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Condition-based maintenance of wind turbine blades

Master's Thesis in Mechanical Engineering

by

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June 13, 2022

ABSTRACT

The blades of offshore wind farms (OWTs) are susceptible to a wide variety of diverse sources of damage. Internal impacts are caused primarily by structure deterioration, so even though outer consequences are the consequence of harsh marine ecosystems. We examine condition-based maintenance (CBM) for a multiblade OWT system that is exposed to environmental shocks in this work. In recent years, there has been a significant rise in the number of wind turbines operating offshore that make use of CBMs. The gearbox, generator, and drive train all have their own vibration-based monitoring systems, which form most of their foundation. For the blades, drive train, tower, and foundation, a cost analysis of the various widely viable CBM systems as well as their individual prices has been done. The purpose of this article is to investigate the potential benefits that may result from using these supplementary systems in the maintenance strategy. Along with providing a theoretical foundation, this article reviews the previous research that has been conducted on CBM of OWT blades. Utilizing the data collected from condition monitoring, an artificial neural network is employed to provide predictions on the remaining life. For the purpose of assessing and forecasting the cost and efficacy of CBM, a simple tool that is based on artificial neural networks (ANN) has been developed. A CBM technique that is well-established and is based on data from condition monitoring is used to reduce cost of maintenance. This can be accomplished by reducing malfunctions, cutting down on service interruption, and reducing the number of unnecessary maintenance works. In MATLAB, an ANN is used to research both the failure replacement cost and the preventative maintenance cost. In addition to this, a technique for optimization is carried out to gain the optimal threshold values. There is a significant opportunity to save costs by improving how choices are made on maintenance to make the operations more cost-effective. In this research, a technique to optimizing CBM program for elements whose deterioration may be characterized according to the level of damage that it has sustained is presented. The strategy may be used for maintenance that is based on inspections as well as maintenance that is based on online condition monitoring systems.

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CHAPTER 1 Introduction

Wind power is among the most common forms of clean and renewable energy. Its market share in the energy sector has been steadily expanding over the last 20 years. By the year of 2030, the US Department of Energy hopes to have 20% of the utility market fulfilled by the energy from the winds. On the other side, wind energy only contributed around 3.5 % of the overall energy produced in the USA in 2012 (Tawfiq et al., 2019). The European Wind Energy Association has said that the goal for the year 2030 is to produce between 26 and 34 percent of power from wind (Leung and Yang, 2012)v. It is anticipated that the Chinese wind industry would reach 150 gigawatts (GW) of total output by the year 2015, which is well over the objectives set by the central administration of 100 GW by 2015 and 230 GW by 2020. (Costa et al., 2021). There is no shadow of a doubt that market for wind power all over the globe is consistently growing. Accessing and operating offshore wind farms is challenging, which resulted in higher operation and maintenance (O&M) charges and, as a consequence, higher energy prices. This is true despite the fast increase of offshore wind producing capacity (COE). As per to the Energy Information Administration (EIA) of the United States, the cost of electricity produced by wind turbines located offshore (OWT) is 2.55 times higher than the cost of electricity produced onshore (Doluweera et al., 2020).

Wind turbines are very complex electromechanical devices that are designed to have a lifespan of between 20 and 30 years (Iqbal *et al.*, 2020). The dependability of the turbine is a significant factor in estimating if a wind farm project will be profitable. Studies indicate that the expenses associated with maintaining and repairing wind turbines account for between 25 and 30 percent of the total expenditure (Foley *et al.*, 2012). These things have created a significant incentive for increasing the dependability of wind turbines and streamlining their maintenance and operation in order to cut down on the cost of electricity. According to information compiled from a number of different databases that were gathered from the field, the wind turbine blades are one of the most necessary elements of OWTs (Junginger, Faaij and Turkenburg, 2004). In addition, the usable life span of an OWT blade is significantly shorter than that of the average lifespan of an inland wind turbine blade. This is because blades in seas locations are susceptible to significantly larger mechanical stresses and a broader variety of natural damage than blades in inland locations (Leung and Yang, 2012).

