# Optimization of condition-based maintenance in wind energy systems using numerical approach

by

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# Abstract

Effective maintenance strategies play a critical role in ensuring the operational integrity of wind farms while concurrently reducing costs. Among a variety of maintenance strategies, condition-based maintenance (CBM) stands out as an effective approach nowadays. This is an approach to maintenance that prioritizes actions based on the observed condition of an asset or equipment, rather than following fixed schedules or time-based intervals. It relies on continuous monitoring, data analysis, and predictive algorithms to identify potential issues or failures before they occur. Through optimization of CBM policies, operating and maintenance (O&M) costs can be minimized, while enhancing the reliability of wind turbines and components. This in turn brings significant benefits for the wind industry, fostering its sustainability and competitiveness.

In existing studies, simulation methods were commonly used for CBM policy cost evaluations. The simulation methods demonstrated flexibility in modeling diverse scenarios and factors. However, due to its reliance on sampling, variations occur in the evaluation of CBM costs, leading to non-smooth surfaces in the cost function. This sampling characteristic may lead to issues such as local minima and convergence, thereby complicating the optimization process. A numerical method was originally proposed in a previous study to evaluate the maintenance cost rate of wind farm systems, aiming to address limitations identified in the simulation methods mentioned above. However, it had issues in obtaining reasonable cost evaluation and optimization results.

This thesis develops a modified numerical method based on previous studies for more accurate wind farm CBM cost evaluation. The CBM policy used in this study is the same as those used in the referred studies in the literature. Compared to the existing numerical method, the proposed modified numerical method addresses the issues and achieves more accurate results mainly by

introducing a new 4-dimensional structure for the component age combination probability matrix, and integrating a previously separate age combination probability transition matrix into the main cost evaluation loop. With the modified numerical method, we are able to find the optimal CBM policy, which were not possible before. The results are verified using multiple examples. The cost surface generated by of the numerical method exhibits greater smoothness and cost estimation outcomes are stable, which supporting the optimization process. Thus, the optimal CBM policy corresponding to the minimum maintenance cost rate can be estimated more accurately compared to the simulation method. Sensitivity analysis and comparative studies with the simulation method were conducted to emphasize the advantages of the numerical method. This thesis provides basis for further advancing numerical methods for wind farm CBM policy evaluation and optimization.

# Preface

This thesis is an original work by Yunqiu Zuo under the supervision of Dr. Zhigang Tian. A proper CBM policy or maintenance activities can reduce the failure event, improve the reliability of the wind turbine and reduce the maintenance cost. This thesis modified a numerical method to accurately estimate the maintenance cost rate of wind farm systems. The optimal maintenance policy with lowest maintenance cost rate is found by CBM optimization. The evaluation results of the numerical method are verified to be more accurate and stable than the simulation method through numerical examples, sensitivity analysis and comparative studies.

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# List of Symbols

| | |
|---|---|
| $\mathrm{P_t}$ | Life percentage obtained using ANN |
| $\mu_p$ | Mean of the ANN life percentage prediction error |
| $\sigma_p$ | Standard deviation of the ANN life percentage prediction error |
| $\sigma$ | Standard deviation of the predicted failure time distribution |
| $TL_{n,m}$ | Real failure time of component $m$ in turbine $n$ |
| $TP_{n,m}$ | Predicted failure time of component $m$ in turbine $n$ |
| $T_P$ | The predicted failure time distribution |
| $t_p$ | The predicted failure time value at current age $t$ |
| $N$ | The number of wind turbines in a wind farm |
| $M$ | The number of critical components considered in a wind turbine |
| $Pr$ | Failure probability |
| $Pr_{n,m}$ | The failure probability of component $m$ in wind turbine $n$ |
| $Pr_n$ | The failure probability of wind turbine $n$ |
| $t$ | The age of a general component at the current inspection point |
| $L$ | The maintenance lead time |

| | |
|---|---|
| $d_1$ | Level 1 failure probability threshold value |
| $d_2$ | Level 2 failure probability threshold value |
| $C_E$ | The total expected maintenance cost per unit time |
| $\mu_{p,m}$ | Mean value of the ANN life percentage prediction error for component $m$ |
| $\sigma_{p,m}$ | Standard deviation of the ANN life percentage prediction error for component m; |
| $KV$ | Vector indicates the possible age values, values can be taken $(1,2,\dots,K)$ |
| $K$ | The number of age intervals for a component |
| $I$ | The number of iteration times |
| $T$ | Typical lifetime of component |
| $T_I$ | The inspection interval length |
| $kr$ | Matrix indicating the combination of all wind turbine component age |
| $kr_t$ | Matrix for increased age combination when update age combination probability matrix for next inspection point |
| $PrA$ | Matrix describing the age probability distribution of new component $m$ in turbine $n$, with input $(k_{n,m}, n, m)$ |
| $PrS$ | Matrix describing the RUL probability distribution for each of the turbine components, with input $(K, N, M)$ |

| | |
|---|---|
| $Pr_t$ | Probability of transition based on maintenance actions of all components |
| $P_U(kr)$ | Updated age combination probability matrix of all age combination for wind farm |
| $P_A(kr)$ | Matrix used to calculate updated age combination probability matrix |
| $P_{A_i}(kr)$ | Accumulative $P_A(kr)$ obtained at previous possible age combination |
| $k$ | The possible age value for a specific component |
| $k_{nm}$ | The possible age value for component $m$ in turbine $n$ |
| $\alpha_m$ | Weibull distribution scale parameter for component $m$ |
| $\beta_m$ | Weibull distribution shape parameter for component $m$ |
| $P(kr)$ | Age combination probability matrix of for all age combination for wind turbine system at the beginning |
| $P_{new}$ | Age combination probability of all age combination for wind farm after implementing maintenance actions |
| $P_{new_i}(kr)$ | New age combination probability matrix of previous possible age combination |
| $T_{PrA}(kr)$ | The age combination probability transition matrix that indicates the probability transitions from current age combination of all wind turbine component age to different component age combination |

| | |
|---|---|
| $T_{Pr}(K,N,M)$ | The RUL transition probability matrix that indicates the probability transitions from current combination of all wind turbine component RUL to different component RUL |
| $C_{current}$ | Maintenance cost of each possible component age combination |
| $C_{Current_i}$ | Accumulative costs generated from the last maintenance activity |
| $C_{Total}$ | Accumulative maintenance cost of all possible age combination in an inspection point |
| $C_{Total_i}$ | Accumulative total maintenance cost obtained from maintenance actions on previous possible age combination |
| $C_{Total\_sum}$ | Accumulative maintenance cost until current inspection |
| $C_{Total\_sum_i}$ | Accumulative cost generated at the previous inspection point |
| $T_{Max}$ | The maximum iteration time |
| $C_F(n,m)$ | The failure replacement cost for component $m$ in turbine $n$ |
| $C_P(n,m)$ | The variable preventive replacement cost for component $m$ in turbine $n$ |
| $C_{Pfix}(n)$ | The fixed cost of maintaining a wind turbine $n$ |
| $C_{Farm}$ | The fixed cost of sending a maintenance team to the wind farm |

# List of Acronyms

| | |
|---|---|
| **RES** | Renewable energy sources |
| **O&M** | Operation and maintenance |
| **PM** | Preventive maintenance |
| **TBM** | Time-based preventive maintenance |
| **CBM** | Condition-based maintenance |
| **CM** | Condition monitoring |
| **ANN** | Artificial neural network |
| **FFNNs** | Feed-forward neural networks |
| **PHM** | Proportional hazard models |
| **RUL** | Remaining useful life |
| **DAQ** | Data acquisition |
| **PC** | Personal computer |
| **USB** | Universal serial bus |
| **PCI** | Peripheral component interconnect |
| **IMS** | Information management system |
| **EMD** | Empirical mode decomposition |
| **PI** | Proportional and integral |
| **PMI** | Proportional multiple-integral |
| **UKFs** | Unscented Kalman filters |
| **EKFs** | Extended Kalman filters |

| | |
|---|---|
| **MHKF** | Multiple hybrid Kalman filters |
| **PWL** | Piecewise linear |
| **FDI** | Fault detection and isolation |
| **MCSA** | Motor current signature analysis |
| **STFT** | Short-time Fourier transform |
| **WT** | Wavelet transforms |
| **HHT** | Hilbert-Huang transform |
| **WVD** | Wigner-Ville distribution |
| **SVM** | Support vector machine |
| **DAG** | Directed acyclic graph |
| **DBN** | Dynamic Bayesian network |
| **2TBN** | Two-Timeslice Bayesian Network |
| **HMM** | Hidden Markov Model |
| **HSMM** | Hidden semi-Markov model |
| **KB** | Knowledge base |
| **TSK** | Takagi-Sugeno-Kang |
| **PHM** | Prognostics and health management |
| **HAWT** | Horizontal-axis wind turbines |
| **VAWT** | Vertical-axis wind turbines |
| **MSCNN** | Multiscale Convolutional Neural Network |

# Chapter 1 Introduction

## 1.1 Background

With the rapid development of industrial society, the increasing use of renewable energy has become an important global trend. Although traditional energy sources such as coal, natural gas and oil are widely used for power generation, heating, steam, and other energy sources required for human production and life. However, the extensive use of fossil fuels has brought about many environmental problems such as greenhouse gas emissions, acid rain, and limiting ozone depletion. Therefore, Renewable Energy Sources (RES) have emerged as a cleaner, greener and more sustainable alternative energy source for the future. In 2023, renewable energy sources account for over 30% of global electricity generation, with the share of wind and solar power doubling to 13% [1]. Hydropower, bioenergy and geothermal energy are also considered major renewable energy sources. Renewable energy production is expected to continue to rise as these sources become more cost-competitive and demand for sustainable energy solutions continues to grow.

Wind energy is a sustainable renewable energy that has a much lower environmental impact than burning fossil fuels. Wind energy is variable and therefore requires storage or other dispatchable generation energy for reliable power supply. Wind turbines are devices that convert the kinetic energy of the wind into mechanical or electrical energy. Today, wind power is generated almost exclusively by wind turbines, typically consisting of wind farms that are connected to the grid. In 2022, wind supplied over 2000 TWh of electricity, which was over 7% of world electricity. Wind power has grown by 17% in this year, making it a fast-growing source of electricity [2]. Wind turbines are often installed in remote, elevated, or offshore locations which poses considerable operational challenges as they are often exposed to harsh weather conditions and climatic extremes, which can weaken their functional capabilities and overall performance efficiency, leading to severe downtime and reduced power output [3]. The special location of wind turbines, difficulty in accessing high ground for operation and maintenance, and the rental, transportation, and operation of large equipment make operation and maintenance (O&M) costs a significant portion of turbine expenditures at many wind farms. O&M costs account for up to 30% of the total energy production cost [4] due to remote location, difficulty in accessing maintenance in high ground, and the rental, transportation, and operation of large equipment. Therefore, maintenance of wind turbines is very important, and ensuring the reliability of wind turbines and minimizing maintenance costs has become a critical issue.

The Maintenance of components ensures that they continually perform their planned functions, ensuring the reliability of the components and the system, or the recovery of operations from failures in a timely manner. Reasonable and effective maintenance strategies and procedures can use the least amount of resources, reduce component or system downtime, improve the reliability of the system and thus gain more benefits. Three primary maintenance strategies have been studied in the field of wind energy, which are corrective maintenance (CM), time-based preventive maintenance (PM), and condition-based maintenance (CBM) [5].

CM is typically performed when a wind turbine malfunctions, or a component failure is detected. The implications of such failures are significant and may lead to loss of production, increased costs, and damage to other components. Although CM is straightforward, the consequences can be severe, and the associated costs can be high.

In contrast, PM is the execution of regularly scheduled maintenance activities ahead to help prevent unexpected failures in the future. Time-based maintenance (TBM) is a classical preventive maintenance approach and widely applied in engineering practices due to its simplicity in decision-making and implementations [6]. In TBM, maintenance actions are scheduled at regular time intervals to prevent significant failures. However, this reduction in failures comes at the cost of completing maintenance tasks more frequently than is necessary and failing to exhaust the full lifespan of the various components that have been put into service. The big challenge for TBM is to determine the optimal maintenance intervals to reduce maintenance costs and increase component life utilization.

In CBM, components are monitored and inspected to determine their physical condition, detect early potential failures and determine required maintenance activities before failure occur. Compared to TBM, CBM avoids unnecessary maintenance tasks by taking maintenance actions only when there is evidence of abnormal behavior of the physical assets. If a CBM program is properly established and effectively implemented, it can reduce the number of unnecessary scheduled preventive maintenance operations, thus significantly reducing maintenance costs [7]. Francois and Lina presented an approach to optimize CBM strategies for components which degradation can be classified according to the severity of the damage [8]. A partially observed Markov decision process were used to find optimal condition-based maintenance for wind turbine in [9] and its case study demonstrated that the optimal strategy can adapt to the operating conditions and select the most cost-effective action. Another finding reached was that a dynamic strategy significantly improves reliability and reduced costs compared to a fixed periodic maintenance and static strategy.

Diagnostics and prognostics are two important maintenance decision support in CBM. Diagnostics focus on detection, isolation and identification of faults when they occur. Prognostics attempts to predict faults or failure before they occur [10].

Various approaches have been investigated by researchers in the area of prognostics of wind turbine maintenance. Two main categories of methods have been identified: physics-based methods and data-driven methods. There are some studies reviewing the physics models in the prognostics process and providing related examples in [11-14]. The physical-based method utilizes physical and degradation models to describe the deterioration condition of components and executes reliability prognostics by using mathematical models that incorporate physical laws [15]. One widely used physics model is the crack growth model. Z. Tian used a dynamic model and simulation to investigate the crack propagation level [16]. Wu and Ni studied the stochastic fatigue crack growth model through analytical and experimental results to modify the model to get reliability prediction of tested material [17]. However, developing accurate physical models for complicated components or systems is a challenging task. In contrast, data-driven approaches attempt to derive models directly from routinely collected condition monitoring data instead of building models based on comprehensive system physics and human expertise [18]. It analyzes health condition data such as vibration, acoustics, oil, strain, and thermography collected from sensors installed on the major components such as the rotor, main bearing, gearbox, and generator of the wind turbine to predict their current health condition, reliability, and remaining useful life. Artificial neural network (ANN) methods are the most commonly used data-driven models for remaining useful life (RUL) prediction, with feed-forward neural networks (FFNNs) being particularly popular. [19] developed the ANN method to predict the RUL of equipment in wind turbines and then define the optimal maintenance policy for the whole wind farm. Bayesian network methods and proportional hazard models (PHM) are also widely used data-driven methods. Dynamic Bayesian networks were used in [20] to obtain RUL in the Markov model for wind turbine blades. In [21], a hybrid approach of neural networks and a proportional hazards model were jointly employed in order to analyze the overall performance of the wind turbine.

CBM optimization is a significant part of CBM program. A proper and accurate CBM optimization method can reduce O&M costs, improve the reliability of components and wind turbines as well as bring significant benefits to the wind industry. For instance, the maintenance cost of a power generation system is optimized by considering diverse turbine types and lead times in [22]. However, CBM has two major limitations. First, the cost of implementing condition monitoring test equipment in the system is too high. In addition, condition-based monitoring does not guarantee that accurate information is collected during operation. Therefore, it is a big challenge to effectively apply CBM in practical industrial situations. The current trend is that more and more researchers intend to exploit new technologies and advanced computational techniques for diagnosis and prognosis, such as neural networks and reinforcement learning.

## 1.2 Research motivation

CBM optimization has great potential to improve performance of wind turbine systems and reduce economic losses due to system breakdown. The simulation methods were widely used in maintenance optimization problems as they can be flexibly applied to different industries and can be used in complex scenarios with the required computational power. In the study [23], a wind farm CBM policy was proposed using a simulation method with two failure probability thresholds, considering multiple wind turbines and components to evaluate the cost. Economic dependencies among wind turbines and their components were considered to reduce O&M costs. The simulation methods demonstrated flexibility in modeling a variety of situations and factors, but due to the nature of sampling, the evaluated CBM cost values were variable, and the cost function surface was not smooth. The possible issues caused by sampling were local minima and convergence, which brings difficulty to the optimization process. Therefore, an accurate numerical method is required to address above-mentioned issues. A numerical method was originally proposed in [24] to evaluate the maintenance cost of wind farm systems, aiming to address limitations identified in the simulation methods mentioned above. However, it had issues in obtaining reasonable cost evaluation and optimization results.

In this thesis, a modified numerical method based on previous studies is developed to accurately evaluate the total maintenance cost of the CBM policy. The CBM policy used in this study is the same as those used in the referred studies in the literature. Compared to the existing numerical method, the proposed modified numerical method addresses the issues and achieves more accurate results mainly by introducing a new 4-dimensional structure for the component age combination probability matrix and integrating a previously separate age combination probability transition matrix into the main cost evaluation loop. With the modified numerical method, we are able to find the optimal CBM policy, which were not possible before. The results are verified using multiple examples. The cost surface generated by of the numerical method exhibits greater smoothness and cost estimation outcomes are stable, which supporting the optimization process. Thus, the optimal maintenance policy corresponding to the lowest maintenance cost can be estimated more accurately compared to the simulation method. One challenge of the proposed numerical method is long computing time. The algorithm is still required to be modified to improve the computing efficiency and deal with more comprehensive problems.

Numerical example is a great way to gain insight into complex problems in assumed scenarios. It can convert theoretical concepts and functions into specific calculations based on specific examples. Numerical examples are conducted for the optimization of CBM for wind farms. By using numerical examples, we can see the implication of the numerical method in a specific scenario. Through examples with multiple turbines and multiple components, we will show how the recommended CBM policy can be used to get the lowest maintenance cost. This will present the wind farm developer with a specific maintenance policy that will minimize maintenance costs by arranging the optimal maintenance activities at the proper time.

Sensitivity analysis is used to understand how changes in input variables affect the output of a model or system. It involves systematically adjusting the values of input parameters within a specified range and observing how these changes impact the results. Sensitivity analysis helps assess the robustness of a model by testing its sensitivity to changes in input variables.

Comparative studies are also important to demonstrate the advantages and disadvantages of the proposed methods. Comparative studies among the results from the simulation method and numerical method are presented to show the benefits of the numerical method. In previous study, the simulation method has proved to be suitable for estimating the maintenance costs of industrial components or systems. In the comparative study, the simulation method will be used to solve the same problem of case studies. Through comparing the results of two methods to verify the stability and accuracy of the numerical method.

## 1.3 Objective and research contributions

The objective of this thesis is to develop a modified numerical method, evaluate maintenance cost accurately using the proposed numerical method and find the optimal maintenance policy for wind farm. There are three main contributions of this thesis: 1) Develop a modified numerical method to evaluate cost more accurately and find the optimal CBM policy applying proposed numerical method. 2) Verify the numerical method results of optimal CBM policy. 3) Compare the optimization results of the numerical and simulation method, emphasizing the stability of the numerical method.

In a previous study, the numerical method was originally proposed to evaluate the maintenance cost for wind farm, but the cost value was not reasonable and optimal CBM policy was not found. To achieve the first contribution, the proposed modified numerical method addresses the issues and achieves more accurate results mainly by introducing a new 4-dimensional structure for the component age combination probability matrix and integrating a previously separate age combination probability transition matrix into the main cost evaluation loop. The procedure of calculating age probability matrix and transition matrix is described in detail in chapter 3. This study will use the same CBM policy with two level turbine failure probability thresholds $d_1$and $d_2$ in referred studies. The failure probability of wind turbine will be compared with $d_1$and $d_2$ to determine which turbines and components should be subject to preventive maintenance. Maintenance cost can be estimated based on the PM decided by failure thresholds in CBM policy and CM of failure. A specific numerical example, considering two turbines and each turbine has two components, is proposed to find the optimal CBM policy corresponding to the minimum maintenance cost rate.

For the second contribution, the simulation method is applied to the same numerical example to find the optimal CBM policy with minimum maintenance cost. Two sensitivity analyses are conducted to verify the feasibility of the numerical approach. One sensitivity analysis is developed considering various fixed preventive maintenance cost and comparing the lowest cost obtained by optimal CBM policy by both methods. Another sensitivity analysis is investigating the optimal results of both methods within various fixed cost to wind farm.

In the third contribution, five comparative studies are developed between the numerical and simulation method to emphasize stability of the numerical method. For all comparative studies, the simulation method and numerical method will be used to identify the lowest maintenance costs under the same CBM policies and assumptions as the sensitivity analysis. In comparative study 1, we compare optimization process and lowest cost rate value of two methods considering the iteration time of the simulation method is small. The iteration time is increased in comparative study 2 and it is large in comparative study 3. Comparative study 4 and 5 will compare the stability of both methods considering various fixed preventive maintenance cost and fixed cost to wind farm. The cost surface of the numerical method is smoother and optimization result is more stable than the simulation method through these comparisons.

## 1.4 Thesis organization

This thesis is organized as follows.

**Chapter 1** - Introduction

This chapter introduces the background, research motivation, objective and the contributions of the thesis, and thesis organization.

**Chapter 2** - Literature review and fundamental knowledge

This chapter presents a literature review and basic knowledge about wind farm systems, maintenance strategies in the wind industry and CBM optimization for wind farms. Literature review summarize studies in three popular maintenance strategies: CM, PM, and CBM. The review is focusing more on CBM, including diagnostic method and prognostic method used in CBM. Background knowledge presents basic knowledge of wind turbine and wind farm.

**Chapter 3** - The proposed numerical method of CBM optimization for wind farm

This chapter gives detailed description of proposed numerical method and the procedure of applying modified numerical method to evaluate maintenance cost rate in five sections. It includes component health condition prognostics, failure probability estimation for component and turbine, the proposed CBM policy, general assumptions and descriptions of terms, and the CBM optimization numerical method model and solution method.

**Chapter 4** - Numerical method verification and comparison

This chapter presents numerical examples using proposed numerical method. Sensitivity analysis and comparative studies are demonstrated between simulation and numerical method in CBM optimization. Finally, conclusions will be drawn to illustrate the feasibility and benefits of numerical methods.

**Chapter 5** – Conclusion and future work

This chapter is the summary of this thesis, and it provides the direction of effort in the future work.

# Chapter 2 Literature Review and Fundamental Knowledge

In this chapter, a comprehensive review of maintenance strategies is conducted for wind turbines in Section 2.1. Three popular maintenance strategies, CM, time-based PM, and CBM are introduced and analyzed in terms of maintenance principles, current state of development, advantages and disadvantages, and future trends. The review focuses more on CBM, which is the most promising approach to solve maintenance problems in many industries. Diagnostics and prognostics are two important parts in the process of the CBM approach and both are integral to its effectiveness. Section 2.2 and 2.3 introduce diagnostic and prognostics methods employed within CBM in wind farm systems. In Section 2.4, basic knowledge is presented about wind turbine systems and wind farms. This includes an in-depth discussion of the principles of wind turbine systems and wind farm operation, the configuration of wind turbines and their key components, and analysis of major wind turbine failures. Section 2.5 is the summary of this chapter.

