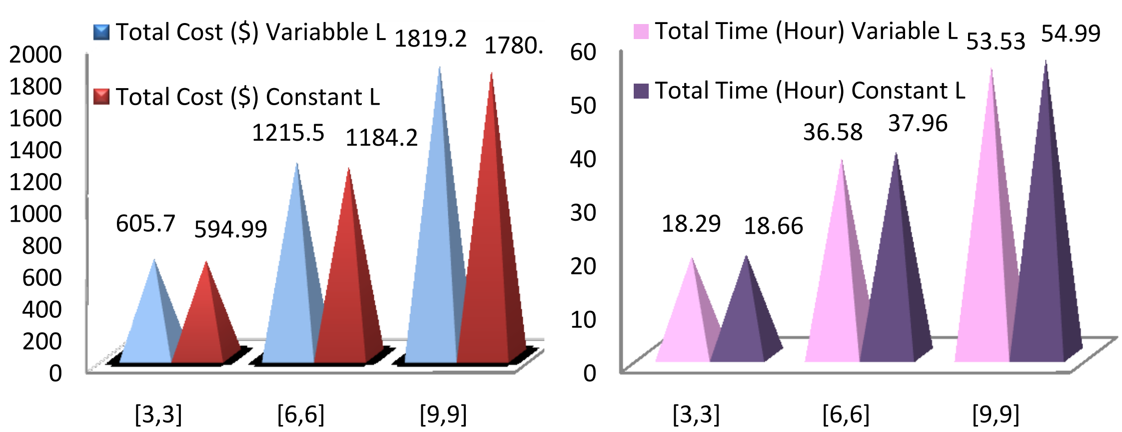
Table 16: The total maintenance time and cost for the farms with different total number of turbine and lead time

Number of Turbines in the farm	Total Cost ($)	Total Time (Hour)
[3,3]	605.70	18.29
[6,6]	1215.50	36.58
[9,9]	1819.20	53.53

Table 17: The total maintenance time and cost for the farms with different number of turbine types and lead time

Number of Turbines Types in the farm	Total Cost ($)	Total Time (Hour)
Two Types	605.70	18.29
Three Types	840.55	24.21
Four Types	1085.2	30.14

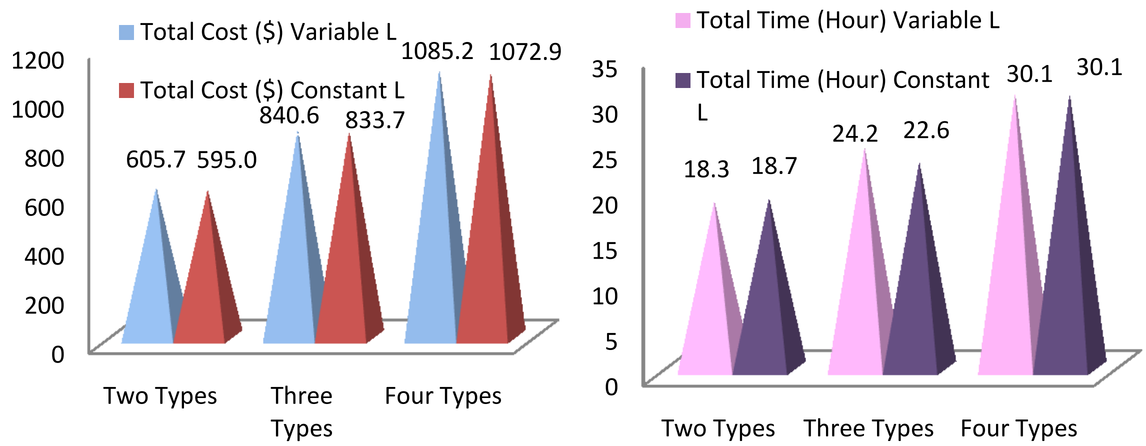
Based on these results, the relationship between the maintenance cost and time and number of turbines in the farm and number of types is linear when the lead time of components variable. According to Figures 21 and 22, we show that the total maintenance cost is affected by the lead time of components. The total maintenance cost is decreased or increased based on the lead time of components.