Internal and exterior damages to the system that the turbine blades are part of are the two forms of damage that may be incurred by wind turbine blades (IEC, 2005). The majority of internal damages are caused by the degeneration or deterioration of the system, which is caused by hydrodynamic forces and mechanical stresses. The wearing, rust, abrasion, fatigue, and fracture development that are often associated with the degradation process advance throughout the course of time as the process continues. In addition to the internal issues, the rotor blades might be damaged on the outside (by shocks) by the marine environment. This would be in addition to the difficulties on the inside (Junginger, Faaij and Turkenburg, 2004). There are two types of harm that are caused by the environment (Wilkinson, Spianto and Knowles, 2006; Leung and Yang, 2012); the first kind of shock is a tiny shock k, such as when there is a sudden shift in the direction or speed of the wind. This type of shock produces an instantaneous drop in power generation but does not result in any breakdown of the system. Wind turbines may be rendered inoperable and forced to undergo system replacement if they are subjected to a calamitous shock such as a huge tidal wave, thunderstorm, or weather freeze (Foley *et al.*, 2012).

Because of its influence on cost, risk, and efficiency, maintenance competence is a critical concern for sectors that use physical properties. Preventative and corrective maintenance are the two types of maintenance plans. After a failure, corrective maintenance is performed. By maintaining or replacing components, preventative maintenance (PM) is utilized to reduce downtime (DT). This consists of doing regular inspection, where an upkeep service is planned ahead of time according to the current state of health of a unit or subsystem that is being monitored. It involves the adoption of a monitoring system, including vibration analysis for essential machine systems in windfarms, where servicing actions are driven by the component's actual state. This is necessary in order to accomplish this. Condition-based maintenance (CBM) enables a decrease in both DT and maintenance procedures in theory (Lu *et al.,* 2018). The goal of condition monitoring is to safeguard that wind turbines continue to operate by continuously measuring and analyzing them, hence increasing turbine availability, and lowering costs. Traditional corrective and preventative maintenance methods have been replaced in contemporary industry by condition-based maintenance (CBM) practices as a direct result of improvements in sensor technology (Besnard and Bertling, 2010).

The thesis proposes a cost-effective, efficient, and preventive approach to turbine blade maintenance centered on condition-based maintenance that does not result in complete breakdown of the turbine blade. Blade maintenance may be determined by a number of condition-based maintenance techniques, including a visual examination, assessment with monitoring system, or an online framework that can monitor the status of the rotor blades in real - time basis.

1.1 Problem Statement

Utility wind turbines, like magnificent giants, are developing further away and offshore. While designers focus on building longer, heavier, and more efficient turbine blades, wind farm operators and investors face a unique challenge: maintaining older blades in good working order. Unexpected failure occurrences and limited inventory are significant problems for wind-power operators to overcome. Repair work to blades is naturally more difficult to arrange. Blade damage can occur in a variety of settings, including manufacturing, transit, and tower building and erection. Leading-edge erosion, weather, and other causes, on the other hand, are more prone to produce field maintenance issues. The absence of predictability and past data makes blade preventive maintenance difficult. Because these components have traditionally had huge volumes of DT per failure and can be easily monitored, the vast majority of CBM solutions are vibration-based and concentrate on the driveline of wind turbines, which includes the generators, transmission, and related gears.

1.2 Motivation

It is important to reduce the cost of maintenance for wind turbines, and a method is required that evaluates the depletion of wind turbines and predicts the life expectancy and maintenance requirement for the turbine. Artificial neural network has been used for predicting the maintenance of wind turbine, however a cost comparison based on optimization procedure is required for maintenance of wind turbines. The optimization method can minimize the cost of maintenance on a long term, based on optimal threshold values.

1.3 Objectives

- To study existing research on condition-based maintenance of wind turbine blades
- Theoretical background on the use of CBM to repair blades
- Develop a simple tool using Artificial neural Network (ANN) for analyzing and predicting CBM cost and effectiveness

- Failure replacement cost and preventive maintenance cost will be studied using ANN in MATLAB.
- Minimizing the maintenance cost in long term, one optimization procedure is conducted to acquire the optimum threshold values.