## 2.1 Maintenance strategies for wind turbines

As industry develops, there is a significant increase in the demand for machines with higher reliability and safety, along with a desire to reduce risk and improve profitability. As a result, several strategies are being investigated to improve machine reliability while reducing maintenance costs. Existing maintenance strategies employed in wind turbines can be categorized into three groups: CM, time-based PM, and CBM. These three maintenance strategies are described in detail in the following sections.

### 2.1.1 CM strategy

CM is a reactive strategy primarily focused on responding to failures. The replacement or repair actions are performed to restore the system to functional state when a failure occurs. It is simple to understand and implement as there is no or less plan needed and the maintenance is only done when a breakdown has occurred. While PM actions can be carried out in a more planned way, corrective actions are more time sensitive as they directly affect the availability of the system. Upon the detection and confirmation of a failure, the corresponding maintenance action involving repair or replacement can be initiated. This approach can help to identify the specific human and equipment resources required to respond to a particular failure and avoid unnecessary resource allocation, which can contribute to cost savings. However, it is essential to note that during CM, the system is typically in an inoperative state. Estimating maintenance time becomes challenging, and the economic losses resulting from breakdowns can be substantial. Consequently, CM is more suitable for components where failure downtime would not lead to a significant economic impact [25]. It may be not applicable to large and critical machinery and equipment, as their maintenance downtime can significantly negatively impact production. Considering the limitations inherent in this reactive approach, researchers are actively exploring alternative, more proactive methods of maintenance.

Several studies are attempting to develop new models aimed at promoting informed decision-making for the implementation of CM. In [26], a mathematical model was proposed to assist wind farm stakeholders in making critical resource-related decisions for corrective maintenance at offshore wind farms, considering uncertainties in turbine failure information. Gan established a two-stage maintenance policy considering shocks and imperfect maintenance, proposed a reliability model with changing dependence between degradation and shocks, and optimized the limits of imperfect maintenance activity for two reliability stages [27]. The study [28] proposed a cost-effective dynamic Bayesian network modeling scheme to be used in the planning of CM actions on systems having hidden components which have stochastic and structural dependencies.

### 2.1.2 PM strategy

PM is strategic maintenance that is proactively performed before a component or system fails, aiming to prevent breakdowns. The primary objective of PM is to mitigate the occurrence of CM by scheduling regular inspections pre-emptively addressing failure-prone components. Through optimization, the best maintenance decisions regarding age thresholds, failure threshold or the number of age groups can be determined. This optimization process is designed to minimize redundant visits and associated labor costs, effectively reducing overall maintenance expenditures [29]. The selection of PM activities depends on the reliability of each component and the associated overall cost. Recognizing that maintenance costs vary greatly from component to component emphasize the importance of enhancing reliability and mitigating costly maintenance tasks, ultimately contributing to the overall goal of minimizing overall maintenance costs. The determination of planned inspection intervals over time is a complex process that considers various factors, including production capacity, weather-related accessibility, and the standardization of production costs across different sites. This multifaceted approach ensures a comprehensive and well-informed scheduling of interventions, aligning with the overarching goals of optimizing maintenance efficiency and minimizing associated costs [30].

The limitation associated with PM is the necessity for regular and stringent inspections of a considerable amount of equipment and demanding the expertise of professionally trained personnel, which may heighten the risk of operational costs. The effectiveness of PM depends heavily on the accuracy of inspection results. If the inspection results are inaccurate, the maintenance resources invested may not have a positive impact on productivity and production efficiency. Therefore, ensuring the implementation of scheduled inspections and the accuracy of inspection results is an issue when PM is applied to a system.

In current O&M practices, enforcing PM policies based on time information from wind turbine systems is still a popular approach. TBM is a traditional PM technique. The key elements of TBM include establishing a maintenance schedule, conducting routine inspections, and performing necessary maintenance activities according to the scheduled plan. In [31], an optimal age-based group maintenance policy was proposed for a multi-unit series system whose components are subject to different gradual degradation phenomena. Their results showed that the use of this maintenance strategy has a great potential to reduce the maintenance costs of complex multi-unit systems, especially if the setup costs of maintenance tasks are high. [32] proposed opportunistic maintenance approaches for wind farms to take advantage of the maintenance opportunities. It considered three types of PM actions, including perfect, imperfect and two-level action. Comparative study with the widely used CM policy demonstrated the advantage of the proposed opportunistic maintenance methods in significantly reducing the maintenance cost. [33] presented an approach for implementing PM by using historical failure data to determine the optimal PM interval required to maintain desired reliability of atypical module or subassembly. The results from the analysis indicated that for an optimal PM interval to exist, the PM task has to be economically and technically feasible. In [34], a reliability and maintenance models was developed for a single-unit system subject to hard failures under random environment of external shocks.

Imperfect preventive repair and preventive replacement are implemented and optimal maintenance policy that minimized the expected cost per unit time of the system is obtained.

### 2.1.3 CBM strategy

CBM is an advanced maintenance strategy, as it relies on the analysis of condition monitoring data collected from the component. This approach proves effective in providing real-time diagnoses of existing failures and prognosis potential failures that may arise in the future. The objective of CBM is to proactively take actions before a severe breakdown occurs, undertaking necessary maintenance based on the current condition estimation of components. A CBM program usually consists of six steps: data acquisition, data processing, feature extraction, fault diagnostics, fault prognostics and decision making.

The beginning stage of CBM is data acquisition, the primary purpose of which is to collect and store sensor data from monitored equipment for subsequent health condition analysis. Being able to acquire useful condition data from equipment is the foundation of the entire CBM process. Data acquisition (DAQ) systems are widely used in this process. DAQ plays a vital role in this process, with their primary function being to sample signals, such as voltage and current signals, that measure actual physical conditions. These systems convert the obtained samples into digital values which are then processed by, for example, a computer [35]. The basic components of a DAQ system include sensors and transmitters, field wiring, signal conditioning, DAQ hardware, DAQ software, and a personal computer (PC) with an operating system. The role of sensors and transmitters is to convert the physical phenomena of the monitoring equipment into electrical signals, and then convert the electrical signals into digital data that can be represented on a computer, digital system, or memory board. Commonly used transducers are light level, temperature, force or pressure, position, and sound sensors, each with its own input and output devices. Various types of sensors, such as position sensors, pressure sensors, temperature sensors, vibration sensors, force sensors, and humidity sensors, can be used for different monitoring purposes. Although new data collection equipment continues to develop, there are still challenges in obtaining high quality machine run-to-failure data. Obstacles to data collection, such as a lack of personnel with the necessary skills, the need to replace legacy systems, and budgetary constraints, require effective solutions to ensure that the CBM process runs smoothly.

In the following stage, data processing is a key step in transforming raw data into a usable and desirable format. This step involves multiple sub-processes, including data cleaning, analysis and interpretation. Two different types of data are typically involved: condition monitoring data and event data. Condition monitoring data includes various indicators such as vibration data, acoustic data, oil analysis data and measurements related to temperature, pressure or humidity. This type of data can be collected automatically by using sensors or other measurement techniques, or it can be obtained manually through regular interventions such as daily inspections. Event data is related to a product that occurred in a specific situation, or detailed information about maintenance tasks performed on the product. Unlike condition monitoring data, event data usually requires manual data entry due to its specific and contextual nature. The data processing step helps improve condition monitoring and event data to ensure prepared for subsequent analysis and interpretation. This transformation helps to extract meaningful insights and valuable information from the collected data sets.

In process feature extraction, feature representation method will be used to define the features. Typically, any features can be identified through feature representation. However, not all of these features are necessarily useful and not all of these features contain information relevant to the machine condition. Therefore, meaningful features that help analyze the machine condition must be identified and selected through feature extraction. In [36], Zhang et al. made  a study on a new feature extraction method of ultrasonic signals based on empirical mode decomposition (EMD). This method aimed to enhance the extraction of relevant information of ultrasonic signals and provide a more effective and refined feature set for machine state analysis.

Fault diagnostics is one significant process in CBM. A fault is defined as an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable, usual, standard condition [37]. These faults are classified into three types: actuator faults, sensor faults, and device faults, also known as component faults or parameter faults. Fault diagnosis consists of the key components of fault detection, fault isolation and fault identification. During fault detection, the main goal is to check for an abnormal or faulty condition and to determine the exact time when the fault occurred. Fault isolation focuses on determining the location of the faulty component in the system. [38] represented basic concepts on fault detection, fault diagnosis, and fault tolerance systems with methods in CBM diagnostics. Section 2.2 describes the CBM diagnostics methodology in detail.

Prognostics is another important part in CBM. It is the ability to predict the RUL of a failing component or subsystem accurately and precisely. This involves three main methods: the physical model-based method, data-driven method, and knowledge-based method. More detailed of CBM prognostics method will be demonstrated in Section 2.3.

Maintenance decision-making is the final step in CBM and is the basic objective of predicting RUL. RUL is the estimated time of the component that is able to perform its intended function. A primary goal of CBM is to maximize profitability with minimal repair costs. The way to achieve this based on economic considerations is using cost models. Jia presented the maintenance decision-making method based on remaining useful life considering different optimal targets and full life experiment of gearbox was given to demonstrate the preferred decision-making with the influence of the remaining useful life [39].

A large number of research and study activities have been made in various aspects of CBM. A review written by Jardine et al. described the important steps in CBM and emphasizes diagnosis and prognosis implementation CBM with related techniques [10]. In addition, Peng et al. reviewed the current status of machine prognosis in CBM and illustrated popular methodologies [7].

CBM optimization is the process of improving and refining condition-based maintenance strategies to achieve maximum efficiency and minimum cost in equipment maintenance practices. It is a crucial process for organizations seeking to improve their maintenance practices and enhance operational performance. CBM optimization aims to enhance various aspects of CBM implementation, including data collection, analysis, decision-making, and resource allocation, to ensure that maintenance activities are performed at the right time, with the right resources, and for the right reasons. [40] introduced an opportunistic CBM strategy designed to enhance the maintenance cost efficiency of Offshore Wind Turbines. Additionally, it investigated the economic relationships between various components. They developed an ANN prediction model to anticipate the distribution of component failure times, leveraging data from condition monitoring. In [41], a CBM optimization approach was proposed for wind turbine systems considering the economic dependency of different wind turbine types. [42] proposed a prognostic induced CBM optimization method aimed at identifying optimal maintenance decisions that maximize net revenue. A data-driven efficiency modeling method, which was integrated into the net revenue optimization framework. This method accounted for the economic losses resulting from system degradation when evaluating the maintenance benefits. In [43], a method was devised for modeling the reliability of wind power systems and optimizing CBM, taking into account wind uncertainty and the condition of wind turbines through health condition prediction. Additionally, they explored optimization for minor repair activities to determine the optimal number of joint repairs.

## 2.2 CBM diagnostic methods for wind turbines

Fault diagnosis methods are generally categorized into different classes, including model-based methods, signal-based methods, knowledge-based methods, hybrid methods and active fault diagnosis methods [44]. Kabir et al. [45] provided a brief overview of recent developments in condition monitoring and fault diagnosis techniques for offshore wind turbines. The focus of their introduction was on various components of wind turbine including gearboxes, bearings, rotors, blades, and generators. In [46], the structure of the wind turbine and potential failures of critical components were reviewed. In addition, the study analyzed various research findings related to the diagnosis of wind turbine components. A detailed comparison of the advantages and disadvantages of the newly implemented diagnostic methods was presented.

### 2.2.1 Model-based fault diagnostic methods

Model-based fault diagnosis is a method used to detect, isolate, and identify faults in systems by comparing the actual behavior of the system with the expected behavior predicted by a mathematical model. [47] introduced an innovative intelligent fault diagnosis approach designed to autonomously recognize various health conditions of wind turbine gearboxes. Given the multiscale nature of vibration signals inherent in gearboxes, this paper proposed a novel architecture Multiscale Convolutional Neural Network (MSCNN). This architecture is designed to conduct multiscale feature extraction and classification simultaneously, addressing the diverse characteristics of the signals.

### 2.2.2 Signal-based fault diagnostic methods

Signal-based fault diagnosis relied on analyzing signals or data collected from sensors or other sources to detect, isolate, and diagnose faults in systems. Signal-based fault diagnosis methods can be classified into three types: time-domain approach, frequency-domain approach, and time-frequency method.

The time-domain method is based on the time waveform itself. Time domain refers to the analysis of mathematical functions, physical signals, or time series of economic or environmental data, with respect to time. Li, and Wang [48] applied a conventional neural network to time-domain vibration signal six fault diagnosis, taking the bearing as an example, and an intelligent diagnosis method of bearing based on convolution neural network is proposed.

Motor current signature analysis (MCSA) is an effective frequency-domain method to sense motor fault. An online induction motor diagnosis system using MCSA with advanced signal-and-data-processing algorithms was proposed in [49]. Vibration signal analysis is also a commonly used method to monitor faults for wind turbine equipment such as gearbox. A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings was presented in [50].

There are four main approaches in the time-frequency method: short-time Fourier transform (STFT), wavelet transforms (WT), Hilbert-Huang transform (HHT), and Wigner-Ville distribution (WVD). A review describes various time-frequency analysis that have been proposed and applied to machinery fault diagnosis in [51]. Support vector machine (SVM) is a new computational learning method used in condition monitoring and fault diagnosis. It is based on Vapnik-Chervonenkis theory, and the main concept of this theory is revisiting the problem statement appropriate for the modern learning method that makes a clear distinction between the problem formulation and solution approach used to solve the problem [52]. Nowadays, SVM is becoming more popular in machine learning methods due to its excellence of generalization ability than the traditional method such as the neural network. [53] proposed an SSA-optimized SVM wind turbine fault diagnosis model with high accuracy rate, strong optimization ability, and fast convergence rate and performance. [51] investigated the detection and identification of windmill bearing fault by using a one class SVM. Models with varying sensitivity levels were simultaneously trained in parallel by adjusting the tuning parameters of the model.

## 2.3 CBM prognostic methods for wind turbines

Prognostics in CBM is a practice of predicting the future behavior or performance of wind turbine system or component based on its current condition and historical data. The purpose of prognostics is to estimate the RUL of an asset, which is the amount of time an asset is expected to continue to operate before reaching a pre-defined threshold or failing. Three primary methods: physical model-based method, data-driven method and knowledge-based method, are described in the following section.

### 2.3.1 Physical model-based methods

Physical model-based prognostic method involves the development of models based on an understanding of the underlying physics of wind power system and the mechanisms of degradation. These models simulate degradation processes and predict future behavior of components. The advantages of this method are that it provides a fundamental understanding of the degradation process, suitable for systems with well-understood physics and may offer insights into the mechanisms leading to failure. One challenge is that it needs in-depth knowledge about the physics of degradation for the specific product. In practice, the model-based approach cannot be used for all machine condition monitoring. In some machine degradation, it includes historical failure in terms of various signals leading up to failure or statistical data sets. The application of this method is often restricted by the complexity of some machines.

### 2.3.2 Data driven methods

Current model-based approaches are inadequate in accurately predicting fault processes. For this reason, data-driven methods have emerged, which use nonlinear networks to address this limitation by applying a robust formal algorithm. In data-driven methods, condition monitoring data is analyzed in a complicated way, aiming at detecting abnormal events and subsequently transforming these events into useful fault insights. This change to data-driven approaches denotes a transition from traditional model-based method and recognizes the inherent complexity and nonlinearity of the failure process. By exploiting the power of formal algorithms within a data-driven framework, these approaches strive to improve the accuracy and effectiveness of fault prediction, thereby contributing to a more detailed understanding of system behavior and performance.

This approach typically uses machine learning techniques to construct accurate models by using the collected data to capture the details of the failure. In contrast to model-based approaches, data-driven methods do not require a great deal of specialized knowledge about the principles or causes of machine failures. However, data-driven methods require higher computational power and demand strict data quality. The accuracy and quality of the input data directly affect the accuracy and applicability of the model. As a result, there have been challenges in the field of data-driven methods, especially in obtaining a sufficient amount of data and ensuring data quality. To effectively apply data-driven methods in fault detection and machine learning, it is crucial to address these challenges.

Data-driven methods can be divided into two categories: statistical approaches and AI approaches. Statistical methods include a wide range of techniques such as multivariate statistical methods, which include static and dynamic principal components analysis (PCA), linear and quadratic discriminant, partial least square, canonical variety analysis, and learning vector quantization (LVQ). State-space models such as Bayesian networks, Hidden Markov models (HMM), Hidden semi-Markov models (HSMM), and regressive models. Some commonly used methods would be reviewed respectively, including the ANN-based method, Bayesian network-related method, HMM and HSMM, and gray model.

An artificial neural network (ANN) is a computational data processing system inspired by the complex network of biological neural structures in the animal brain. ANN is based on a collection of interconnected units or nodes called artificial neurons. [54] provided a comprehensive discussion of the application of artificial neural networks to wind energy systems. It identified the most commonly used methods for various applications and showed how artificial neural networks can replace traditional methods in numerous situations. In [55], an ANN-based condition monitoring approach was implemented for gearbox bearings using real data collected from onshore wind turbines rated at 2 MW, situated in the southern region of Sweden.

Bayesian networks are probabilistic graphical models that utilize directed acyclic graphs (DAGs) to elucidate the structure of conditional dependencies between random variables. This graphical model provides a way to predict the probability associated with each potential cause, which helps to identify the specific causes that lead to an event. In cases where the modeling involves a sequence of variables, the Bayesian network takes the form of a Dynamic Bayesian Network (DBN). The DBN establishes relationships between different variables in sequential time steps. At any given timepoint T, the values of the variables can be computed based on the internal regressors and the immediately preceding values. [56] introduced a novel dynamic Bayesian network (DBN) framework for fault diagnosis and reliability analysis of offshore wind turbine gearbox systems. This framework integrated components' degradation data and a CBM strategy to enhance the diagnostic and maintenance procedures. [57] employed Bayesian networks to estimate the probability distribution for the time of failure and the conditional probability distribution for the time of CBM given the time of failure, considering the CBM strategy.

Hidden Markov Model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with hidden states. Applications of HMMs remain popular due to their rich mathematical structure, the large number of successful applications in practice, and the simplicity of model interpretation. The hidden semi-Markov model (HSMM) has the same structure as the hidden Markov model, but the hidden process is semi-Markov rather than Markov. In diagnosis, HSMM can be used to categorize machine failures based on a sequence of observations. In prognosis, HSMM can be used to simulate the life cycle of a component. Dong and He described the basic concept and procedure of HMM and HSMM in diagnosis and prognosis with a case study in bearing and hydraulic pump health monitoring [58].

### 2.3.3 Knowledge-based methods

In the field of real-world machines, the adoption of accurate physical models is a challenging task. The complexity of the actual framework of a machine often exceeds the simplicity assumed by such models. As a result, physical models may not be applicable in some cases. In these instances, knowledge-based methods come into play, which offer two main approaches: expert systems and fuzzy logic. These knowledge-based approaches provide alternative strategies for solving intricate real-world machine problems, utilizing specialized knowledge and fuzzy logic principles to solve complex problems that may not be amenable to accurate physical modeling.

An expert system is a computer system emulating the decision-making ability of a human expert [59]. The application of this system is thinking like a real professional expert. The basic principle of an expert system is the "if-then" rule rather than program code. The first expert systems were created in the 1970s and then proliferated in the 1980s [60]. Expert systems were the first truly successful artificial intelligences [61].

Two main advantages of expert systems are ease of maintenance and rapid development. The former is reflected in the elimination of conventional code, the reduction of typical problems, and the ease of logical flow calls to the system and reasoning engine. The latter advantage is especially evident when using expert system shells, which can be prototyped in days compared to the months or years required for complex IT projects. The term fuzzy logic was introduced with the 1965 proposal of fuzzy set theory by scientist Lotfi Zadeh [62]. The basic of fuzzy logic is the observation that people make decisions based on vague, imprecise, and no-numerical information. It is a mathematical model for representing ambiguous and noisy information. These models have the capability of recognizing, representing, manipulating, interpreting, and using data and information that are vague and lack certainty [63].

Two main types of fuzzy logic systems are the Mamdani and Takagi-Sugeno-Kang (TSK) systems. These systems simplify the processing of mathematical concepts through fuzzy reasoning, making them easy to construct and understand. Their flexibility allows modification by adding or removing rules.

## 2.4 Introduction of wind turbine system and wind farm

### 2.4.1 Typical configuration of a wind turbine system and critical components

The typical configuration of a wind turbine system is shown in Figure 2.1, there are three main parts: the tower, the blades, and the nacelle with gearbox and generator. The collective functionality of these constituent elements collaboratively enables the transformation of wind energy into electrical energy. The synergistic operation of these components helps to convert wind energy into electrical energy. In the presence of wind, the blades of the system undergo a rotational motion. The kinetic energy generated by the rotation of the blades creates a rotational motion in the generator. As a result, this rotational motion generates electrical energy that can be used for various purposes, such as lighting light bulbs or generating sound output through a stereo system.