(a) **(b)**

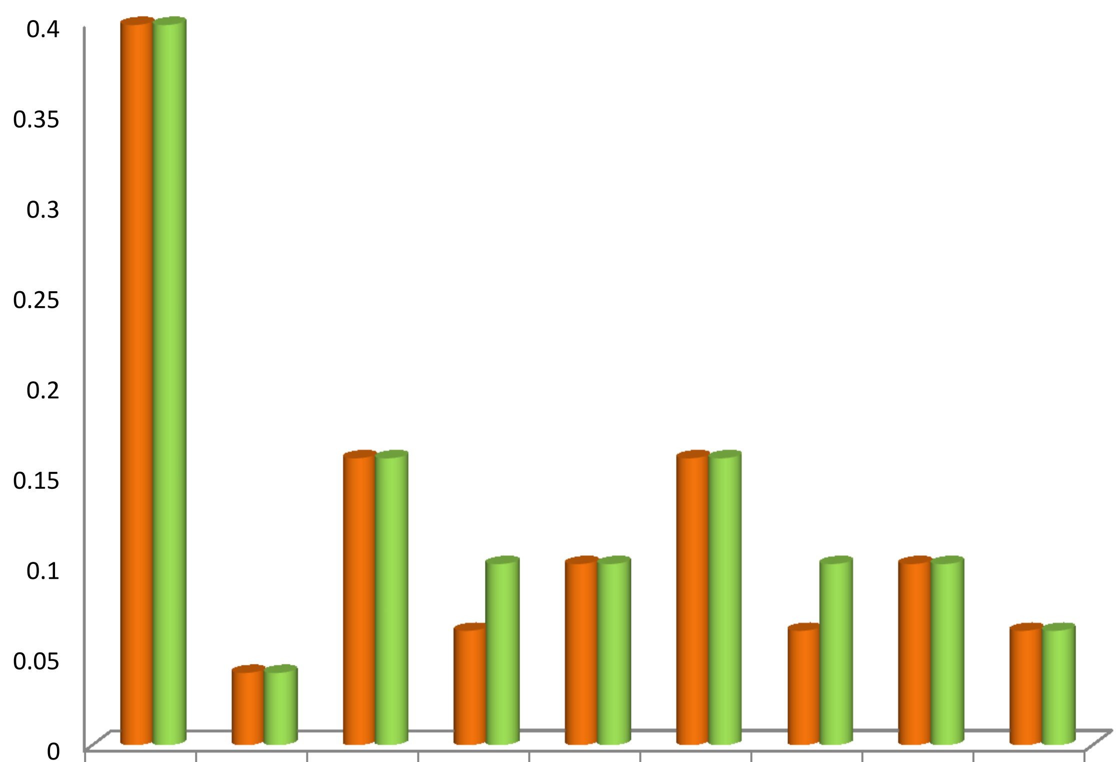
Figure 21: Comparison between constant and variable lead time for different number of turbines in the farm results (a) based on total maintenance cost (b) based on total maintenance time

In Figure 23, we compare the constant and variable lead time cases based on the value of d_1^k for the farms that have two, three or four types of turbines. We conclude that the value of d_1^k has is almost the same because we use the variable d_1^k follow discreet function, while the value of d_2^k decreases (see Figure 23 and 24).



(a) **(b)**

Figure 22 : Comparison between constant and variable lead time for different number of turbines types in the farm results (a) based on total maintenance cost (b) based on total maintenance time



	T1_2T	T2_2T	T1_3T	T2_3T	T3_3T	T1_4T	T2_4T	T3_4T	T4_4T
Constant L d1	0.3981	0.0398	0.1585	0.0631	0.1	0.1585	0.0631	0.1	0.0631
Variable L d1	0.3981	0.0398	0.1585	0.1	0.1	0.1585	0.1	0.1	0.0631

Figure 23: Comparing between constant and variable lead time based on d_1^k value