CHAPTER 2 Literature Review

Wind energy is getting popular among renewable sources of energy and has many applications. In recent years there is high trend in installation of wind turbine because of rise in environmental problems, high fuel prices and emerging technologies related to wind energy. Also, it is inevitable to develop renewable energy sources because of greenhouse gases emissions. Wind turbines works on the principal of converting wind energy to mechanical energy. Which are further used for many purposes one of which is production of electrical energy. Wind turbine can be installed individually or in groups which is also called wind farm. The electricity produce can be use individually or can be connected to national grid. However, there are some limitations to installations of wind turbines which are practical, technical, or economic issues.

2.1 Onshore Wind Turbines

The turbines that are built and located on land is called onshore wind turbines. The wind electricity generation increased in 2020 by 144 TWh (+11%) (Tian and Wang, 2022). Generating capacity reached an all-time high of 108 GW, more than doubling from the previous year, mainly due to a commissioning rush in China and the United States, which accounted for 79 percent of global wind installation. However, because majority of the projects were completed in Q4 of 2020, the entire influence of this construction boom on power production will be seen in 2021. On-site construction of the substructure for onshore wind turbines is required; however, the superstructure, rotors, as well as other elements are pre-manufactured at other locations and then delivered to the construction site (Costa *et al.*, 2021).

2.2 Offshore wind turbines

The turbines that are built and located in sea or oceans is called offshore wind turbines. As the available wind speeds are more than onshore wind turbine so the capability to produce power is more than onshore turbines (Jiang, 2021). In 2020, offshore generating capacity increased by 29% to 25 TWh, with generation capacity of 6 GW, the same as in 2019. In all, 1 592 TWh of power was generated by wind turbines in 2020, a 12 percent increase over 2019. Offshore wind turbines needs specialized transport also the construction cost is quite high (Guo, Wang and Lian, 2022). New technologies has significantly reduces cost of offshore wind turbines and now in competition with other sources of power production in terms of cost in Europe (Wu *et al.*, 2019).

2.3 Wind Turbine Components

The mechanical energy is produces by wind kinetic energy which is converted by the wind turbine to produce electricity which uses wind power for this purpose. Its structure is made of mechanical, electrical, and civil components which is very complicated. Rotor blades, hub assemblies, nacelles, yaw mechanisms, generators, transmission systems, towers, and foundations are the primary components that make up a conventional wind energy system. The figure displays the many components that are typical in wind turbines.

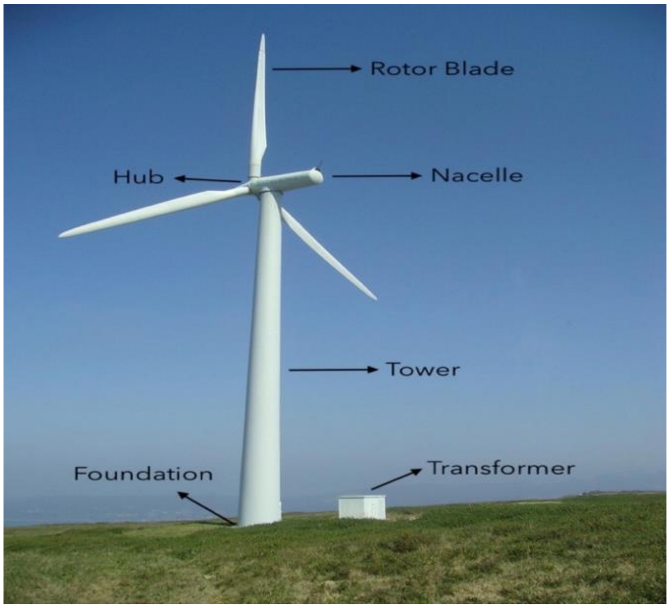


Figure 1 Typical overview of a wind turbine (Guo, Wang and Lian, 2022)

2.3.1 Tower

The tower's principal responsibility is to provide support for and maintain the turbine's position. It houses the rotor blades, weights, and yaw assembly of the nacelle, in addition to all of the electrical components. The tower should be able to successfully endure massive loads of wind and vibration that are applied to the foundation. An important aspect of wind turbine construction is True vertical alignment and tilting up to 1 degree is allowed.