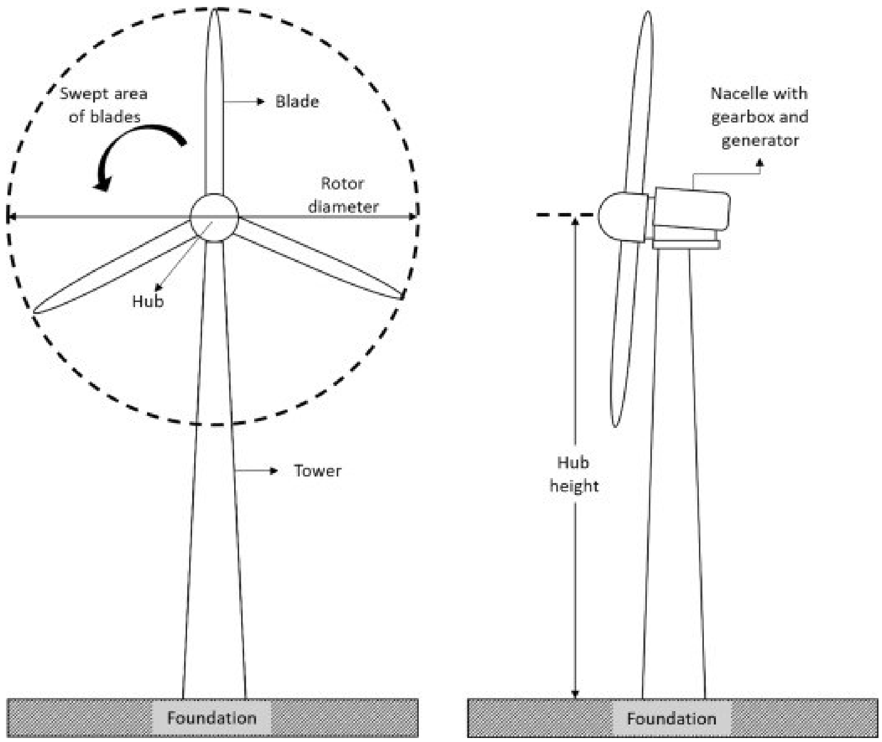



Figure 2.1 Configuration of horizontal axis wind turbines [64]

There are four critical components in a traditional wind turbine system, which are the rotor blades, the main bearing, the gearbox and the generator shown in Figure 2.2. At the core of the wind turbine, the rotor blades play a pivotal role in capturing the kinetic energy of the wind and transforming it into rotational motion. Factors such as the shape, length, and number of blades significantly influence the turbine's performance, affecting power output and operational characteristics. Bearings are critical components of rotating equipment that carry shaft loads and minimize friction, providing shaft position and system flexibility. A variety of bearings for wind turbine applications are available to meet specific needs. The wind turbine gearbox is a pivotal component within wind energy systems, serving as a crucial interface between the low-speed rotor and the high-speed generator. This step-up in rotational speed enables the generator to produce electrical power efficiently. The gearbox acts as a mechanical multiplier, allowing for optimal power transfer and maximizing energy conversion from wind to electricity. Situated within the nacelle, the generator is a crucial component responsible for converting the mechanical energy received from the rotor blades into electrical energy. Various generator types, including asynchronous and synchronous generators, are employed in wind turbines, each with its own advantages and considerations. The efficiency of the generator directly affects the entire energy conversion process and plays a vital role in maximizing the power output of the turbine.

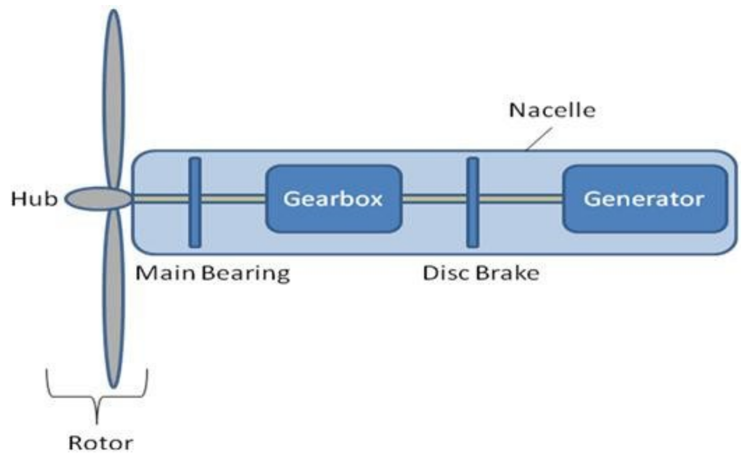



Figure 2.2 Main components of wind turbine system [65]

### 2.4.2 Operation principle of wind turbine system and wind farm

A wind turbine harnesses the potential of wind energy by exploiting aerodynamic principles akin to those observed in the functionality of airplane wings or helicopter rotor blades. As the wind traverses the turbine's blades, a discrepancy in air pressure between the two sides of the blade arises, leading to a concomitant generation of lift and drag forces. Primarily dominated by the force of lift, these forces initiate the rotation of the turbine's rotor. The rotor, in turn, establishes a connection with the generator, directly in the case of a direct drive turbine or through a combination of a shaft and a gearbox for rotational amplification, resulting in the usage of a smaller physical generator. The conversion of aerodynamic force into rotational motion of the generator facilitates the production of electricity.

Wind power plants generate electrical energy through the deployment of an assemblage of wind turbines concentrated within a specific area. The positioning of a wind power plant is influenced by various factors encompassing wind patterns, the topographical characteristics of the surrounding area, availability of electrical transmission infrastructure, and other pertinent sitting considerations. Within a utility-scale wind plant, individual turbines autonomously produce electrical power, which is subsequently channeled to a substation. From there, the generated electricity is seamlessly integrated into the grid, ultimately serving as a reliable source of energy for our communities. Wind turbines possess the capacity to rotate along either a horizontal or vertical axis, with the former exhibiting a longer historical lineage and widespread prevalence. Large three-bladed horizontal-axis wind turbines (HAWT) with the blades upwind of the tower produce the overwhelming majority of wind power in the world today and our research is also based on this type of wind turbine.

### 2.4.3 Failure modes in wind turbines

Failures in wind turbine can be categorized into two sources: some are caused by long-term operation and aging, and others are caused by short-term overload and sudden breakdown [66]. As the rotor and drive train undergo rotational motion, failure rates are primarily attributed to wear and fatigue during operational cycles. The wind turbine has four critical components, each with different failure rates. The failure rates also depend on the location of the wind farm, the type of foundation, and the type of transmission system. As technology is less mature, meaning larger scale and more complex transmission systems, the failure rates tend to be higher, and reliability is lower. Additionally, certain failures are perceived as occurring randomly without discernible patterns or predictability. The major failures of critical components in wind turbine systems: rotor blades, main bearing, gearbox and generator, are introduced in detail as follows.

The failure of wind turbine rotor blades is a critical issue that can significantlyy impact the performance, reliability, and safety of wind energy systems. The first cause is material degradation. Rotor blades are subjected to harsh environmental conditions, including exposure to ultraviolet radiation, temperature variations, moisture, and airborne particles. Over time, these environmental factors can cause material degradation, such as erosion, corrosion, delamination, and surface cracking. Material degradation weakens the structural integrity of the blades, leading to potential failure under normal operational loads. Besides, manufacturing defects, such as improper curing, voids, resin-rich or resin-poor areas, and improper bonding of composite materials, can compromise the strength and durability of rotor blades. Defects introduced during the manufacturing process may go undetected, but they can initiate stress concentrations or propagate cracks, ultimately leading to blade failure. Finally, Wind turbine rotor blades are subjected to cyclic loading caused by wind forces, gusts, and turbulence. This cyclic loading induces fatigue stress, which can accumulate over time and lead to progressive structural damage. Fatigue failure can occur at critical locations, such as blade roots, blade tips, or adhesive joints, where stress concentrations are typically higher. Other causes include design and structural issues, lighting strikes and extreme events, and maintenance and inspection negligence.

Fatigue and overloading are the causes of the main bearing failure. Wind turbine main bearings are subjected to continuous cyclic loading due to wind forces, variations in wind speed, and rotor imbalance. The repetitive stress cycles can lead to fatigue damage in the bearing components, particularly in the rolling elements and raceways. Overloading of the bearing beyond its design limits, whether due to excessive wind speeds or mechanical issues, can accelerate fatigue failure. The second failure is insufficient lubrication. Proper lubrication is vital for the smooth operation and longevity of main bearings. Inadequate lubrication, including insufficient quantity, poor quality, or improper lubricant selection, can lead to increased friction, wear, and overheating. Insufficient lubrication film formation can result in metal-to-metal contact, leading to premature bearing failure. Contamination and corrosion can also lead to failure events. Wind turbine environments are prone to contamination by dirt, dust, moisture, and other airborne particles. Contaminants can infiltrate the bearing housing, leading to abrasive wear, increased friction, and accelerated fatigue. Additionally, exposure to corrosive elements, such as saltwater or acidic conditions, can cause corrosion of bearing surfaces and compromise their structural integrity. The last one is misalignment and improper installation. Improper installation practices, including inadequate alignment of the main bearing with the rotor and nacelle, can result in excessive loads and misalignment. Misalignment increases stress on the bearing components, leading to premature wear, fatigue, and ultimately, bearing failure. Proper alignment during installation and regular monitoring of alignment are crucial for preventing such issues.

Wind turbine gearboxes operate under demanding conditions, subject to high loads, varying wind speeds, and dynamic loads caused by wind gusts and turbulence. These factors impose significant stress on the gearbox components, leading to potential wear, fatigue, and lubrication challenges. Wind turbine gearboxes are subjected to cyclic loading caused by varying wind speeds, gusts, and turbulence. These cyclic loads induce fatigue stress, which can accumulate over time and lead to progressive structural damage. Fatigue failure can occur in gear teeth, bearings, shafts, or other critical components within the gearbox, particularly at locations where stress concentrations are higher. Proper lubrication is also crucial for the smooth operation and longevity of wind turbine gearboxes. Proper maintenance, monitoring, and lubrication practices are crucial for mitigating these issues and extending the gearbox's lifespan.

The failure of wind turbine generators is a critical concern that can significantly impact the performance, reliability, and power generation capability of wind energy systems. There are four main reasons leading to the failure of generator: electrical system issue, mechanical stress fatigue, bearing and lubrication problems, and environmental factors. Electrical system failures can occur in wind turbine generators due to issues such as insulation breakdown, short circuits, electrical overloads, or voltage spikes. These issues can lead to overheating, arcing, or damage to the generator windings, resulting in reduced efficiency, increased wear, or complete generator failure. Wind turbine generators are subjected to mechanical stresses and vibrations due to rotor imbalances, wind gusts, and rotational forces. Over time, these mechanical stresses can lead to fatigue failure in the generator components, including the rotor shaft, bearings, or supporting structures. Fatigue cracks, mechanical wear, or misalignment can eventually cause the generator to malfunction or cease operation. Bearings play a critical role in supporting the rotating components of wind turbine generators. Bearing failures can occur due to factors such as inadequate lubrication, contamination, misalignment, or excessive loads. Insufficient lubrication can lead to increased friction, overheating, and premature wear, eventually resulting in bearing failure and potential damage to the generator. Wind turbine generators are exposed to harsh environmental conditions, including temperature variations, moisture, saltwater, and airborne particles. These environmental factors can lead to corrosion, erosion, or degradation of the generator components, particularly in offshore wind farms. Corrosion and erosion can compromise the insulation, electrical connections, or mechanical integrity of the generator, leading to failure.

## 2.5 Summary

This section provides an extensive review of previous studies on three existing maintenance strategies for wind turbines, with a particular focus on the CBM approach. It describes the core processes of CBM and highlights the methods that have been widely adopted in its important processes. This section provides insights into the various methods applied by CBM for prognostics and diagnostics. In addition, it provides a basic concept and knowledge such as the wind turbine configuration, critical components and corresponding failure causes.

# Chapter 3 The Proposed Numerical Method of CBM Optimization for Wind Farm

A numerical method is proposed originally in study [24] and this method provides smoother cost surface which can benefit optimization process. However, the cost evaluation results are not reasonable, and optimization is not achieved according to the outcome in this study. To evaluate cost rate accurately and resolve optimization problems, we propose a modified model based on original numerical method. The modified numerical model develops a new 4-dimensional structure for the component age combination probability matrix and integrating a previously separate age combination probability transition matrix into the main cost evaluation loop. The detailed procedure of applying updated numerical method to evaluate maintenance cost rate is described by five sections in this chapter.

In section 3.1, an ANN based prognostic method in [67] is introduced. This method is used to obtain lifetime percentage and prediction error for component. According to the output of ANN model, the predicted failure time distribution of component at a certain inspection point can be developed.

Section 3.2 presents the failure probability estimation for component and turbine based on ANN prognostic approach. CBM prognostic method used in section 3.1 helps to get the predicted failure time distribution of component. The failure probability for a component at a certain inspection point can be calculated as conditional probability based on predicted failure time distribution. The detailed calculation process is presented in this section.

A CBM policy with two failure probability threshold values at the wind turbine level will be introduced in section 3.3. Two types of maintenance activities are considered in this policy: failure replacement when failure occurs and preventive maintenance when the probability of turbine exceeds higher level failure threshold. Maintenance activities will be assigned to replace the faulty components when replacements are needed in the wind farm. Assumptions and description of terms of the numerical method are introduced in section 3.4.

In the last section 3.5, the procedure of proposed numerical method for evaluating the maintenance cost of CBM policy involving five steps will be developed. These steps include: numerical initialization; calculate age combination probability transition matrix $T_{Pr}(kr)$ for each age combination, new age combination probability matrix $P_{new}(kr)$ due to CBM decision and total cost $C_{Total}$ for all age combination at current inspection point; update the age combination probability distribution matrix $P_U(kr)$ at each inspection interval; update the total cost at each inspection point; calculate the cost rate. The section from 3.5.1 to 3.5.5 will describe step 1 to step 5 of applying the numerical method.

## 3.1 Component health condition prognostics

Health condition prognostics aims to predict the future state or condition of a system or its components. Prognostics goes deeper than simple condition monitoring to provide insight into the remaining useful time of a device or component. By analyzing historical data and current conditions of component at an inspection point, prognostic models can estimate how much time is left before failure or severe degradation occurs. Some advanced prognostic methods are able to estimate the associated prognostic uncertainty. The uncertainty is a measure of the reliability or confidence level of the predicted failure time. It provides an understanding of how certain or uncertain the prognostic model in its predictions. Model-based methods and data-drive methods are two types of prognostic models widely used in CBM for calculating RUL of component. A model-based approach for CBM involves the use of mathematical or computational models to predict the future condition of equipment and make maintenance decisions accordingly. This model is based on equipment physical models and damage propagation models to perform reliability prognostics. One big challenge of using model-based method is model complexity. Developing accurate models for complex systems can be difficult. The underlying physics or behavior of certain equipment may be hard to capture accurately in a model. Data-driven models rely on analyzing historical data and real-time condition monitoring data to make predictions about the health and future performance of equipment. These methods use machine learning and statistical strategies to identify patterns, trends and anomalies in the data and do not need physics-of -failure models.

Among different data-driven approaches, ANN-based methods have proven to be very effective and versatile in predicting component health condition. In this model, one input layer, two hidden layers and one output layer are defined. A feed forward neural network model proposed in [67] will be used to obtain predicted failure distribution for components. The input values in the ANN are the component age values and condition monitoring measurements at the current and previous inspection point. The ANN model uses failure histories and suspension histories. The failure history of a component covers its entire operating life, from the start of operation to the end of its useful life. This history includes failure events and the corresponding inspection data accumulated during this time period. In suspension history, the component is taken out of service before the failure occurs. Through training the ANN model by failure histories and suspension histories, the model is able to predict the RUL value based on the component age and condition monitoring measurements. The output value in this ANN model is life percentage at current inspection time, denoted by $P_i$. The predicted failure time will be obtained based on current age and life percentage calculated from ANN. For example, if the current age of a component at certain inspection point is $300$ days and the life percentage is $60\%$ getting from ANN model, the predicted failure time will be $300/60\% = 500$ days.

To obtain the predicted failure time distribution, we use the method proposed in [68]. The main idea of this method is using mean $\mu_p$ and standard deviation $\sigma_p$ of lifetime percentage error obtained form ANN model to build the predicted failure time distribution at certain inspection point. Suppose the age of component is $t$ and ANN life percentage value is $P_t$. The predicted failure time considering life percentage error is $t/(P_t - \mu_p)$ and the standard deviation is $\sigma_p \cdot t/(P_t - \mu_p)$. That is, the predicted failure time $T_p$ at the current inspection point follows the normal distribution as:

$$T_p \sim N\left(\frac{t}{P_t - \mu_p}, \quad \frac{\sigma_p\, t}{P_t - \mu_p}\right) \tag{1}$$

where $P_t$ is the life percentage output at age $t$, $\mu_p$ and $\sigma_p$ is the mean value and standard deviation of ANN lifetime percentage prediction errors. $\sigma_p$ is assumed to be constant and does not change over time. $\mu_p$ and $\sigma_p$ is estimated during the ANN training and testing processes. As the ANN life percentage errors are assumed to follow the normal distribution, the predicted failure time also follows the normal distribution.

## 3.2 Failure probability estimation for component and turbine

Through using prognostic method mentioned in section 3.1, the failure time distribution can be obtained for each component by using condition monitoring data and history data. In the CBM policy that will be presented in next section, the maintenance decision for components will be made based on their failure probability at the inspection point. We have to compare the failure probability of turbines and the failure thresholds we define to decide the needed maintenance actions. To calculate the failure probability of turbines, we need to get the failure probability of all components in each turbine. According to the predicted failure time distribution we obtained in ANN model, the failure probability of each component can be estimated. It is assumed that the predicted failure time follows the normal distribution as discussed in section 3.1. The failure probability of a component can be calculated as a conditional probability and the method to calculate it is shown below. It is assumed that the mean and the standard deviation of the ANN lifetime prediction error are $\mu_p$ and $\sigma_p$. According to [68], the general failure probability $Pr$ of a component can be derived using the following formula:

$$Pr = \frac{\int_t^{t+L} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-t_p}{\sigma})^2}\, dx}{\int_t^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-t_p}{\sigma})^2}\, dx} \tag{2}$$

where, $L$ is the maintenance lead time, which is defined as the interval between the time the maintenance decision is made and the time when the maintenance is implemented. The lead time for maintenance encompasses various sequential activities, including assembling the maintenance team, procuring spare parts, preparing repair equipment, and traveling to the wind farm. Therefore, maintenance decisions at the current inspection point will only have an impact on the wind turbine after the lead time is over and have no influence on the failures during the lead time. Therefore, it is wise to make optimal maintenance decisions based on the probability of a fault occurring during the preparation time, thus reducing the associated risk of failure. To reasonably simplify the problem, we assume $L$ is the same for all maintenance actions in this study. $t$ is the age of the component at the current inspection point, $t_p$ is the predicted failure time estimated by ANN, and $\sigma$ is the standard deviation of the predicted failure time distribution. We can get the mean and standard deviation value of predicted failure time based on the relationships between predicted failure time and predicted lifetime percentage error, as shown below:

$$t_p = \frac{t}{P_t - \mu_p}, \qquad \sigma = \frac{\sigma_p \, t}{P_t - \mu_p} \tag{3}$$

The concept of a wind turbine system can be understood as a series configuration in which the failure of one component can affect the overall functioning of the system. The key components of a wind turbine include the rotor, gearbox, generator, and main bearing, etc. Each of these components is integrally linked to the operation of the wind turbine and contributes to its reliability and performance. Therefore, the failure probability of turbine $n$ with $m$ components can be defined as follows:

$$Pr_n = \prod_{m=1}^{M} (1 - Pr_{n,m}) \tag{4}$$

The failure probability for each turbine $Pr_n$ will be used to make maintenance decisions based on the CBM policy below.

## 3.3 The CBM policy

In the field of real-life maintenance, different types of maintenance actions are considered, including imperfect repair, perfect repair, imperfect replacement, and perfect replacement. Imperfect repair and replacement refer to the maintenance action where a degraded or failed component is restored to a functional state but not to its original, as-new condition. After the imperfect maintenance, the component may still have some residual defects or reduced performance compared to its initial state. Perfect repair or replacement involve replacing a degraded or failed component with a brand-new component. The new component is assumed to have the same reliability and performance characteristics as the original one in its initial state. To simplify the maintenance problem, only perfect replacement is considered in this study, and the component health condition is assumed fully restored to a state as good as new after replacement.

In this study, the CBM policy with two failure probability threshold values in turbine level proposed by Tian in [23] is applied for wind farm systems. The policy is explained as follows:

(1) Perform failure replacement if any component fails.

(2) As time goes, evaluate the probability of failure of each critical component in each wind turbine and the failure probability of the whole turbine $n$. Whenever a certain wind turbine $n$ has $Pr_n > d_1$, where $Pr_n$ is the failure probability of the wind turbine $n$ and $d_1$ is pre-specified level 1 failure probability threshold value, then perform preventive replacement on certain components in this wind turbine.

(3) If preventive replacements need to be done in a certain turbine, the replacement work will start from the component with the highest failure probability and replacement action will stop until

$Pr_n < d_2$, where $d_2$ is pre-specified level 2 failure probability threshold value of the whole wind turbine.

(4) If there are failure replacement or preventive replacement required, the maintenance team, needed replacement equipment as well as the maintenance tools and other necessary resources will be assigned to the wind farm to execute the maintenance work.

Two level failure probability threshold values are defined in the CBM policy to support the maintenance decision making. The key point of this policy is to find the optimal value of two failure probability $d_1$ and $d_2$ which can give us the lowest total maintenance cost.

## 3.4 Assumptions and description of terms

Without loss of generality, the CBM policy considers $N$ identical wind turbines in the wind farm, where each turbine contains $M$ critical components. It is assumed that those components of the same type are identical across all turbines, and the degradation process of a component does not impact the health of other components within the same turbine. The lifetime of component $m$ is modeled as a Weibull distribution with a scale parameter $\alpha_m$ and shape parameter $\beta_m$ [78-79].

To facilitate analysis, the possible age of each component is divided into $K$ discrete age intervals and the same $K$ is applied to all component types in this study. The typical lifetime of component will be set as a specific value $T$. The first $K-1$ age intervals are set as constant intervals, and the interval length is $T_I$, $T_I$ is typical lifetime divided by $K$. In possible age of component, the first defined age interval contains the age from 0 to age $1T_I$. Similarly, the second interval covers the possible age from $1T_I$ to $2T_I$. The last interval encompasses the possible component age from $(K-1)T_I$ to $\infty$. These $K$ intervals contain all possible age of the components, and this will be used to develop age probability distribution in the following calculation process.

For instance, the lifetime of main bearing follows Weibull distribution with scale parameter 3000 and shape parameter 3. It is assumed that the typical lifetime of this component is 30 years and possible age of this main bearing is divided into 20 intervals. Figure 3.1 shows the Weibull lifetime distribution of main bearing and 20 divided intervals. The length of interval $T_I$ is $30 \times 360/20 = 540$ days. Red dotted line divides the distribution to 20 intervals. The first interval contains the possible age from 0 to 540 days. The second interval covers the possible age from 540 days to 1080 days. The length of first 19 intervals is the constant as 540 days and the last intervals is from $540 \times 19 = 10260$ days to $\infty$.