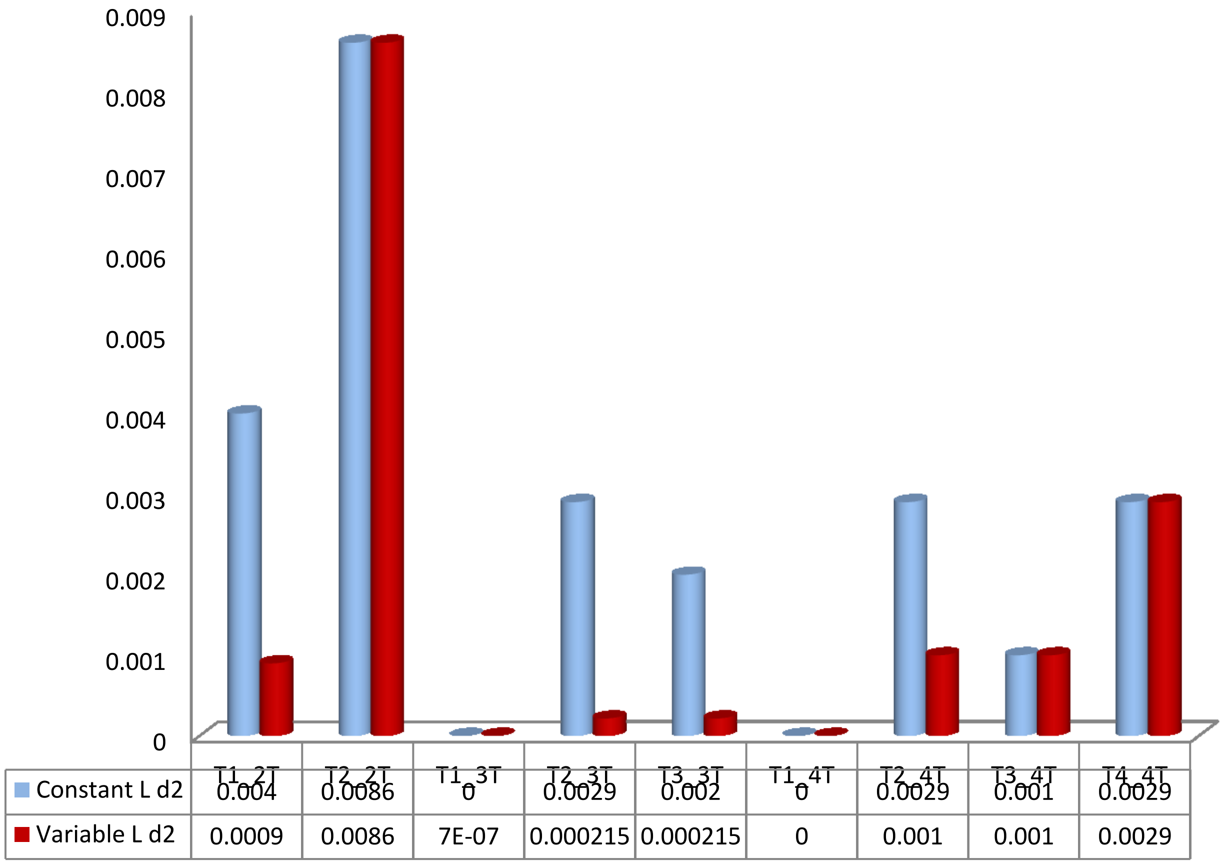


Figure 24: Comparing between constant and variable lead time based on d_2^k value

4.4. Conclusions

Based on the results, the total maintenance cost and time in CBM policy are affected by the total number of turbines in the farm in linear relation and direct proportional. In CI policy, the total maintenance cost is affected by the number of turbines Moreover, the maintenance time is affected by increasing the number of turbines with increasing the number of turbine types. The total cost for CBM policy is less than CI in all cases.

The variable lead time effects the total maintenance cost while the total maintenance time remains the same. Also, the failure thresholds are affected by the lead time of components, since the failure probability of turbines change based on the lead time.

Chapter Five

Conclusions and Future Research

5.1.Conclusions

Maintenance optimization has become one of the most prominent projects because of its revenue benefit. In wind power, using maintenance optimization is new, but it has become more and more important due to the increase demand for wind energy.

We have introduced the methodologies for optimizing maintenance for wind power system considering that it has more than one type of turbines and variable lead time for components. Previous approaches optimize maintenance for farms with one type of turbines and components with constant lead time. In this thesis, we develop the CBM policies for farms that have more than on type considering several cases, such as different number of turbines in the farm. In particular, in CBM, we optimized the maintenance cost and time by defining two failures probability thresholds at the wind turbine level for each turbine type (d_1^k and d_2^k). The value of d_1^k is larger than d_2^k as constrain for the model. We compared the CBM results with CI maintenance because it is the traditional maintenance method for the wind power systems to demonstrate that the CBM is better for the wind power system. Moreover, we demonstrate that the CBM has great ability to reduce the total maintenance cost of wind farms for cases which are presented as experiments. The failure thresholds at turbine level are affected by the lead time of components.

5.2.Future Research

The developed model can give an optimum maintenance cost for the wind farms. However, the real farms can be more complicated and there are more conditions during maintenance time. Therefore, there are opportunities to improve these methodologies by considering these conditions. Future research can be done to extend the current study as following:

- Considering the failure probability during different seasons. The wind turbines performance is affected by the weather, for example during winter there is possibility to freeze the turbines.
- Adding constraints for maintenance team moves in the farms. Sometimes the maintenance team works in more than on farm, that fact that makes the availability of maintenance team less.
- Determining the number of spare items for components. The inventory policy for the systems is affected by the number of failure components and demand, which means we can use the failure probability to determine the inventory for each type.
- Considering additional variables and optimizing theses variables.

The real wind turbine data are important for reliability analysis and maintenance schedule. Sharing data and standard report a good opportunity for improving maintenance and optimum the results of researches.

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