2.3.2 Lattice towers

To construct lattice towers welded steel profiles are used. The truss motion and bigger base dimensions aid in more effective load resistance. Furthermore, the open tower reduces wind loads on the structure. The little tower sections are inexpensive to produce and carry to the job site.

Because of the large number of pieces that must be assembled, lattice towers have a high on-site building cost. Lattice towers also have a significant maintenance cost because each joint has the potential to collapse, especially in colder locations where icing might occur (Leung and Yang, 2012).

Figure 2 Lattice tower (Big Stone Renewables Services) (Saidur *et al.*, 2011)

2.3.3 Concrete towers

Concrete towers provide several advantages, including enhanced endurance, cheaper maintenance costs, and a modular design that may be used in practically any turbine application. Concrete towers can also be divided in virtually any direction to make transportation easier. Concrete towers, on the other hand, take longer to build on-site, depending on the assembly method. There is also a considerable risk of failure since cracks can easily spread during the curing process (Breton and Moe, 2009).

Figure 3 Concrete tower (Breton and Moe, 2009)

2.3.4 Hybrid towers

Hybrid towers are a mix of concrete and tubular or lattice and tubular construction. The base diameter of a conventional tubular tower would surpass transportation constraints at very high tower heights. Augmenting the bottom section of the tower with a stronger concrete or lattice base could lower average tower costs while increasing the turbine's annual power production.

Figure 4 Hybrid tower (Saidur *et al.*, 2011)

2.3.5 Foundation

A wind turbine's foundation is built in such a way that it transfers loads to the ground in order to maintain the device's stability within the prescribed limitations for deviation and tilting. Different types of loading during operation of wind turbine including bending movement, wave, dead loads etc. are all carried by the foundation. The structure self-weight, which includes all the components of turbine are carried out by the foundation. Massive bending moments are due to extra loads on wind turbine (Guo, Wang and Lian, 2022). Figure depicts some commonly used sub structures in the wind energy sector.

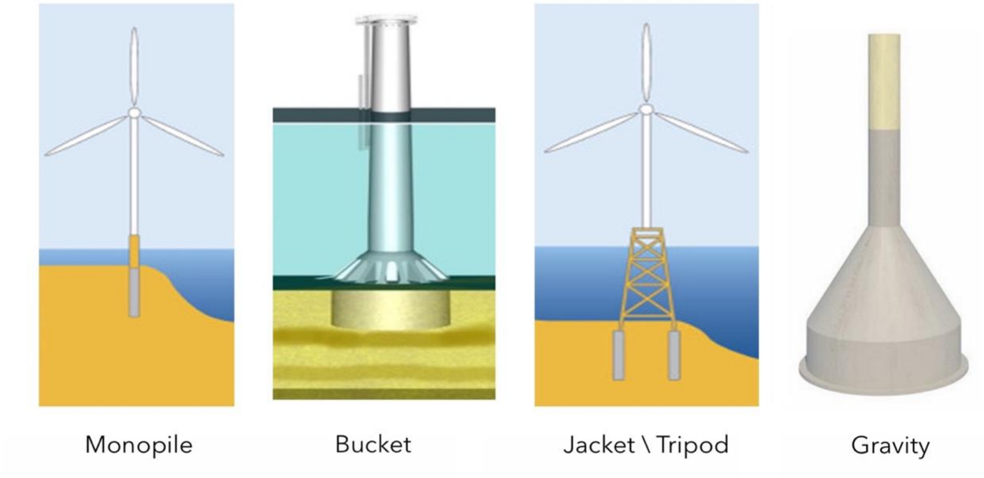


Figure 5 Types of wind turbine foundation (Wu *et al.*, 2019)

2.3.6 Rotor Blades

Rotor blades are sizable hybrid constructions. They are mostly comprised of composite materials and include bolted blade–hub linkages, lightning protection, and a broad variety of loadbearing components and parts among their many other in-built design elements. They are subjected to environmental stresses, severe loads, and fatigue throughout their lifetime in an offshore wind farm because of the location of the facility. The configuration of the rotor blades has a high influence on the performance of the wind turbine because it determines the amount of kinetic energy from the wind that is converted into mechanical energy (torque). Aerodynamic concepts were used in the design process, which resulted in the blades having a high lift-to-drag ratio. The number of blades is selected with consideration given to system dependability, component prices, and aerodynamic effectiveness (Ennis *et al.*, 2019).