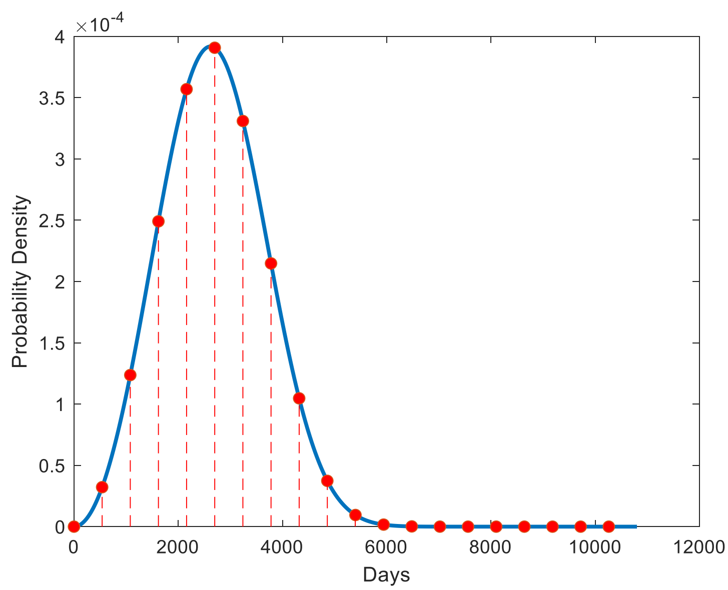



Figure 3.1 Weibull distribution of main bearing and divided intervals

$KV$ is the vector indicating the possible age values, $KV = (1,2,\dots,K)$. $k$ is the age vector, an its elements can take values from $KV$. When $k = 1$, it means the age is in the first possible age interval from 0 to age $1T_I$. Similarly, when $k = 20$, it means the age of component is in the last possible age interval from $(K-1)T_I$ to $\infty$. The lifetime of each component is assumed to follow Weibull distribution, so the probability of component potential age in each interval can be calculated. $PrA$ is the matrix describing the age probability distribution for each component in each turbine. $PrA(k_{nm}, n, m)$ is the age probability distribution of component *m* of turbine *n* and it is developed to calculate the probability of all possible age combination for components. Here, $k_{nm}$ represents the possible age state values of component *m* of turbine *n*, which can take values from vector $KV = (1,2,\dots,K)$. The calculation of age distribution for component is described in section 3.5.1.

## 3.5 CBM optimization model and solution method

Based on CBM policy described in section 3.3, the optimization model for obtaining lowest maintenance cost can be simply formulated as follows:

$$\begin{aligned} &\min C_E\,(d_1, d_2) \\ &s.t. \\ &\quad 0 < d_2 < d_1 < 1 \end{aligned} \tag{5}$$

where $C_E$ is the total expected maintenance cost per unit of time by using maintenance policy with two level failure probability thresholds $d_1$ and $d_2$. The value of failure probability thresholds between 0 and 1. $d_1$ is the first level threshold and $d_2$ is the second level threshold. The value of $d_1$ is bigger than $d_2$. The objective of CBM optimization is finding the optimal value of $d_1$ and $d_2$

to minimize the total maintenance cost $C_E$ . At the beginning of optimization, we have to calculate the total maintenance cost with two failure probability thresholds $d_1$ and $d_2$ by numerical method.

In original numerical method, a 3-dimensional structure for the component RUL distribution matrix $PrS(k_{nm}, n, m)$ was introduced to calculate the RUL distribution for $M$ components in $N$ turbines. $K$ is the number of possible component RUL. A 7-dimensional RUL probability transition matrix $T_{Pr}$ was developed in pre-evaluation process for updating component RUL distribution matrix. For example, $PrS(10, 1, 2)$ indicates the probability of RUL of the component 2 in wind turbine 1 is 10 unit. The modified numerical method proposed a new 4-dimensional structure for the component age combination probability matrix $P_U(k_{11}, k_{12}, k_{21}, k_{22})$ and integrating a previously separate age combination probability transition matrix $T_{PrA}(k_{11}, k_{12}, k_{21}, k_{22})$ into the main cost evaluation loop. For example, $P_U(2, 5, 12, 7)$ indicates probability of the age combination of four component in wind farm is 2, 5, 12 and 7 separately. $T_{PrA}(2, 5, 12, 7)$ indicates the transit probability from current component age combination to other age combination. The RUL probability transition matrix $T_{Pr}$ in original numerical method was in pre-evaluation process and this matrix was not changed when iteration increases. Modified numerical method will calculate separate age combination probability transition matrix $T_{PrA}(k_{11}, k_{12}, k_{21}, k_{22})$ at each inspection point and this is used for updating age combination probability matrix $P_U(k_{11}, k_{12}, k_{21}, k_{22})$, which helps to obtain more accurate cost evaluation outcome. Figure 3.2 shows a flowchart of the proposed numerical method, and the procedure including 5 steps are described in more detail in the following paragraphs.

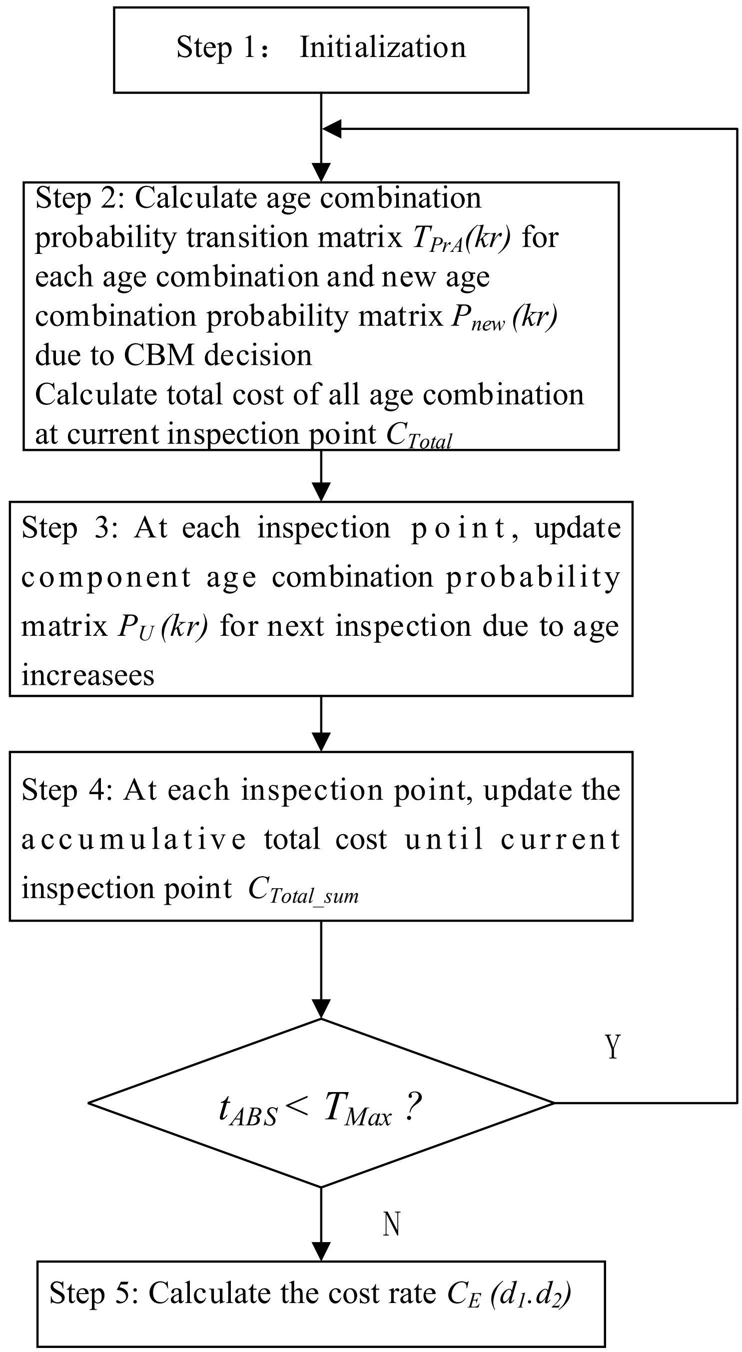



Figure 3.2 Flowchart of the overall numerical method for cost evaluation

### 3.5.1 Step 1: Initialization

It is assumed that there are $N$ wind turbines in the wind farm, and $M$ critical components are considered for each turbine. Specify the maximum iteration time $T_{Max}$, and the inspection interval $T_I$. $T$ is the possible age for the component and this value will be based on lifetime of components under realistic conditions. The value of $T_I$ is based on the typical lifetime $T$ of component and the number of inspection interval $K$ mentioned in general assumption. This value is selected to obtain the accurate results with high computation efficiency. For each component $m$ , specify the cost values, including the failure replacement cost $C_F$ and the variable preventive replacement cost $C_P$. The fixed cost of preventive maintenance in a certain wind turbine, $C_{P\ fix}$ and the fixed cost of sending a maintenance team to the wind farm, $C_{Farm}$, also need to be specified. The cumulative total maintenance cost is set to be $C_{Total\_sum} = 0$, current time is $t_{ABS} = 0$.

Initially, all components are assumed to be new, the age probability distribution matrix $PrA(k_{nm}, n, m)$ including all component in each turbine is initialized based on Weibull distribution. It is established to depict the probability of all possible age values in corresponding interval within each turbine. For instance, $PrA(1, n, m)$ denotes the probability of age being the first interval spanning from age $0$ to $T_I$ in the Weibull distribution for this component. In contrast, $PrA(20, n, m)$ represents the probability of age being the final age interval with age spanning from $(K-1)T_I$ to $\infty$. The age probability distribution for component $m$ in turbine $n$ can be formulated as follows:

$$PrA(k_{n,m}, n, m) = \int_{(k_{nm}-1)T_I}^{k_{nm}T_I} \frac{\beta_m}{{\alpha_m}^{\beta_m}} t^{\beta_m - 1} e^{-(\frac{t}{\beta_m})^{\beta_m}} dt, t \geq 0 \qquad (6)$$

The case where $kr_{nm}$ equals 20 corresponds to the final interval, and it can be acquired through the following equation:

$$PrA(20, n, m) = 1 - \sum_{k_{nm}=1}^{K-1} PrA(k_{nm}, n, m) \tag{7}$$

$P(kr)$ component age combination probability matrix is defined initially as the matrix to calculate the probability for various combinations of component age at the beginning. Its formula is as follows:

$$P(kr) = \prod\nolimits_{(n.m)} PrA(k_{nm}, n, m) \tag{8}$$

$kr$ is the vector of age state of all components in wind farm and it is defined below:

$$kr = (k_{11}, k_{12}, \dots k_{1M}, k_{21}, k_{22}, k_{2M}, \dots, k_{N1}, k_{N2}, k_{NM}) \tag{9}$$

### 3.5.2 Step 2: Calculate age combination probability transition matrix $T_{PrA}(kr)$ for each age combination, new age combination probability matrix $P_{new}(kr)$ due to CBM decision and total cost $C_{Total}$ for all age combination at current inspection point

To evaluate the maintenance cost, age combination probability transition matrix $T_{PrA}(kr)$ is required to be determined firstly. $T_{PrA}(kr)$ signifies the probability of transition from the present age state combination to all feasible component age combination in all turbines. $P_{new}(kr)$ is the new age combination probability matrix after CBM decision. $C_{Current}$ is the maintenance cost for each component age combination at current inspection point. To obtain the transition matrices $T_{PrA}(kr)$, $P_{new}(kr)$ and $C_{Current}$, a flowchart is designed as shown in Figure 3.3, depicting the 3step-by-step procedure. The essential parts will be explained in detail in subsequent paragraphs.

At initialization stage, component age combination probability matrix $P_U(kr)$ is equal to $P(kr)$, $P_{new}(kr)$ is equal to 0 and total cost of all age combination $C_{Total}$ is 0 at the first inspection point. It is assumed there are 2 wind turbines, each turbine has 2 components in a wind farm and component age is divided into 20 intervals. Component age combination vector $(kr)$ indicates $20^{2\times 2}$ possible combination of all components in wind farm. $(kr)$ starts from $(1,1,1,1)$, which means the age state of four components are the same as 1. Then, $(kr)$ moves to next possible value $(1,1,1,2)$ until reached $(20,20,20,20)$, which means all $20^{2\times 2}$ possible age combinations are considered. Age combination probability transition matrix $T_{PrA}(kr)$ and $C_{Current}$ will be calculated for each age combination. New component age combination probability distribution matrix $P_{new}(kr)$ and total cost of all age combination $C_{Total}$ will be updated when each component age combination is considered.

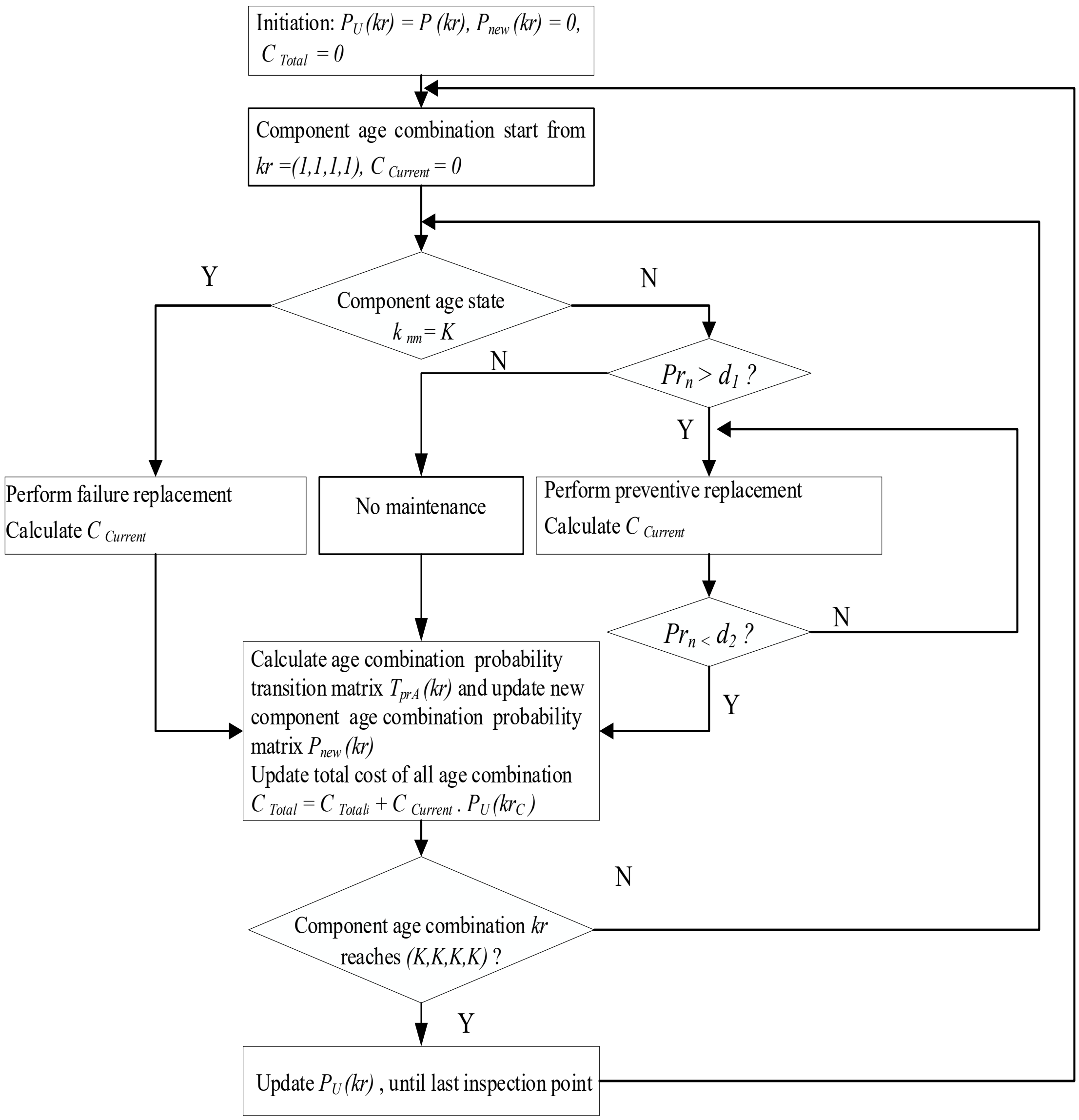



Figure 3.3 The flow chart of calculating age combination probability transition matrix $T_{PrA}(kr)$, new component age combination probability distribution matrix $P_{new}(kr)$ and total cost of all age combination $C_{Total}$

To determine $T_{PrA}(kr)$, several cases should be considered. If failure replacement or preventive replacement are conducted, some components are replaced with new one. Therefore, the age probability of new components should be updated in transition matrix. If there is no maintenance action, no age probability transition will occur. $C_{Current}$ is also determined based on different maintenance actions by CBM policy.

The determination of $T_{PrA}(kr)$ and $C_{Current}$ considering three cases including failure replacement, preventive replacement and no maintenance action respectively is described in detail in the following.

Case 1: Failure replacement is implemented.

To determine transition matrix, $Pr_t(k_{nm}, n, m)$ is generated to indicate probability of transition of all components. It is initially set as 0. At current inspection point, for component $m$ in turbine $n$, if $k_{nm} = K$, which means $RUL$ is 0. In this case, the component is identified as failed. Therefore, failure replacement is required for this component. In age-based preventive replacement, a component that is still functional is replaced once it reaches a predetermined age threshold. The $k_{nm}$ used for determining failures of component is possible age state derived from Weibull distribution, it is different with real component age in preventive replacement. Therefore, the key difference between failure replacement and age-based preventive replacement is that failure replacement is based on the actual condition and performance of the component such as RUL reaching 0, while age based preventive maintenance is based on the chronological age of the component.

The age combination probability transition matrix $T_{PrA}(kr)$ will change due to replace failure component to new one. The probability of transition of new component is considered as initial age distribution:

$$Pr_t(k_{nm}, n, m) = PrA(k_{nm}, n, m) \quad (10)$$

$C_{current}$ will be calculated due to failure replacement, it includes the fixed cost to the farm $C_{Farm}$, which is the cost for transportation of components and equipment to wind farm, installation of a large facility, and failure replacement cost $C_F(n, m)$ includes the expense of purchasing a new part or component to replace the failed one, expense on tools or equipment required for replacement, and labor cost for the technicians remove the failed component and install a new one.

$$C_{Current} = C_{Current_i} + C_{Farm} + \sum_{n,m} C_F(n, m) \cdot IF(n, m) \quad (11)$$

$IF(n, m) = 1$ if the component fails, and $IF(n, m) = 0$, otherwise. $C_{Current_i}$ is the costs generated from the last maintenance activity.

Case 2: Preventive replacement is implemented.

When $k_{nm} < K$, which means $RUL > 0$. The failure probability will be calculated at inspection point for all components and turbines. ANN model is created for each type of components for further failure probability calculation. Weibull distributions are assumed to be appropriate for components lifetime, and the distribution parameters $\alpha_m$ and $\beta_m$ can be estimated for each component $m$. For each type of component, based on the available failure and suspension histories, an ANN prediction model can be trained, and the mean and standard deviation of the

ANN life percentage prediction error, denoted by $\mu_{p,m}$ and $\sigma_{p,m}$, can be calculated. The value of mean and standard deviation of life percentage is from [82].

At a certain inspection point when the time $t_{ABS} = 0$, the age of component $m$ in turbine $n$ is represented by $t_{n,m}$, and its real failure time is known at this point, which is $TL_{n,m}$. Based on the discussion in Section 3.2, the predicted failure time distribution can be obtained as $N(TP_{n,m}, \sigma_p \cdot TP_{n,m})$. Now, based on Equation (2), the current failure probability during the lead time for the component is:

$$Pr_{n,m} = \frac{\int_{t_{n,m}}^{t_{n,m}+L} \frac{1}{\sigma_p TP_{n,m}\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-TP_{n,m}}{\sigma_p TP_{n,m}})^2} dx}{\int_{t_{n,m}}^{\infty} \frac{1}{\sigma_p TP_{n,m}\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-TP_{n,m}}{\sigma_p TP_{n,m}})^2} dx} \tag{12}$$

Finally, the failure probability for each turbine can calculated using equation (4) based on the failure probabilities of its components.

Based on CBM policy, the decision of maintenance actions is based on identifying the specific components or turbines that require attention. If the $Pr_{n,m} > d_1$, preventive maintenance action is required for certain components, the new component will replace the old one. The age combination probability transition matrix $T_{Pr}(kr)$ will change due to preventive replacement. The probability of transition $Pr_t(k_{nm}, n, m)$ for new component is calculated using equation (10).

The cost will be updated as follows:

$$C_{Current} = C_{Current_i} + C_{Farm} + \sum_{n,m} C_P(n,m) \cdot IP(n,m) + \sum_{n} C_{Pfix}(n) \cdot IP_{fix}(n) \tag{13}$$

$IP(n,m) = 1$ if a preventive replacement is performed, and $IP(n,m) = 0$ otherwise. $C_{Pfix}(n)$ is the fixed preventive replacement cost on the turbine level. $C_{Pfix}(n)$ and $C_{Farm}$ will only be considered once for all maintenance actions in the same wind turbine. Fixed preventive replacement costs are expenses that remain relatively constant regardless of the frequency or extent of preventive maintenance activities. It includes regular inspections, routine maintenance tasks, and ongoing costs like staff salaries and condition monitoring systems. Variable preventive replacement costs fluctuate depending on the specific maintenance needs and the condition of the equipment. Variable costs include items such as replacement parts, repair labor, and external contractor fees.

Case 3: No maintenance actions.

If there is no failure replacement and preventive replacement, $Pr_t(k_{nm}, n, m)$ for the component is set as 1 and there is no cost transition at this point.

$$Pr_t(k_{nm}, n, m) = 1 \tag{14}$$

Therefore, the age combination probability transition matrix and the total cost are determined based on 3 cases by the algorithm described above.

$$T_{PrA}(kr) = \prod_{n,m} Pr_t(k_{nm}, n, m) \tag{15}$$

New age combination probability matrix after implementing replacement is denoted by $P_{new}(kr)$. $P_{new}(kr)$ at current inspection point can be obtained by applying the age combination probability transition matrix $T_{Pr}(kr)$ to age probability of corresponding age combination $kr_C$, the formula is as follows:

$$P_{new}(kr) = P_{new_i}(kr) + T_{PrA}(kr) \cdot P_U(kr_C) \tag{16}$$

$P_{new_i}(kr)$ is new age combination probability matrix of previous possible age combination.

The total maintenance cost $C_{Total}$ is accumulating maintenance cost of each age combination cost $C_{current}$ multiply its corresponding age combination probability $P_U(kr_C)$.

$$C_{Total} = C_{Total_i} + C_{Current} \,.\, P_U(kr_C) \tag{17}$$

$C_{Total_i}$ is the total maintenance cost obtained from maintenance actions on previous possible age combination.

### 3.5.3 Step 3: Update the age combination probability matrix $P_U(kr)$ at each inspection interval

The age combination probability matrix is updated at each inspection point to account for changes in the system. During each iteration, the age combination probability matrix is determined based on new age combination probability matrix $P_{new}(kr)$ after CBM decision. Subsequently, this updated distribution is utilized in the next iteration.

As indicated in section 3.4.2, the matrix $P(kr)$ will be initialized first, indicating the initial age distributions for all the wind turbine components. $P_U(kr)$ is set as $P(kr)$ at the first inspection point. When move to next inspection point, $P_U(kr)$ will be updated due to age increases. $P_A(kr)$ is the matrix determined to calculate $P_U(kr)$. $P_A(kr)$ is initially set as 0 at each inspection point.

$kr_t$ represents the age vector combination of all components at next inspection point. To calculate updated age combination probability matrix, two cases are considered in the following:

Case 1: When $k_{nm} = K$, which means RUL of component is 0. $kr_t$ is the matrix for increased component age combination and $P_A(kr_t)$ is calculated as follows:

$$\begin{aligned} kr_t = \{& min[(k_{11}+1),K], min[(k_{12}+1),K] \dots min[(k_{1M}+1),K], \dots, \\ & min\,[(k_{21}+1),K], min\,[(k_{22}+1),K], min\,[(k_{2M}+1),K], \dots, \\ & min[(k_{N1}+1),K], min[(k_{N2}+1),K], min[(k_{NM}+1),K]\} \end{aligned} \tag{18}$$

$$P_A(kr_t) = P_{A_i}(kr_t) + P_{new}(kr) \tag{19}$$

$P_{A_i}(kr_t)$ represents accumulative $P_A(kr_t)$ obtained at previous possible age combination.

Case 2: When $k_{nm} < K$, $P_A(kr)$ is calculated by equation:

$$P_A(kr+1) = P_{A_i}(kr+1) + P_{new}(kr) \tag{20}$$

$$P_U(kr) = P_A(kr) \tag{21}$$

$P_{A_i}(kr+1)$ represents accumulative $P_{A_i}(kr+1)$ obtained at previous possible age combination.

### 3.5.4 Step 4: Update the total cost at each inspection point

The accumulative total cost until the present inspection point is represented by $C_{Total\_sum}$, which is updated at each inspection point. The formula is as follows:

$$C_{Total\_sum} = C_{Total\_sum_i} + C_{Total} \tag{22}$$

where $C_{Total}$ represents the cost incurred at each inspection point due to maintenance actions, such as preventive and failure replacements, which are determined by the maintenance policy. The accumulative total cost is updated at each iteration by adding the cost generated at the previous inspection point $C_{Total\_sum_i}$. This process is repeated until the last inspection point is reached, at which point the accumulative total cost for the entire lifetime is obtained.

### 3.5.5 Step 5: Calculate the cost rate

For each combination thresholds of $d_1$ and $d_2$, the $C_{Total\_sum}$ value is updated at each iteration until the maximum iteration time $T_{Max}$ is reached. Various approaches exist for evaluating maintenance costs, such as total maintenance cost, annual maintenance cost, and maintenance cost rate. Among these, the maintenance cost rate is a popular method as it provides a way to compare maintenance costs on a per-day basis. The cost rate is calculated using the following formula:

$$C_E(d_1, d_2) = \frac{C_{Total\_sum}}{T_{Max}} \tag{23}$$

where $T_{Max}$ is the time of the maximum iteration. It can be calculated by:

$$T_{Max} = IT_I \tag{24}$$

where $I$ is the total number of the iteration and $T_I$ is the length of interval. The maximum iteration time is the product of the number of maximum iteration and inspection interval length.

## 3.6 Summary

This chapter introduces detailed description of the modified numerical method algorithm. There are five sections from component health condition prognostics, failure probability estimation for component and turbine, CBM policy, general assumptions and description of terms, to CBM optimization model and solution method. The last section 3.5 is the key part, which introduces procedure of modified numerical method for CBM optimization. There are five steps for applying modified numerical method. Step 1 is numerical initialization. A new age combination probability transition matrix developed in step 2 and a new 4-dimensional structure for the component age combination probability matrix developed in step 3 are most important parts. Step 4 and 5 are for updating total cost and calculating cost rate.

# Chapter 4 Numerical Method Verification and Comparison

This chapter presents the verification of numerical method, and stability analysis of numerical and simulation methods employed in the optimization of CBM strategies. Through a series of numerical examples and comparative studies, the feasibility and stability of the numerical method is evaluated and compared against the simulation approach. Section 4.1 illustrates a numerical example, and the numerical method is applied in this example to obtain CBM optimization results. Subsequently, the simulation method with sufficient iterations, is employed on the same example in section 4.2. The optimization results obtained through both methods are conducted to verify the effectiveness of the numerical method. To enforce the verification of the numerical method, two case studies are developed. In section 4.2.3, Example 1 explores the impact of varying fixed preventive maintenance costs on the optimal CBM policy using both numerical and simulation method, thereby providing additional verification for the numerical approach. Section 4.2.4 Example 2 investigates the influence of changing fixed costs associated with wind farms on the optimal CBM strategy using both methods, further confirming the solidity of the numerical method. Section 4.3 is dedicated to assessing the stability of the numerical and simulation methods through comparative studies. Five comparative studies are developed between these two methods in this section. Comparative Study 1 examines the impact of limited simulation iterations on the stability of optimization outcomes of simulation method. In comparative study 1, the number of simulation iteration is set to be smaller, specifically to 1080 iteration time, and the lowest maintenance cost rate with thresholds are obtained. Seven repeated experiments are conducted to compare the cost rate variation of these two methods. Based on the comparative study 1, comparative study 2 increases the number of simulation iteration to 18000 iteration time and compare the results of both methods. Furthermore, comparative study 3 is comparing the stability of both method when simulation iteration is large enough and this study is based on CBM optimization results in section 4.1.2 and section 4.2.2. This study involves seven repeated experiments to determine the consistency of the optimal CBM policy of two methods. In addition, Comparative Studies 4 and 5 provide insights into the stability analysis of the optimal CBM policy with respect to various fixed preventive maintenance costs and wind farm fixed costs, respectively.

## 4.1 A numerical example

### 4.1.1 Example introduction

A numerical example is developed to demonstrate the numerical method for implementing CBM policy in a wind farm. To simplify the problem, we assume that there are two wind turbines in the wind farm and each turbine has two components: the rotor (including the blades) and the main bearing. We assume that the failure time of the components follows the Weibull distribution, and the corresponding parameters of each component are presented in Table 1. The Weibull distribution can effectively model various types of failure rates, including increasing, decreasing, and constant failure rates. This makes it suitable for different types of wind turbine components, which may have different reliability characteristics over time. Extensive empirical evidence suggests that the Weibull distribution accurately describes the failure behavior of many mechanical and electronic components, including those in wind turbines. Its ability to fit actual field data makes it a practical choice for reliability analysis and maintenance planning. Wind turbine components often have extensive historical data available from operational and failure records. The Weibull distribution can effectively utilize this data to model and predict future failures. Study [74] investigated the use of Weibull distribution in analyzing SCADA data for fault detection in wind turbines. [75] discussed the application of the Weibull distribution in conducting FMEA for wind turbines, providing a robust framework for understanding and mitigating component failures.

The component lifetime distribution parameters are specified based on the data given in Ref. [69] and [70]. The specific costs of different maintenance actions for each component are also shown in Table 1, it includes the failure replacement cost, variable and fixed preventive replacement costs, and fixed cost to the wind farm. The cost value for each maintenance action is specified based on the cost-related data given in Ref. [71] and [72]. The ANN prediction method is used to predict the failure time distribution of the wind turbine components and suppose the standard deviations of the ANN life percentage prediction errors are 0.12 and 0.10, respectively, as shown in Table 4.1. The standard deviation values are selected by referring to that estimated using the bearing degradation data in Ref [68] and [73].

Table 4.1 Parameter values for major components

| Components | Rotor | Main bearing |
|---|---|---|
| Scale parameter $\alpha$ (days) | 3,000 | 3,750 |
| Shape parameter $\beta$ | 3.0 | 2.0 |
| Failure replacement cost ($k) | 112 | 60 |
| Variable preventive maintenance cost ($k) | 28 | 15 |
| Fixed preventive maintenance cost ($k) | 25 | |
| Fixed cost to the wind farm ($k) | 50 | |
| ANN lifetime prediction error (Standard deviation values) | 0.12 | 0.10 |

### 4.1.2 CBM optimization results using the numerical method

In this case, the maintenance lead time is assumed to be 30 days for all components. The inspection interval is set to be 1.5 years, and there are 20 inspections for a component during a typical lifetime for 30 years. 36 sets of different failure threshold combinations are calculated to find the lowest maintenance cost.

The total maintenance costs and cost rates for wind farm can be estimated by using the numerical method described in chapter 3. The cost values of 36 pairs of thresholds are presented in Table 4.2. Figure 4.1 illustrates a three-dimensional plot depicting the relationship between maintenance costs and failure probability threshold values $d_1$ and $d_2$ , with both $d_1$ and $d_2$ represented on a logarithmic scale. Notably, the total maintenance costs value is influenced by the variations in the combinations of $d_1$ and $d_2$ thresholds and the lowest cost rate is attained with corresponding failure threshold values. Therefore, the optimal CBM policy can be found when the lowest maintenance cost value appears. When both $d_1$ and $d_2$ are set to relatively large, the maintenance cost is the highest with \$194.70/day. The first level failure threshold value $d_1$ and second level failure threshold value $d_2$ value are set to be decreasing and the cost rate figure shows a downward and upward trend. The optimal failure probability threshold values are found to be: $d_1 = 2.1544 \times 10^{-3}$ , $d_2 = 1 \times 10^{-6}$ and the optimal maintenance cost per unit of time is \$129.97/day. The optimal maintenance cost obtained by numerical method is the lowest cost of all tested failure thresholds. When evaluating lowest cost, the numerical method terminates after a number of iterations, which may not be sufficient for convergence to the global optimum. In addition, complex problems with multi-dimensionality increase the computational complexity and the likelihood of the algorithm converging to a suboptimal solution due to limited computational resources. Therefore, we did not have a way to prove that that the optimal solution is absolutely optimal. Figure 4.2 and 4.3 provides detailed visualizations of the relationship between maintenance costs and individual failure probability threshold values, with one threshold maintained at its optimal value while the other varies. Figure 4.2 shows the cost rate versus $d_1$ plot while $d_2$ is kept at $d_2 = 1 \times 10^{-6}$ ,which the lowest maintenance cost rate is found and the cost versus $d_2$ plot while $d_1$ is kept at $d_1 = 2.1544 \times 10^{-3}$ is presented in Figure 4.3. Specifically, these figures illustrate the pronounced variability in maintenance cost rates corresponding to changes in $d_1$, compared to the relatively minor fluctuations observed with alterations in $d_2$. Hence, it is obvious that adjustments in $d_1$ thresholds exert a more significant impact on maintenance cost estimations than alterations in $d_2$ thresholds. Furthermore, Curve fitting is applied to the entire cost surface and the results are shown in Figure 4.4, Figure 4.5, Figure 4.6.

Table 4.2 Cost values ($/day) of 36 pairs combined failure thresholds.

| | | $d_1$ | | | | | |
|---|---|---|---|---|---|---|---|
| | | $4.6416 \times 10^{-2}$ | $2.5 \times 10^{-2}$ | $1.3 \times 10^{-2}$ | $2.1544 \times 10^{-3}$ | $4.6416 \times 10^{-4}$ | $2.1544 \times 10^{-4}$ |
| $d_2$ | $1 \times 10^{-4}$ | 194.7000 | 186.7064 | 177.3487 | 131.3097 | 146.4757 | 174.3688 |
| | $1 \times 10^{-6}$ | 194.7000 | 186.7064 | 177.3487 | 129.9717 | 143.2200 | 168.5211 |
| | $2.15 \times 10^{-9}$ | 194.7000 | 186.7064 | 177.3487 | 130.6099 | 142.4294 | 168.2753 |
| | $1 \times 10^{-10}$ | 194.7000 | 186.7064 | 177.3487 | 132.0142 | 144.8557 | 170.1415 |
| | $2.15 \times 10^{-13}$ | 194.7000 | 186.7064 | 177.3487 | 133.9111 | 146.2159 | 172.4440 |
| | $1 \times 10^{-14}$ | 194.7000 | 186.7064 | 177.3487 | 135.4471 | 148.8234 | 175.2710 |

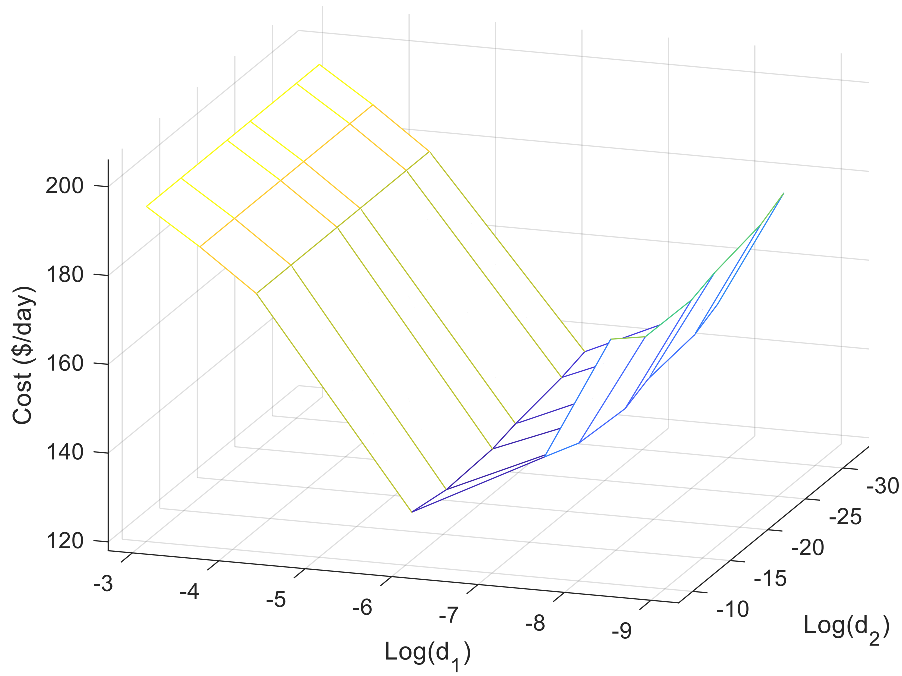



Figure 4.1 Cost rate versus failure probability threshold values in the logarithmic scale of the numerical method

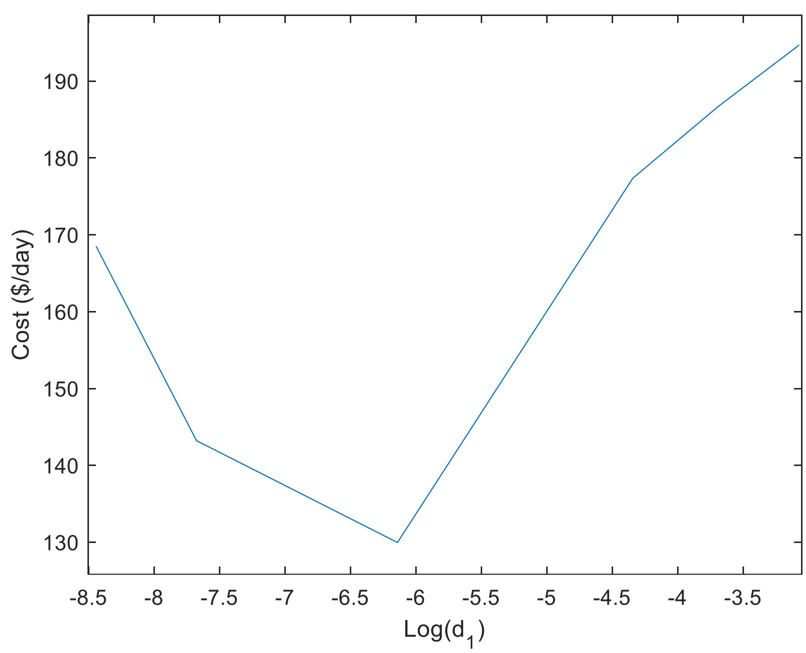



Figure 4.2 Cost rate versus threshold $d_1$ in the logarithmic scale of the numerical method ($d_2 = 1 \times 10^{-6}$ )

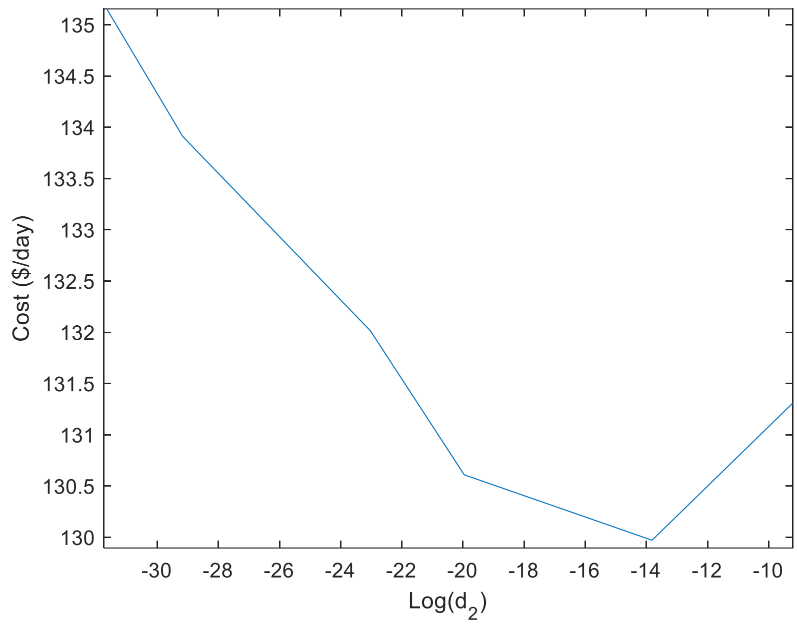



Figure 4.3 Cost rate versus threshold $d_2$ in the logarithmic scale of the numerical method ($d_1 = 2.1544 \times 10^{-3}$ )

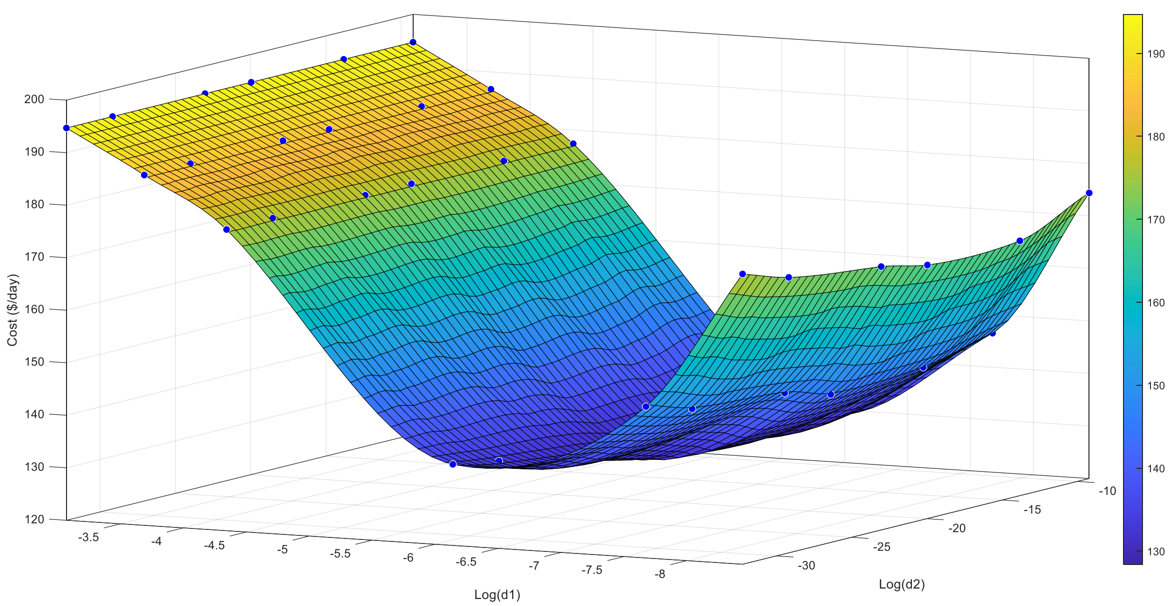



Figure 4.4 Cost rate versus failure probability threshold values in the logarithmic scale of the numerical method using curve fitting

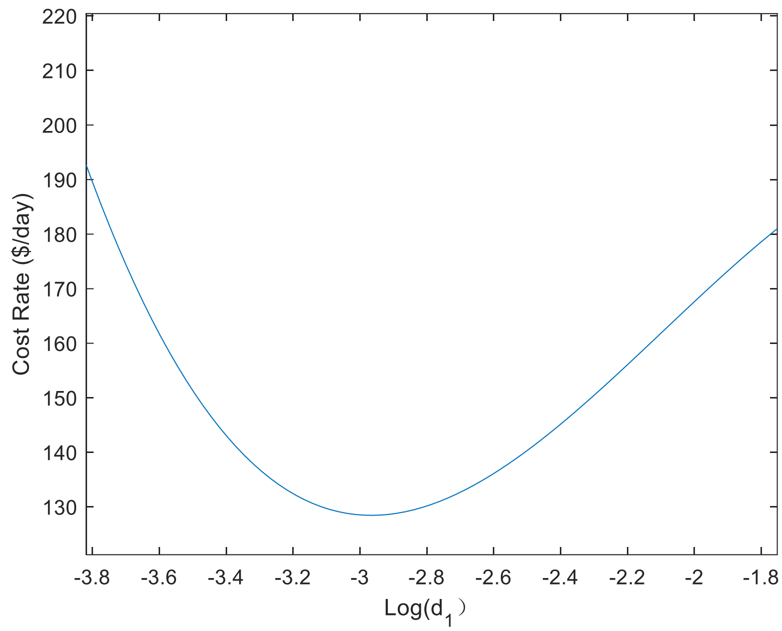



Figure 4.5 Cost rate versus threshold $d_1$ in the logarithmic scale of the numerical method using curve fitting ($d_2 = 1 \times 10^{-6}$ )

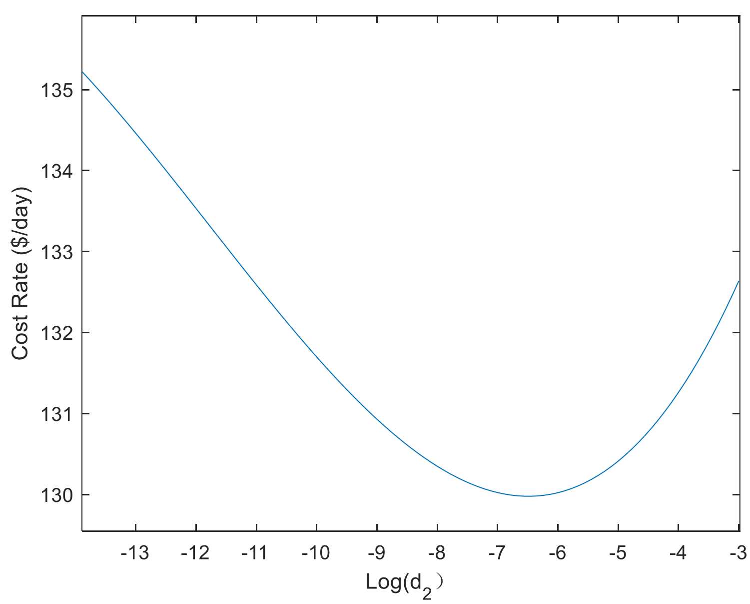



Figure 4.6 Cost rate versus threshold $d_2$ in the logarithmic scale of the numerical method using curve fitting ($d_1 = 2.1544 \times 10^{-3}$ )

With the optimal failure threshold values $d_1 = 2.1544 \times 10^{-3}$ and $d_2 = 1 \times 10^{-6}$ , the cost rate is evaluated across varying iterations and the results are shown in Figure 4.7. The maximum iteration limit is set to be 80. The cost rate rises rapidly in initial iterations, the rate of increase is slowing down gradually in subsequent iterations. An observable trend emerges where in the cost rate converges towards a steady-state value beyond a certain number of iterations and the cost rate surface is quite smooth. This convergence emphasizes the stability of the cost rate over long iterations, indicating that the optimization process reaches an equilibrium state.