Theoretically, if there is a huge number of blades with zero width operating at a higher tip speed ratio, there will be a high level of efficiency. However, wind turbine has fewer blades due to other factors like cost, design limitations, reliability etc. Most of turbine has only three rotors' blades on its horizontal axis. In order to perform long term a turbine blade must have low mechanical and inertial strength. Typically, the blades will be made out of aluminum or fiberglass filled polyester, carbon composite reinforced plastics, wooden or epoxy laminates, or any combination of these materials (Hiendro *et al.*, 2013).

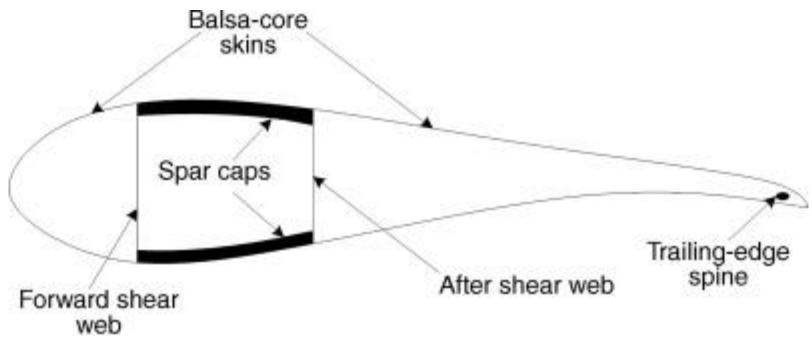


Figure 6 Schematic diagram of the blade (Miller, Samborsky and Ennis, 2019)

2.3.7 Nacelle

The drive train as well as other tower-top components are located in the nacelle of a wind turbine. In reaction to wind fluctuations, it is positioned on a yaw bearing which allow it to rotate. The nacelle must be easily accessible for maintenance operations and repair. Normally, an access is provided by elevator and ladders within the tower. Normally, the nacelle is produced in a factory and then transported to the top of the tower by use of specialized equipment used for lifting. Most of the modern wind turbines have a real-time condition monitoring equipment built into the nacelle. The nacelle is usually two to three times the length of the rotor blades, though it can be taller to allow the blades to reach higher wind speeds. To change the system's features, the nacelle's controlling mechanism saves data on wind speed and direction, rotor speed, and generator capacity. As a result, the controller uses the yaw mechanism to allow the turbine to move in the direction of the wind (Bogaraj, Kanakaraj and Kumar, 2015).

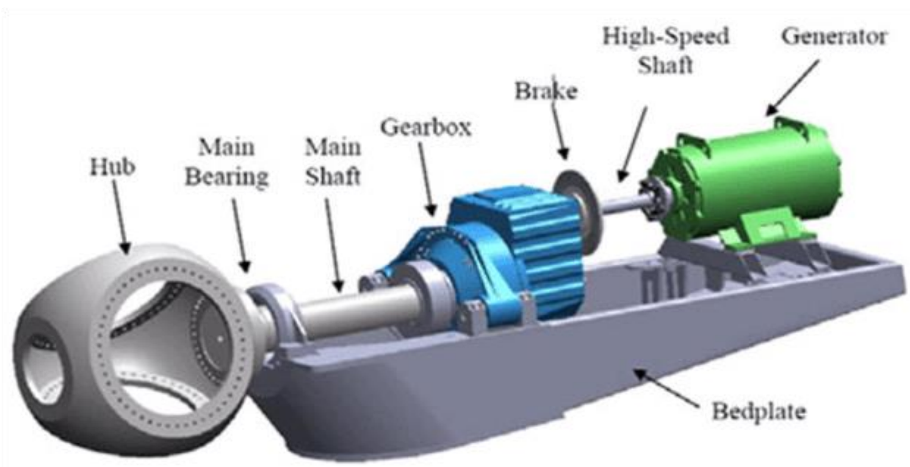


Figure 7 Main components of Nacelle (Besnard and Bertling, 2010)

2.3.8 Rotor Hubs

The blades to the main shaft are connected by the rotor which is a component of a wind turbine which also holds the blades. It's very important for keeping the blades in position for maximum aerodynamic efficiency, and also for rotating to power the generator. Depending on the kind of generator and the rotor blade design, hubs come in a range of forms and combinations.