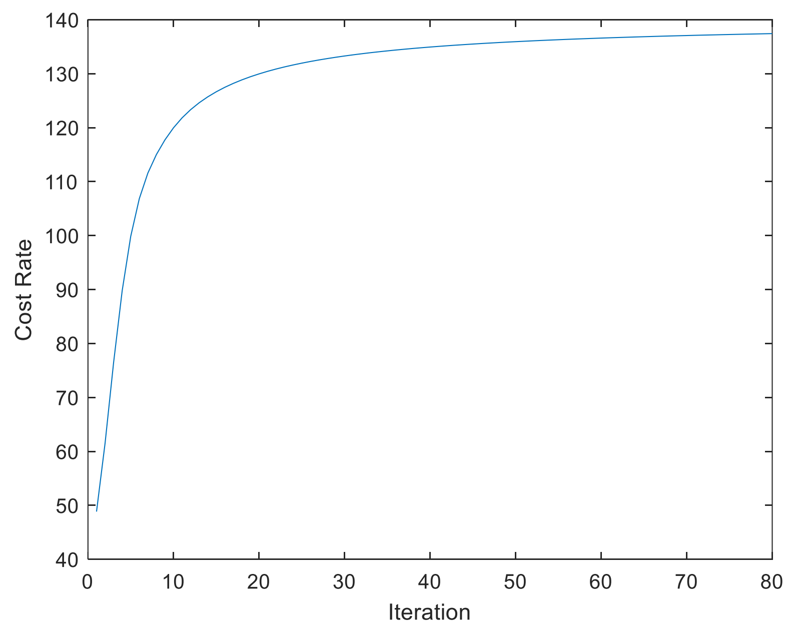



Figure 4.7 Cost rate versus number of iterations of the numerical method

## 4.2 Verification of numerical method

### 4.2.1 Simulation method for verification

To verify the results of the numerical method, a simulation method is applied to the identical example outlined in section 4.1.1. By comparing the minimal maintenance costs obtained from both simulation and numerical methods, the feasibility of the numerical method can be verified. Simulation method is a statistical technique for solving mathematical problems reliant on random sampling. Today, with advancements in computational power, the simulation method has become integral in diverse disciplines, including engineering, business, healthcare, environmental science, and social sciences.

In previous studies, the simulation method has demonstrated utility in estimating the wind farms maintenance cost. The simulation method proposed in [23] is used to estimate the maintenance cost rate. The maintenance policy for simulation method is the same for the numerical method with two level failure probability thresholds. The maintenance cost rate $C_E$ for the wind farm can be computed utilizing the equation in [23]:

$$C_E = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} IF_{n,m}c_{f,m} + \sum_{n=1}^{N}(\sum_{m=1}^{M} IP_{n,m}c_{p,m} + IT_n c_{p,T}) + I_{Farm}c_{Farm}}{T_{Max}} \tag{24}$$

where $c_{f,m}$, $c_{p,m}$, $c_{p,T}$, $c_{Farm}$ is the failure replacement cost for component $m$, the variable preventive replacement cost for component $m$, the fixed cost of maintaining a wind turbine, and the fixed cost of sending a maintenance team to the wind farm. $IF_{n,m}$, $IP_{n,m}$, $IT_n$, $I_{Farm}$ indicate whether a failure replacement being performed on component $m$ in turbine $n$, whether a preventive replacement is being performed on component $m$ in turbine $n$, whether a preventive replacement being performed in turbine $n$, whether a maintenance team is being sent to the wind farm. $T_{Max}$ is the maximum simulation time.

The simulation method is applied to solve the same example in section 4.1.1. Maintenance lead time is assumed to be 30 days and the inspection interval is set at 10 days. We use identical lifetime distribution parameters and cost data for the components and wind farm maintenance actions, as presented in Table 1. With this study, our objective is to assess the capability of the numerical method to accurately estimate maintenance costs. By using the same input parameters and CBM policy, we facilitate a direct comparison of the results derived from the simulation and numerical methods, thus measuring the feasibility of the numerical methods.

### 4.2.2 CBM optimization results using simulation method

The simulation method is applied with a substantial number of iterations, totaling approximately 50,000 times. The cost rate is plotted against the failure probability threshold values in Figure 4.8. The failure probability threshold values are given in the logarithm scale. The total maintenance cost is affected by the two failure probability threshold values. When both $d_1$ and $d_2$ values are set to 1, implying that only failure replacement is considered, the cost rate reaches its peak value, approximately \$185 per day. As the value of two threshold gets smaller, the cost rate value shows a decreasing and increasing trend. Subsequently, as the values of these two thresholds decrease, indicating the inclusion of preventive maintenance measures alongside failure replacement, the dynamic changes of the cost rate occur accordingly.

The optimal maintenance policy is identified based on minimizing the total maintenance cost rate, leading to the determination of the corresponding optimal failure probability threshold values: $d_1 = 0.1$, $d_2 = 1 \times 10^{-7}$. The corresponding optimal maintenance cost per unit of time is \$119.14/day. The cost rate versus $d_1$ plot in the logarithmic scale while $d_2$ is kept at the optimal value $1 \times 10^{-7}$ is presented in Figure 4.9, and the cost rate versus $d_2$ plot while $d_1$is kept at 0.1 is depicted in Figure 4.10. Figure 4.11 shows the curve of cost rate versus number of iterations with optimal failure threshold values. The cost rate curve exhibits significant fluctuations when the iteration count is relatively low, indicative of the initial stages of optimization. However, as the iteration count increases, the magnitude of these fluctuations decreases, signifying the convergence of the optimization process towards a more stable configuration. This observation highlights the iterative nature of the optimization process, with stability increasing as the number of iterations increases.

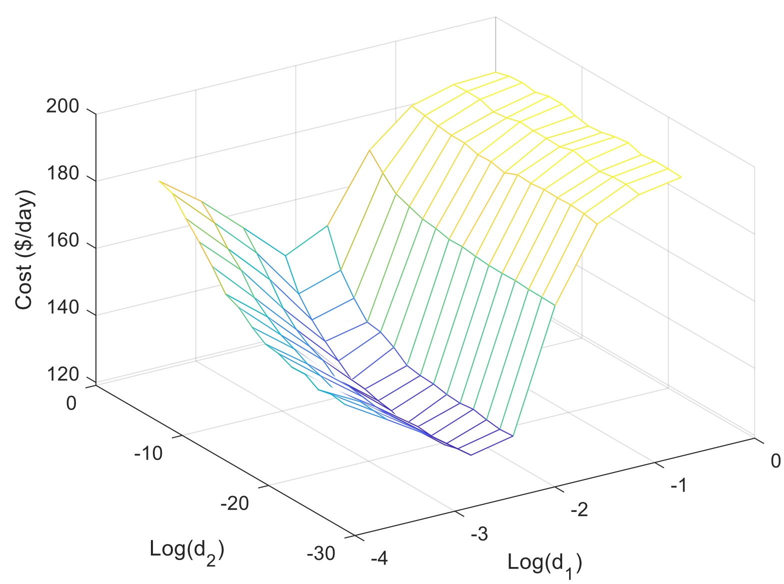



Figure 4.8 Cost versus failure probability threshold values in the logarithmic scale of the simulation method

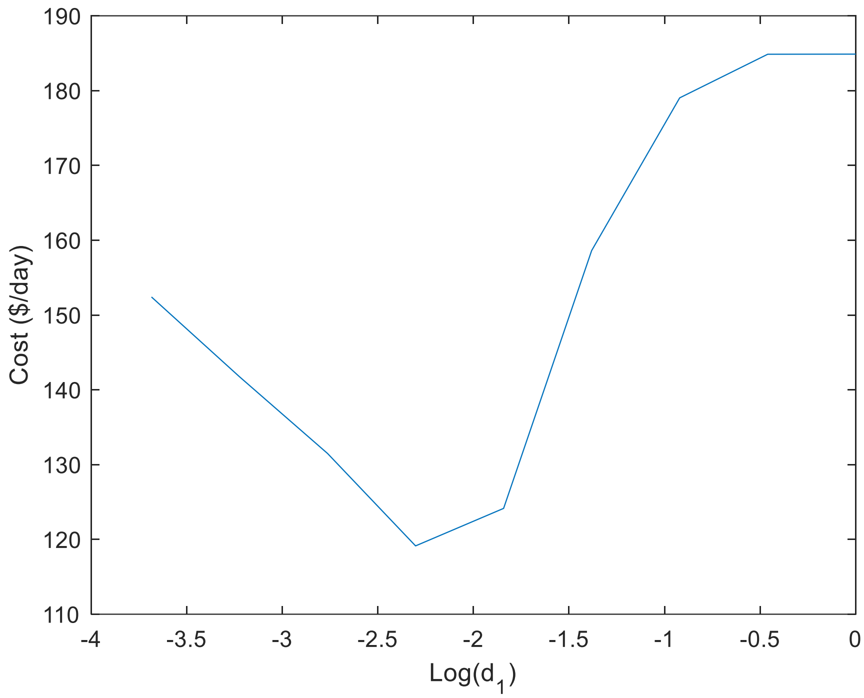



Figure 4.9 Cost versus threshold $d_1$ of the simulation method in the logarithmic scale ( $d_2 = 1 \times 10^{-7}$)

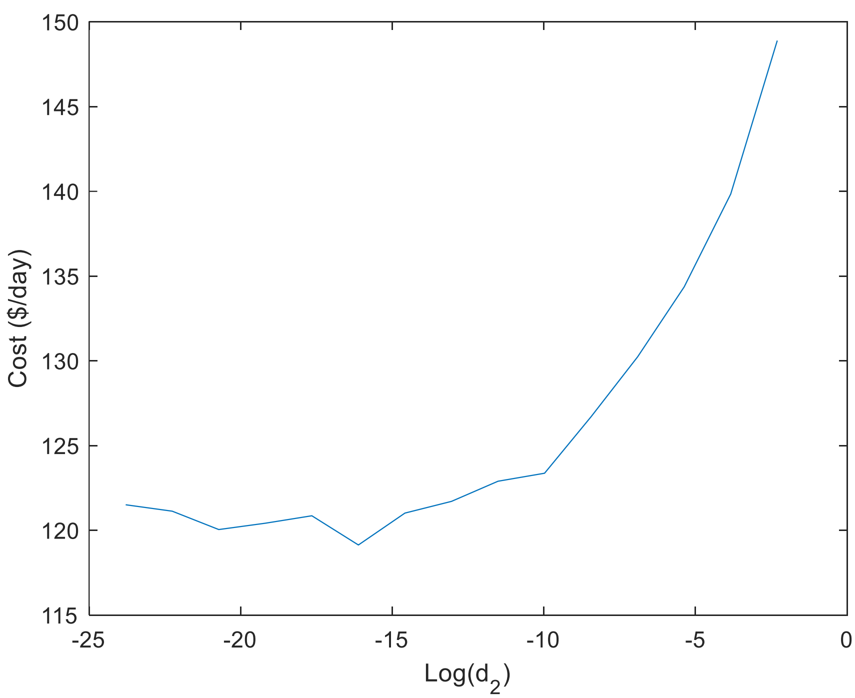



Figure 4.10 Cost versus threshold $d_2$ of the simulation method in the logarithmic scale ($d_1 = 0.1$)

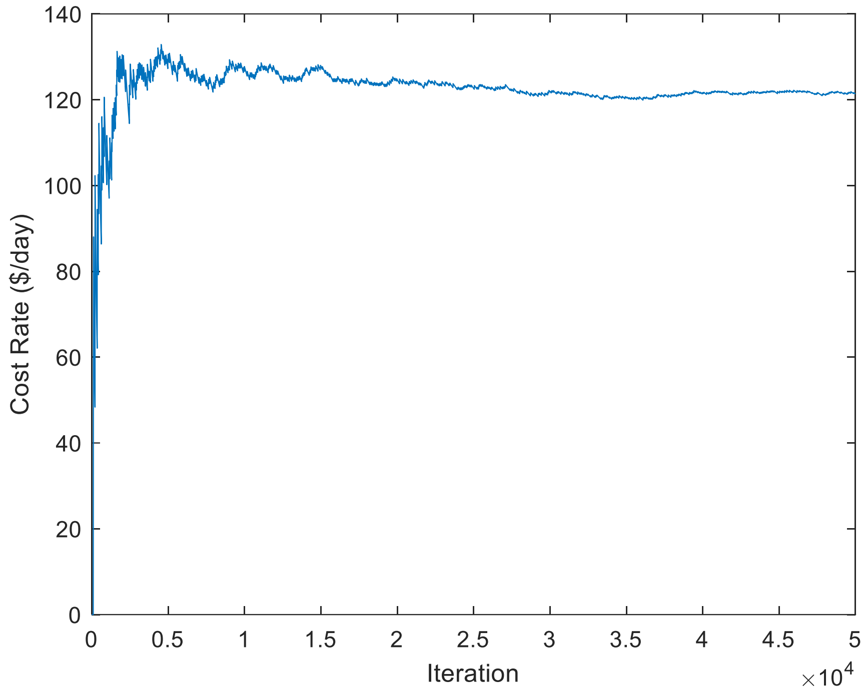



Figure 4.11 Cost rate versus number of iterations of the simulation method

To verify the numerical method, the cost rate value of numerical method and simulation method is shown in Table 4.3. For the same example, the lowest maintenance cost rate using simulation method is \$119.14 per day with optimal threshold value $d_1 = 0.1$, $d_2 = 1 \times 10^{-7}$. The lowest cost rate using numerical method is \$129.97 per day with optimal threshold value $d_1 = 2.1544 \times 10^{-3}$and $d_2 = 1 \times 10^{-6}$. Comparing these results, the difference between the minimal maintenance cost rates obtained from the simulation and numerical methods is \$10.83 per day. The cost rate value obtained from numerical method is close to simulation method, which is able to demonstrates that the numerical method is able to estimate the maintenance cost for wind farm system in an accurate way.

Table 4.3 Cost rate and threshold value comparison for simulation and numerical method

| Method | Cost rate ($/day) | Threshold $d_1$ | Threshold $d_2$ |
|---|---|---|---|
| Simulation | 119.14 | 0.1 | $1\times10^{-7}$ |
| Numerical | 129.97 | $2.1544\times10^{-3}$ | $1\times10^{-6}$ |

### 4.2.3 Sensitivity analysis 1: CBM optimization considering various fixed preventive maintenance cost

To demonstrate the effectiveness of numerical method for different scenarios, the fixed preventive maintenance cost is varied to distinct values. Both the numerical and simulation methods are subsequently employed to obtain the lowest maintenance cost rates corresponding to these variations. The various fixed preventive maintenance cost value and corresponding cost rate for two methods are summarized in Table 4.4 and visualized in Figure 4.12. As the fixed preventive maintenance cost increases, there is a corresponding rise in the total maintenance cost rate for both methods. The cost rate value derived from the numerical method exhibit minimal differences compared to those obtained from the simulation method for each fixed preventive cost value. This consistency emphasizes the ability of the numerical methods to accurately estimate total maintenance cost rates across a variety of fixed preventive maintenance cost scenarios. Thus, the results confirm the validity and reliability of the numerical methods in adapting to different maintenance cost parameters, enhancing their applicability and usefulness in real-world environments.

Table 4.4 Lowest cost rate of various fixed preventive maintenance value for simulation and numerical method.

| | Fixed preventive maintenance cost value ($k) | | | | | | |
|---|---|---|---|---|---|---|---|
| Method | 10 | 15 | 20 | 25 | 30 | 35 | 40 |
| Simulation | 103.38 | 105.33 | 113.25 | 119.14 | 121.29 | 126.75 | 128.51 |
| Numerical | 111.57 | 117.70 | 123.84 | 129.97 | 136.11 | 142.24 | 148.38 |

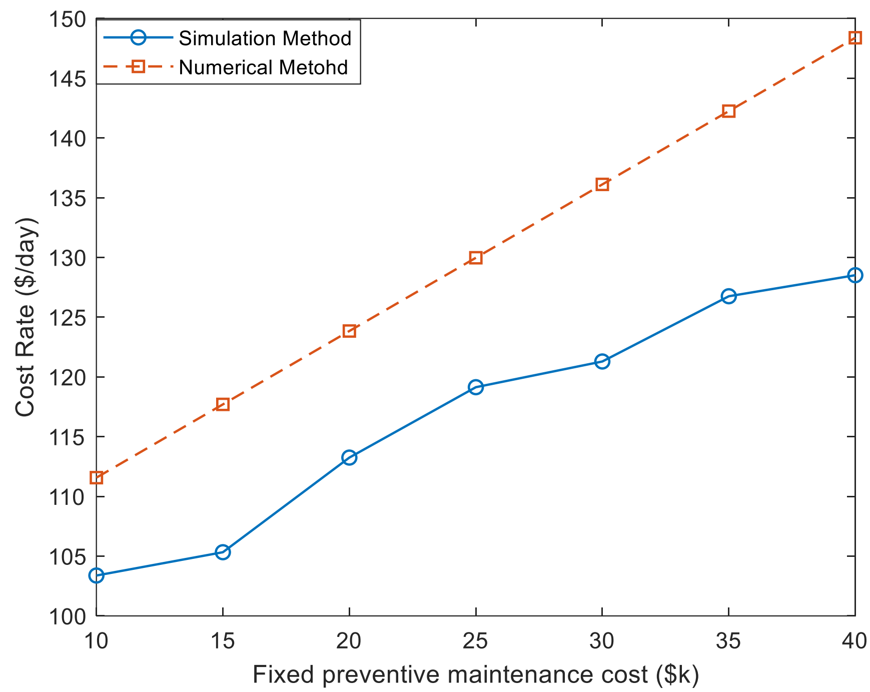



Figure 4.12 Various fixed preventive maintenance cost value and corresponding cost rate for the simulation and numerical method

### 4.2.4 Sensitivity analysis 2: CBM optimization considering various fixed cost to wind farm

In Sensitivity analysis 1, the fixed preventive maintenance cost is varied to verify the numerical method, while in Sensitivity analysis 2, another parameter, the fixed cost to the wind farm, is set to different values for verification purposes. The specific values of assumed fixed costs to wind farm and the corresponding lowest cost rates obtained from both the numerical and simulation methods are detailed in Table 4.5 and visually represented in Figure 4.13. As the value of the fixed costs of the wind farm increases, the cost rate values derived from the two methods tend to increase. The consistency observed between the numerical and simulation methods in the comparison of total maintenance cost rates indicates the feasibility of the numerical method in estimating maintenance costs for various fixed cost to wind farm scenarios.

Table 4.5 Lowest cost rates of various fixed cost to the wind farm for simulation and numerical method.

| | Fixed cost value to the wind farm ($k) | | | | | | |
|---|---|---|---|---|---|---|---|
| Method | 35 | 40 | 45 | 50 | 55 | 60 | 65 |
| Simulation | 102.21 | 106.15 | 109.87 | 117.70 | 123.00 | 128.16 | 133.94 |
| Numerical | 114.72 | 119.80 | 124.89 | 129.97 | 135.06 | 140.14 | 145.22 |

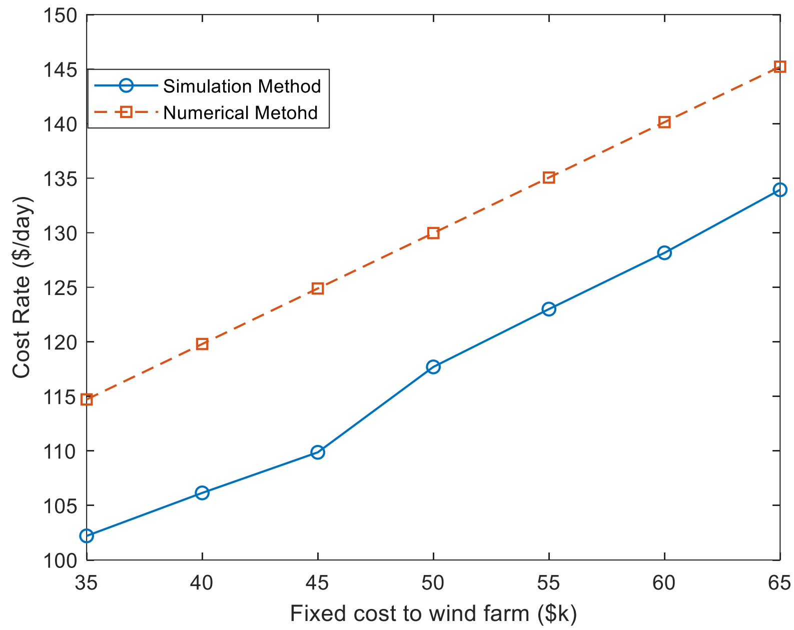



Figure 4.13 Various fixed cost to wind farm and corresponding cost rate for the simulation and numerical method

## 4.3 Comparative study with simulation method

While the simulation method is a powerful and widely used method, it has some limitations. Due to sampling-based characteristics, one disadvantage is that the feasibility of simulation results depends greatly on the quantity of the random sampling. If the sampling amount is not sufficient, the simulation results may be meaningless, leading to unreasonable estimates. Indeed, in reality, a number of practical constraints limit the feasibility of employing large numbers of samples, especially in complex systems where computational resources may be limited. Factors such as computational efficiency, time constraints, and resource availability may limit the number of samples that can be generated and analyzed in a given period of time. In scenarios where limited computational resources constrain the ability to utilize a sufficient number of samples in simulation methods, the reliability of results may be compromised. In such cases, the numerical method offers a valuable alternative that can provide reliable estimations of system behavior without the need for extensive sampling. Comparative study 1 and 2 between two methods in section 4.3.1 and 4.3.2 focus on considering the limitations of simulation samples.

Another constraint of simulation method is that it has no guarantees of exact solutions. Simulation methods provide estimates with a certain level of confidence, but do not guarantee an exact solution. While increasing the sample size can enhance the accuracy of simulation results, there is remains a degree of uncertainty in the process. This uncertainty poses challenges in the optimization process, particularly when precise solutions are required for decision-making. Comparative study 3 is developed to express the variability and uncertainty in simulation results and contrast with the stability and consistency by the numerical method.

Comparative study 4 and 5 compare the stability and consistency of two methods with various fixed preventive maintenance cost and fixed cost to wind farm respectively.

### 4.3.1 Comparative study 1: Considering small iteration time of the simulation method

The comparative study 1 is performed between simulation and numerical method when the number of samples is smaller in simulation method. The number of samples are related to the maximum iteration time in algorithm. The maximum iteration time of the numerical method is the same as sensitivity analysis in section 4.1.2, and thus, the optimal outcomes from that section are utilized as a benchmark for subsequent seven repeated experiment. For the simulation method, the maximum iteration time is set to a large value to get an accurate result for validating the numerical method in section 4.2.2. This comparative study illustrates the effectiveness of simulation methods under conditions of small sample size as iteration times 1080 . By applying the simulation method with small iteration time to the same example and assumptions delineated in Section 4.1, we aim to measure its performance and comparative accuracy with the numerical methods.

The cost rate is plotted against the failure probability threshold values, as illustrated in Figure. 4.14. The lowest replacement maintenance cost rate can be determined from the figure, where the corresponding failure probability threshold values are found to be $d_1 = 0.0631$, $d_2 = 6.3096 \times 10^{-6}$. The corresponding lowest maintenance cost per unit of time is $91.1738/day. The cost rate versus $d_1$ plot in the logarithmic scale while $d_2$ is kept at the optimal value $6.3096 \times 10^{-6}$ is presented in Figure 4.15, and the cost rate versus $d_2$ plot while $d_1$is kept at $0.0631$ is depicted in Figure 4.16. However, it is clear that the cost rates estimated by the simulation method exhibit significant fluctuations for different combination thresholds, and therefore the minimum maintenance cost cannot be definitively considered as optimal. This variation highlights the importance of ensuring a sufficient number of samples during the simulation process for the accuracy and reliability of the optimization results.

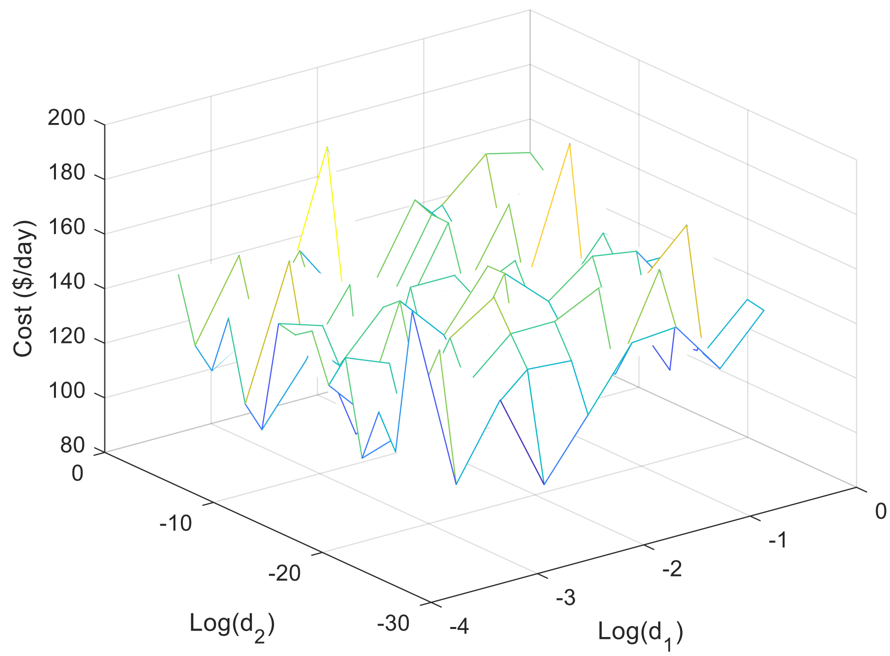



Figure 4.14 Cost versus failure probability threshold values in the logarithmic scale considering small simulation iteration time

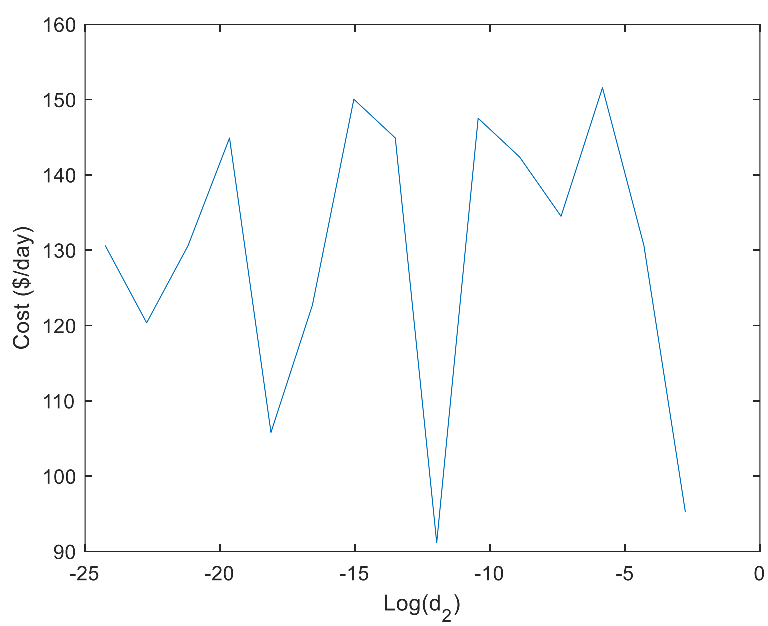



Figure 4.15 Cost versus threshold $d_1$ in the logarithmic scale considering small simulation iteration time ($d_2 = 6.3096 \times 10^{-6}$ )

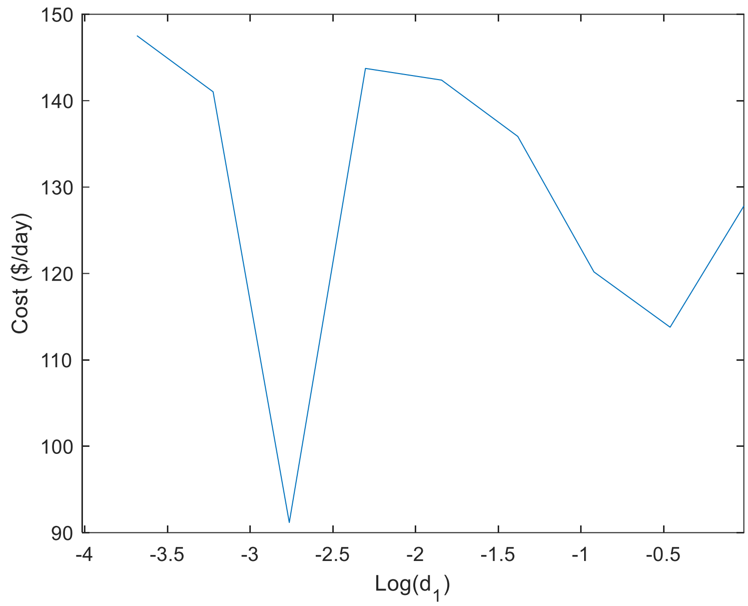



Figure 4.16 Cost versus threshold $d_2$ in the logarithmic scale considering small simulation iteration time ($d_1 = 0.0631$ )

To compare the reliability of simulation and numerical methods, a series of seven repeated experiments is conducted for each method, utilizing the threshold values corresponding to their respective lowest cost rates. For the numerical method, we find the lowest maintenance cost rate is \$129.97 per day through CBM optimization with failure threshold value $d_1 = 1 \times 10^{-2}$ and $d_2 = 1 \times 10^{-6}$ in section 4.1.1. This optimal failure threshold value remains constant in numerical method for seven repeated experiments and maintenance cost rates are estimated. For the simulation method, repeated experiments are executed using the failure threshold values $d_1 = 0.0631$ and $d_2 = 6.3096 \times 10^{-6}$ associated with its lowest maintenance cost rate. The failure thresholds and corresponding lowest maintenance cost rate for simulation and numerical method is shown in Table 4.6. The comparison results are shown in Figure 4.17.

Table 4.6 Lowest cost rate and corresponding threshold value for simulation and numerical method with small iteration time of the simulation method

| Method | Cost rate ($/day) | Threshold $d_1$ | Threshold $d_2$ |
|---|---|---|---|
| Simulation | 91.17 | 0.0631 | $6.3096\times10^{-6}$ |
| Numerical | 129.97 | $2.1544\times10^{-3}$ | $1\times10^{-6}$ |

In seven repeated experiments, the cost rate value of numerical method remains consistently at $129.97 per day, which is the same value of the optimal CBM policy. Conversely, the cost rate derived from the simulation method exhibits notable fluctuations, with an approximate variance of $100 per day between the highest and lowest values. This variability in simulation results is attributed to the inherent characteristics of the sampling process. When the number of samples is insufficient, the method may fail to encompass an adequate range of possible scenarios, thereby inadequately reflecting the actual situation.

Therefore, while simulation methods remain valuable tools for capturing system dynamics and uncertainty, the numerical method offers a practical and efficient alternative, especially in scenarios where large-scale sampling is not feasible. By providing stable and reliable estimations of system behavior, the numerical method addresses the challenges posed by limited sampling size, making it a valuable tool for decision-making in complex engineering and systems management contexts.

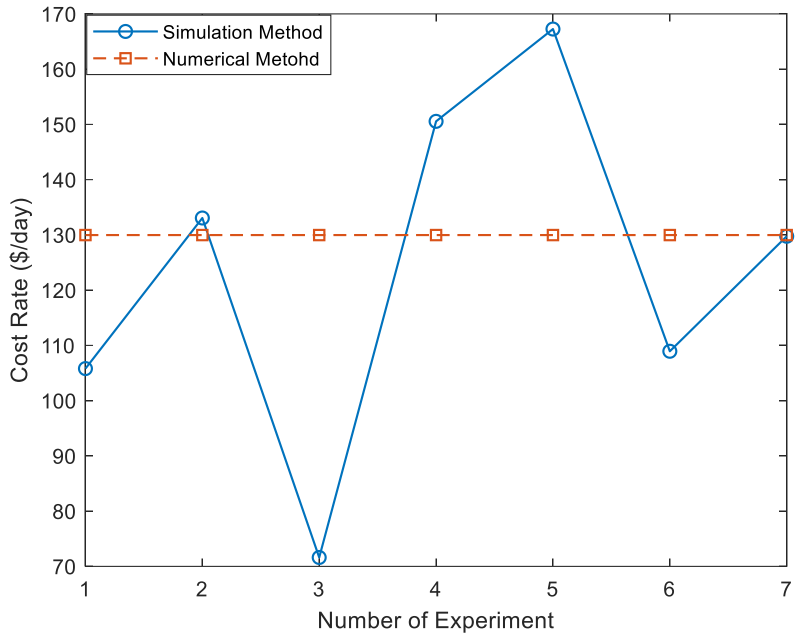



Figure 4.17 Repeated experiments for simulation and numerical method increased simulation iteration time

### 4.3.1 Comparative study 2: Considering increased iteration time of the simulation method

Based on the results in comparative 1, the maximum simulation iteration time is set larger as 18000 times in this comparative study. Figure. 4.18 shows the cost rate versus failure probability threshold values in the logarithmic scale. Through the figure, the minimum maintenance cost rate can be discerned, identified at corresponding failure probability threshold of $d_1 = 0.0398$, $d_2 = 1.8478 \times 10^{-11}$. The corresponding minimum maintenance cost is $99.04/day. Subsequently, in Figure 4.19, the logarithmic representation of the cost rate versus $d_1$ is illustrated while maintaining $d_2$ at its optimal value of $1.8478 \times 10^{-11}$. Figure 4.20 presents the relationship between the cost rate and $d_2$ while $d_1$ remains fixed at $0.0398$. It becomes evident that the estimated cost rates, derived through the simulation method, exhibit notable fluctuations across varying threshold combinations. Consequently, the identification of an optimal minimum maintenance cost rate is challenging.

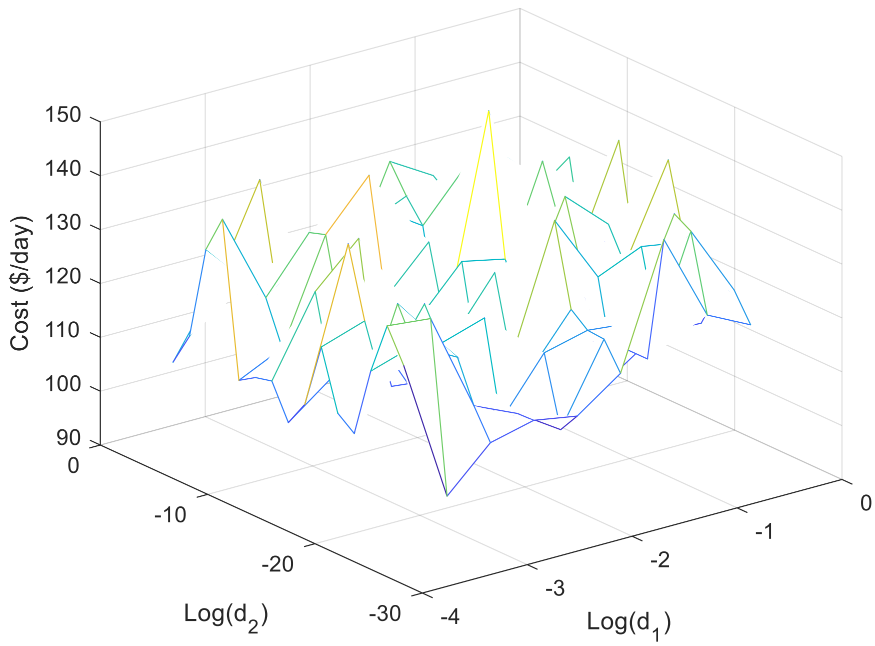



Figure 4.18 Cost versus failure probability threshold values in the logarithmic scale considering increased simulation iteration time

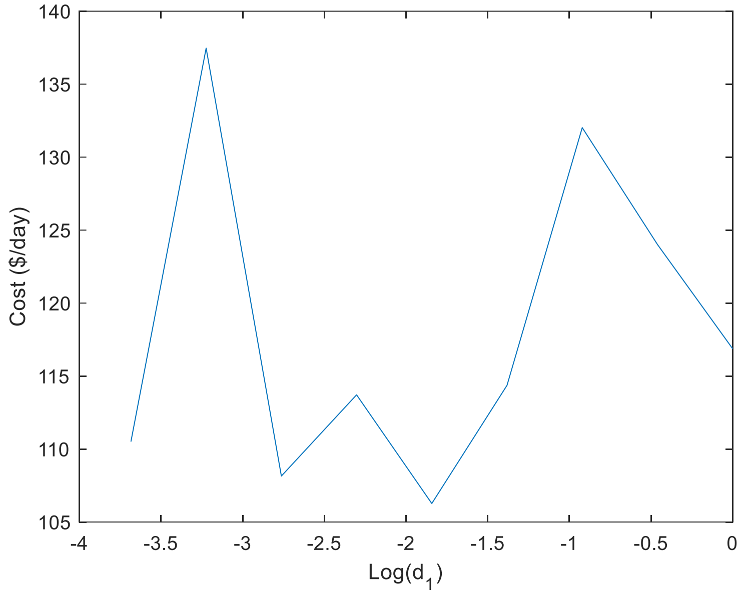



Figure 4.19 Cost versus threshold $d_1$ in the logarithmic scale considering increased simulation iteration time ($d_2 = 1.8478 \times 10^{-11}$)

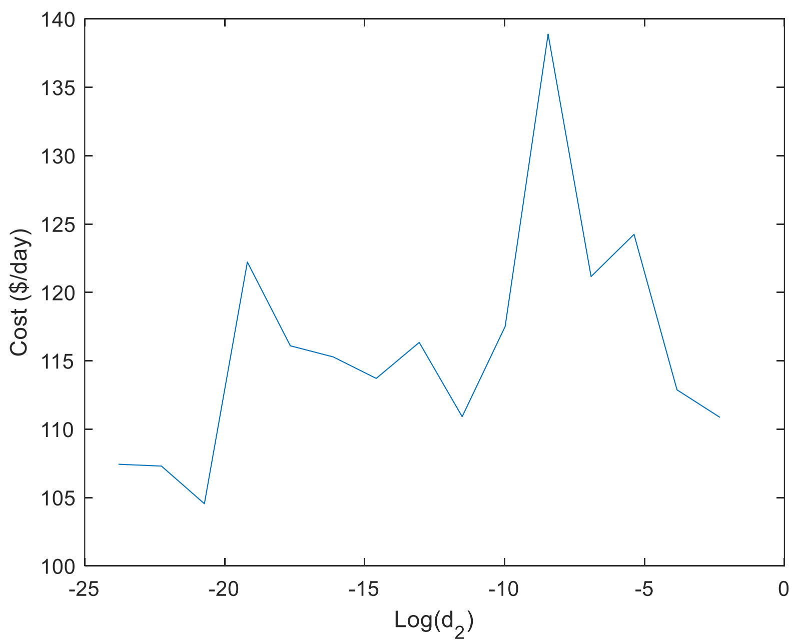



Figure 4.20 Cost versus threshold $d_2$ in the logarithmic scale considering increased simulation iteration time ($d_1 = 0.0398$ )

The lowest maintenance cost rate with corresponding failure thresholds of simulation and numerical method is shown in Table 4.7. Seven repeated experiments are conducted based on results obtained in both methods and shown in Figure 21. The cost rate derived from the simulation method fluctuated in repeated experiments, with an approximate variance of $30 between the highest and lowest value. Upon comparison with a previous comparative study 2, where the maximum iteration time of the simulation method was extended from 1080 to 18000, it was observed that the magnitude of these fluctuations decreased. Despite this reduction, the fluctuations still exert a significant impact on the optimization process.

Table 4.7 Lowest cost rate and corresponding threshold value for simulation and numerical method with increased iteration time of the simulation method

| Method | Cost rate ($/day) | Threshold $d_1$ | Threshold $d_2$ |
|---|---|---|---|
| Simulation | 99.04 | 0.0398 | $1.8478\times10^{-11}$ |
| Numerical | 129.97 | $2.1544\times10^{-3}$ | $1\times10^{-6}$ |

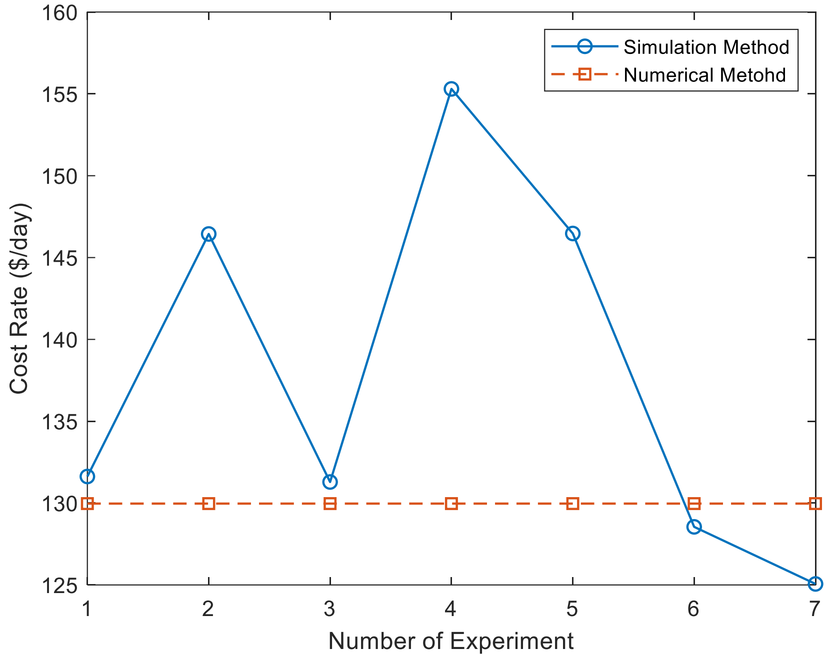



Figure 4.21 Repeated experiments for simulation and numerical method considering increased simulation iteration time

### 4.3.2 Comparative study 3: Considering large iteration time of the simulation method

Section 4.1 and 4.2 present the CBM optimization results of numerical and simulation methods. Figure 4.7 and 4.11 is the cost rate curve versus number of iterations of numerical and simulation methods. In figure 4.7, the cost surface of numerical method is quite smooth, and the cost rate remains stable throughout the iterations. This consistency indicates that the numerical method converges to a specific cost rate value, demonstrating its efficiency in optimization. In contrast, Figure 4.11 shows the cost surface of simulation method, where the cost surface fluctuates significantly at the initial of iteration. As the number of iterations increases, the magnitude of these fluctuations decreases, although they persist to some extent. This observation indicates that although the simulation method tends to stabilize as the number of iterations increases, it retains a degree of variability throughout the optimization process.

The comparative study 3 is performed between simulation with large number of iteration and numerical method. Seven repeated experiments are conducted for both methods, utilizing the respective optimal failure thresholds. The comparison results are shown in Figure 4.22. For the numerical method, the cost rate remains constant across all seven experiments, maintaining a value of $129.97 per day. This consistent performance highlights the method's stability and reliability in optimization processes. In contrast, the simulation method produced varying values for the cost rate over the seven experiments, fluctuating between $117.69 and $122.75 per day. These fluctuations demonstrate the inherent instability of the simulation method and obstruct the achievement of optimal values due to the inability of the simulation method to consistently converge.

In comparison, the numerical method has a more stable cost rate, which is helpful in determining the optimal value. This stability increases the efficiency of the method in the optimization process and gives it an advantage over simulation methods in situations where accurate and reliable results are required.

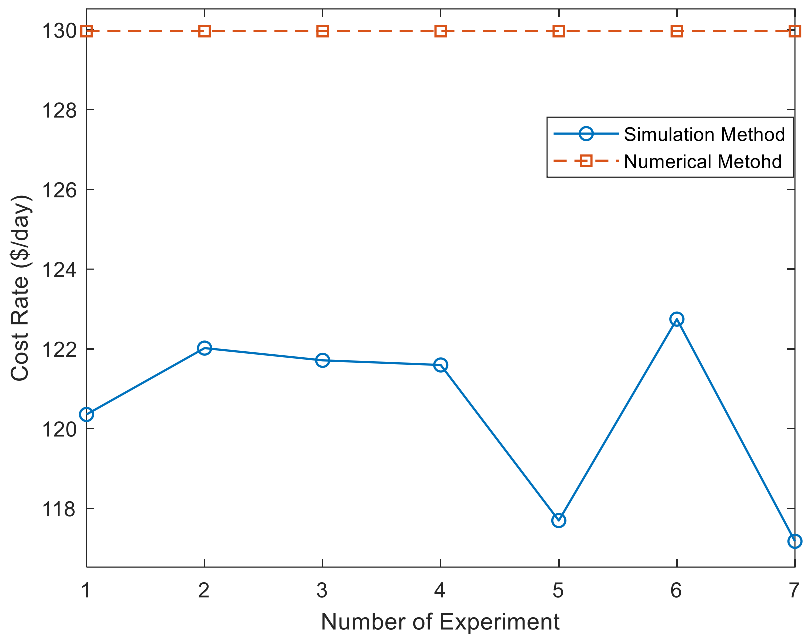
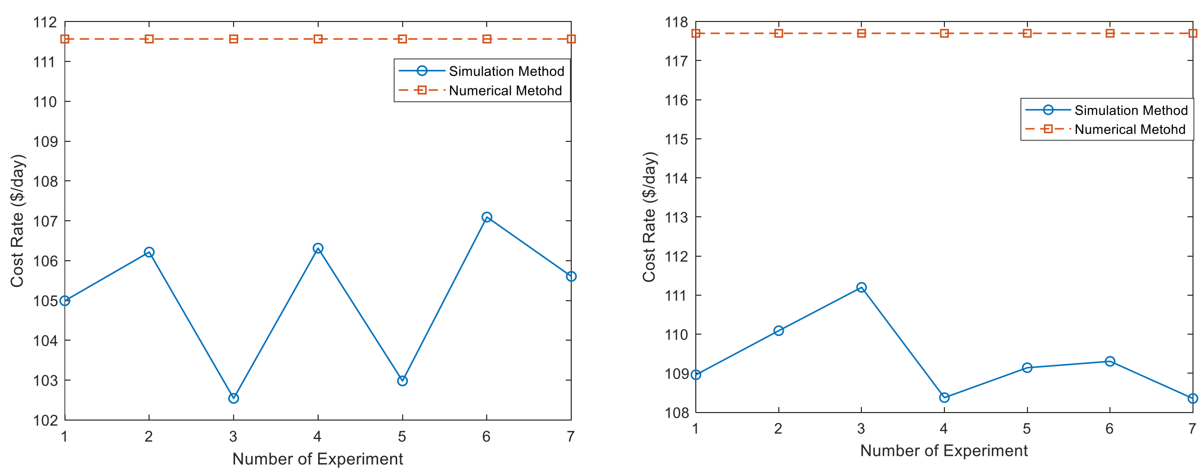



Figure 4.22 Repeated experiments for simulation and numerical method considering large simulation iteration time

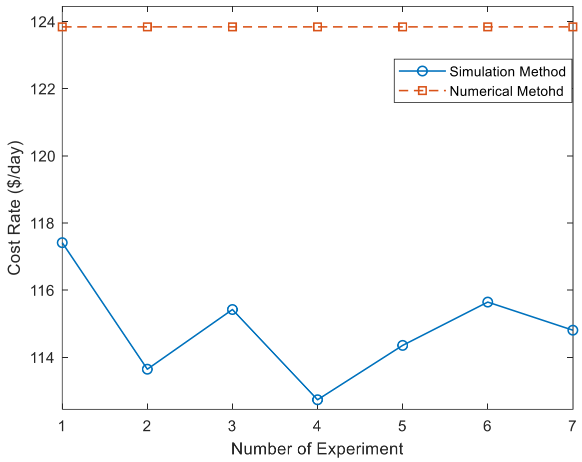
### 4.3.3 Comparative study 4: Considering various fixed preventive maintenance cost

In comparative study 3, the numerical method is proved to be more stable than simulation method by using one case. Comparative study 4 expands upon the previous findings by conducting further comparative studies between simulation and numerical methods, focusing on varying fixed preventive maintenance cost values. The optimal failure threshold and lowest total maintenance cost rate is determined by CBM policy using two methods for each fixed preventive maintenance cost in section 4.2.3 sensitivity analysis 1. The optimal failure threshold obtained for each fixed preventive maintenance cost is subsequently utilized for repeated experiments. The lowest cost rate of various fixed preventive maintenance cost for simulation and numerical method is shown in Table 4.

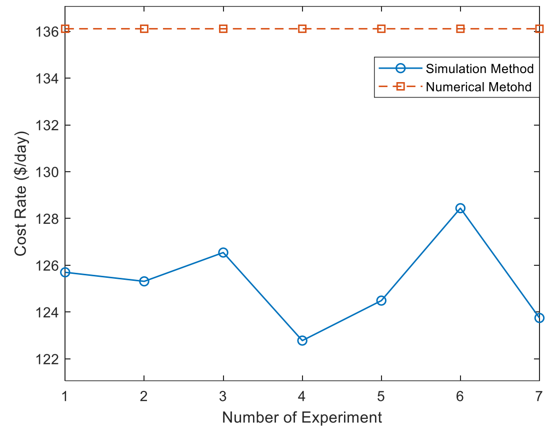
The results of seven repeated experiments for various fixed preventive maintenance value is shown in Figure 4.23. For numerical method, the cost rates remain at the same value with the lowest cost obtained by optimal CBM policy for each fixed preventive maintenance cost value in seven repeated experiments. In contrast, the cost results obtained in each repeated experiment differ from the lowest cost of the CBM policy, indicating a lack of consistency in estimation. The comparison results between simulation and numerical method demonstrate that the numerical methods provide greater stability in estimating maintenance cost rates for a variety of fixed preventive maintenance cost values compared to simulation methods. The ability of numerical methods to consistently match the optimal costs obtained through the CBM policy highlights its reliability and stability in estimating maintenance costs under different scenarios.



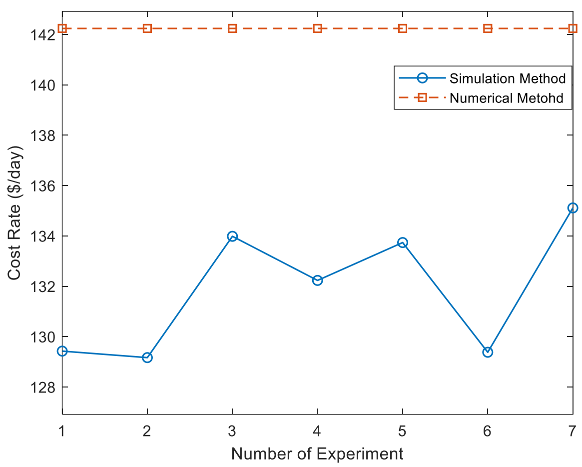

(a) Fixed preventive maintenance cost is $10,000 (b) Fixed preventive maintenance cost is $15,000



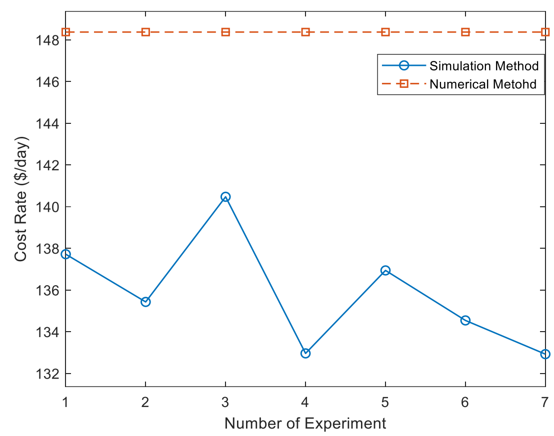

(c) Fixed preventive maintenance cost is $20,000




(d) Fixed preventive maintenance cost is $30,000




(e) Fixed preventive maintenance cost is $35,000



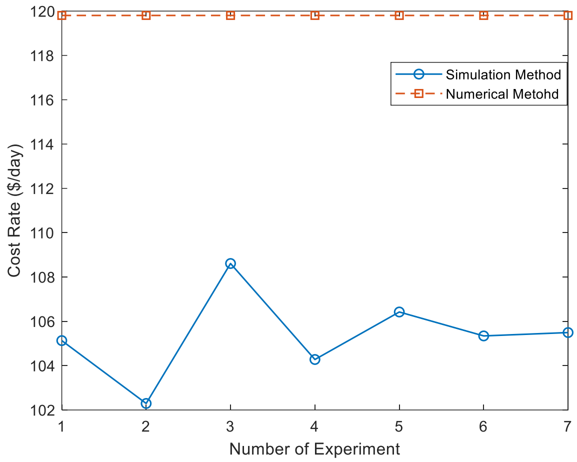

(f) Fixed preventive maintenance cost is $40,000

Figure 4.23 Repeated experiments of various fixed preventive maintenance value for the simulation and numerical method considering large simulation iteration time

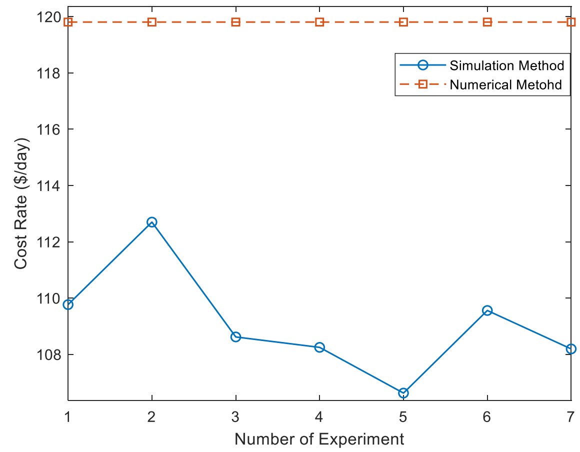
### 4.3.4 Comparative study 5: Considering various fixed cost to wind farm

In comparative study 4, the fixed preventive maintenance cost is various for reflecting different actual circumstances. This sensitivity analysis changes fixed cost to the wind farm and other assumptions are the same for comparative study 4. The optimal failure threshold and lowest total maintenance cost rate is found by CBM policy using two methods for each fixed cost to wind farm in section 4.2.4 sensitivity analysis 2. These optimal failure thresholds are then utilized for repeated experiments. The lowest cost rate of various fixed cost to the wind farm for simulation and numerical method is shown in Table 4.5.

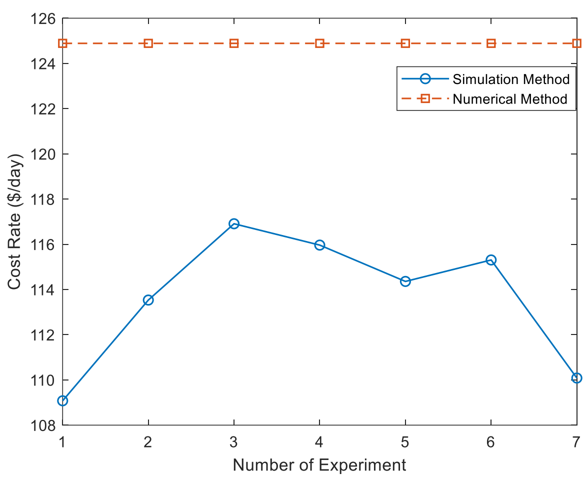
The results of seven repeated experiments for various fixed cost to the wind farm is shown in Figure 4.24. For numerical method, the cost rates for each fixed cost to the wind farm are consistent with the same lowest cost value obtained by optimal CBM policy in seven replicated experiments. In comparison, the cost results obtained by the simulation method in each of the repeated experiments are different from the lowest cost from CBM policy. The large fluctuations are still existing in seven replicated experiments. With various fixed cost to the wind farm, the numerical method is more reliable for estimating total maintenance cost rate compared to simulation method.



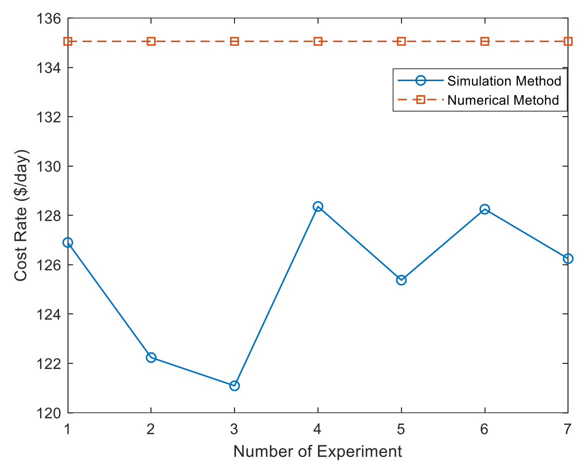

(a) Fixed preventive maintenance cost is $35,000



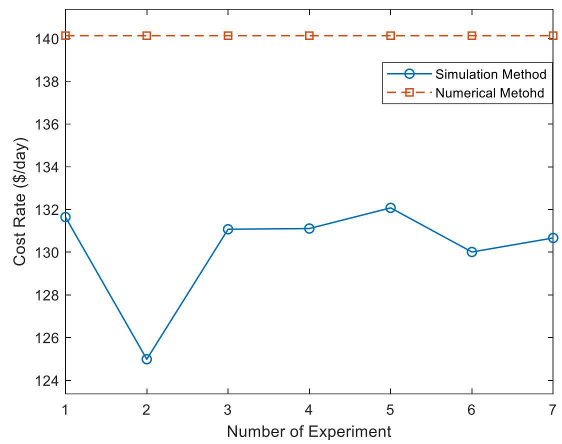

(b) Fixed preventive maintenance cost is $40,000



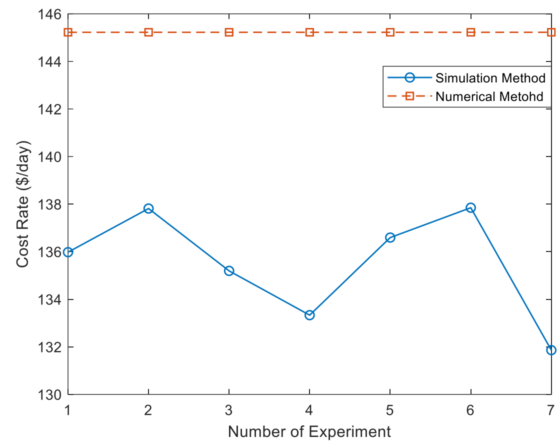

(c) Fixed preventive maintenance cost is $45,000




(d) Fixed preventive maintenance cost is $55,000




(e) Fixed preventive maintenance cost is $60,000




(f) Fixed preventive maintenance cost is $65,000

Figure 4.24 Repeated experiments of various fixed cost to the wind farm for the simulation and numerical method considering large simulation iteration time

## 4.4 Summary

Chapter 4 is structured into three sections. In first section, an example of numerical method is presented and the optimal CBM policy within lowest maintenance cost rate is determined. In section 2, the simulation method is applied in the same example to obtain the optimal CBM policy and lowest cost rate. By comparing the optimal results obtained by both methods, validity and accuracy of the numerical method are affirmed. To further verify the numerical method, two case studies with changing two parameters fixed preventive maintenance cost and fixed cost to wind farm are developed respectively to prove the reasonability and accuracy of numerical method. Section 3 constitutes four comparative studies to emphasize the superiority of the numerical method in terms of accuracy, stability, and reliability in estimating total maintenance cost rates.

The conclusions obtained in chapter are as follows:

For both numerical and simulation method, the first level failure probability threshold $d_1$ exerts a more significant impact on maintenance cost estimations than alterations in $d_2$ thresholds.

For the simulation method, the cost rate curve exhibits significant fluctuations when the iteration count is relatively low. The stability is increasing as the number of iterations increases but variation is still existing. For the numerical method, the cost rate surface is smooth during the iteration process and the cost rate converges towards a steady-state value beyond a certain number of iterations.

For the same example, the numerical method and simulation method are both applied to estimate the maintenance cost rate and find the optimal CBM policy. The lowest cost rate value obtained from numerical method is close to simulation method, which demonstrates that the numerical method is able to estimate the maintenance cost for wind farm system in an accurate way. Two case studies considering various fixed preventive maintenance cost and fixed cost to wind farm also prove the feasibility of the numerical method.

For the simulation method, the cost estimation results are fluctuating significantly when the sample size is limited, and it is not able to provide meaningful results in this situation. When sample size is sufficient, the cost estimation results is more accurate with less fluctuation, but variation still exists and affect the optimization process. For the numerical method, the cost estimation results are not affected by the sample size, and it is more feasible and stable than the simulation method.

In summary, this study stresses the value of numerical methods in more accurate and reliable maintenance cost estimates. Reliance on numerical methods can facilitate informed decision-making and resource allocation, thereby improving the efficiency and effectiveness of engineering project and system management.

# Chapter 5 Summary and Future Work

## 5.1 Summary

For a wind farm, maintenance is an important procedure to ensure normal operating of wind turbine and reduce the downtime cost. A proper maintenance strategy can improve system's reliability, reduce downtime and maintenance costs. The maintenance strategy used in this research is a CBM policy with two failure probability thresholds. The simulation methods were widely used in CBM policy cost evaluation, but the sampling characteristic may lead to issues such as local minima and convergence, thereby complicating the optimization process. A numerical method was originally proposed in a previous study to evaluate the maintenance cost rate of wind farm systems, aiming to address limitations identified in the simulation methods mentioned above. However, it had issues in obtaining reasonable cost evaluation and optimization results.

This thesis develops a modified numerical method based on previous studies for more accurate wind farm CBM cost evaluation and aims to find optimal CBM policy for a wind farm with lowest maintenance cost rate.

The main contributions of this thesis include three aspects: 1) Develop a modified numerical method to evaluate cost more accurately and find the optimal CBM policy applying proposed numerical method. 2) Verify the numerical method results of optimal CBM policy. 3) Compare the optimization results of the numerical and simulation method, emphasizing the stability of the numerical method.

For the first contribution, the reasonable and accurate maintenance cost rate is evaluated by proposed numerical method and optimal CBM policy with lowest maintenance cost is found in this thesis, which addresses the issues and achieves more accurate results. To achieve the first contribution, there are five steps in the numerical method for maintenance cost estimation: initialization; calculate component age combination probability transition matrix, new age combination probability matrix and total cost of all age combination; update component age combination probability matrix in each inspection interval; update cumulative total cost in each inspection point; calculate the cost rate. For a specific example considering two wind turbine and each turbine has two components, a group of failure threshold values are tested, and the maintenance cost rate of each threshold combination is estimated by applying the numerical method through five steps above. The optimal CBM policy is found, which is the combination threshold values with lowest maintenance cost rate. The optimal failure probability threshold values obtained by the numerical method are able to guide the maintenance work of this wind farm. Though the study objective of the numerical method is wind turbine system and wind farm, it can also be widely applied on other systems with multiple critical components.

For the second contribution of verification the numerical method, a simulation method is used for achieving this purpose. The simulation method developed in [23] is able to estimate maintenance cost rate for wind farm. The simulation method is applied to the same example with the numerical method. A group of failure threshold values are tested using the simulation method and the optimal thresholds are found with the minimum maintenance cost rate. For the same example, the lowest maintenance cost rate is estimated by the numerical and the simulation method. The minimum maintenance cost rate of the numerical method is close to lowest cost of simulation method, which proves that the numerical method is able to estimate maintenance cost rate accurately. To further verify the numerical method, one parameter, fixed preventive maintenance cost value is changed to assess the performance of the numerical method. Six different fixed preventive maintenance cost values are assumed for both numerical and simulation method and the optimal results of both methods are compared.

The third contribution aims to compare the feasibility and stability of both methods considering different sample size of the simulation method. Five comparative studies are conducted for both methods. In comparative study 1 and 2, the feasibility and stability of the results of the simulation and numerical method are compared considering limited sample size of the simulation method. Comparative study 3 explore the stability of both method when the sample size of the simulation method is sufficient. Comparative study 4 and 5 compare the stability for both methods with various fixed preventive maintenance cost and fixed cost to wind farm respectively.

## 5.2 Future work

CBM optimization is an important research topic for various field beyond wind farm such as manufacturing, aviation, oil and gas, power generation and so on. This thesis utilizes the numerical method to find the optimal CBM policy with lowest maintenance cost. However, there are some challenges we met during the research process.

One challenge is long computing time of calculating the maintenance cost. The numerical method algorithm uses 4-dimensional age combination probability matrix and transition matrix. These transition matrixes require being updated at each inspection point until the maximum iteration time. Thus, the amount of calculation is huge in the whole process. In the examples, case studies and comparative studies, we made relatively simple assumptions considering two turbines and each turbine has two critical components in a wind farm. For complex system with more turbines and components, computing time will increase exponentially with the increase of the number of components. Therefore, the algorithm is required to be modified to improve the computing efficiency and deal with more comprehensive problems.

One limitation of this study is that the inspection interval is 1.5 years and there are total 20 inspection points considering the computing time. Though the lowest cost rate obtained based on this assumption is close to the simulation method, there is still minor difference. Other smaller values of inspection interval can be considered in the further investigation and compare the cost estimation to the simulation method.

One area can be improved is considering inspection cost in the cost estimation model. In existing model, we are considering failure replacement cost, variable preventive maintenance cost, fixed preventive maintenance cost and fixed cost to the wind farm. Inspection cost is a part of maintenance cost, and it mainly includes labor cost, cost for equipment and tools, and transportation and accommodation. The largest portion of the inspection cost often goes towards labor. This includes the wages or fees for qualified technicians or inspectors who conduct the inspections. Specialized equipment and tools may be necessary to perform certain types of inspections. If the wind farm is located in a remote area or requires travel to access, travel expenses such as transportation, lodging, and meals for inspection personnel may be included in the overall cost. The evaluated maintenance cost would be more accurate if inspection cost is considered in it.

An additional area for improvement is the ANN model. Currently, the ANN model is trained and tested using historical data collected from the component. In the future, as more condition monitoring data and event data are collected from the component, the ANN model can be trained with new data. This will enable the model to provide more accurate results and be used in CBM optimization. Enhanced training with comprehensive and up-to-date data will improve the model's predictive capabilities, leading to better maintenance strategies and increased reliability of the components.

The last improvement area is validation of the numerical method. The numerical method has been verified through simulation using multiple examples, demonstrating its capability to generate reasonable and stable cost evaluation results. However, validation of the numerical method has not been conducted in this thesis and requires further investigation. Validation is crucial as it ensures that the numerical method accurately reflects the real-world system or phenomena it intends to model. In the future, the numerical method should be tested on real-world case studies relevant to the application of CBM for wind turbines. This testing will help confirm that the method's outcomes align with observed data and practical outcomes, thereby enhancing its reliability and applicability in practical settings.

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