2.4 Types of Wind Turbines

Horizontal Axis Wind Turbines (often abbreviated as HAWTs) and Vertical Axis Wind turbines are the two primary categories of contemporary wind generators (VAWTs).Most of utility-scale wind farms incorporates Horizontal axis turbines.

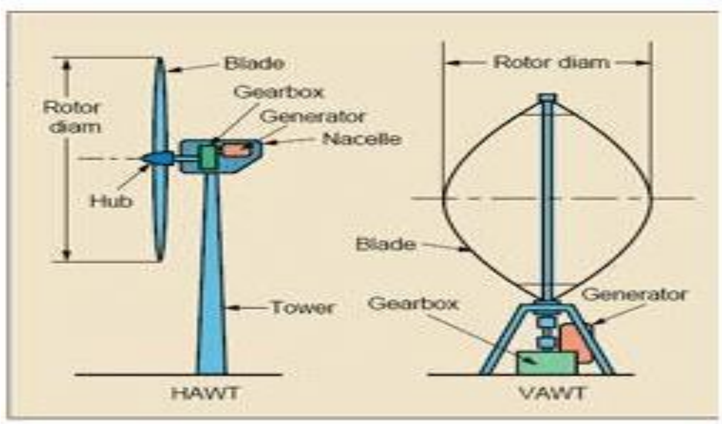


Figure 8 HAWTs vs VAWTs (Ahmed and Abdel Gawad, 2016)

2.4.1 VAWTs

Most of the parts of a vertical axis wind turbine are placed at the turbine's base, while the primary rotor shaft is angled transverse to the wind. Because the blades are positioned vertically, wind can come from any direction. However, the blades on the other side do not contribute to the output power created, when the wind blows on one side of the turbine, which diminishes the efficient of turbine. VAWTs have the benefit of not requiring the sophisticated wind detecting equipment that HAWTs have in order to change itself to the direction of the wind. Finally, VAWTs are designed to endure high wind speeds in stormy weather (Ahmed and Abdel Gawad, 2016).

2.4.2 HAWTs

Unlike VAWTs, the primary rotor shaft of a HAWT is perpendicular to the ground at the top of the tower. The HAWTs have automated system with different sensors for different purpose also its life cycle is very high. Wind sensors are installed on the turbine which allow them to change its position according to wind hence have high efficiency. The nacelle, or upper motor housing, moves not just to position the blades into the wind (yaw), but also to enhance power generation and efficiency. By orienting the tower into the wind, the control systems may reduce unnecessary crosswind fatigue loads on the blades and help the wind turbine last longer (Griffith *et al.*, 2016).

2.5 Maintenance Approaches

It has become a challenge in current dynamic operational settings to effectively manage reliability of a system. In this context, condition-based maintenance (CBM), as compared to more typical methods which are based on time-based maintenance (TBM), is a prominent solution for scheduling maintenance activities. Some of the most common approaches used for maintenance is Preventive maintenance (PM) or Corrective maintenance (CM). Corrective maintenance is done after failure while preventive maintenance is done prior to failure of a component or system. when the result of failure have no impact on losses in revenue or health and safety impact then corrective maintenance is used. Major equipment failures in turbines can be disastrous, resulting in severe operational, health, safety, and environmental repercussions. The effects of failures on the electrical network and revenue production, therefore, determine the viability of a CM approach.

Two types of preventive maintenance techniques are there: condition-based and statistical preventive maintenance. Scheduled Maintenance (SM) is a PM activity that occurs on a predetermined schedule, such as once a year, and is based on failure data. Status Based Maintenance is a PM activity that is planned based on sensor data or component condition.

Time-Based Maintenance (TBM), which is a technique of PM, also known as entails doing routine maintenance tasks at regular intervals. This method is frequently used to comply with OEM warranty requirements and to keep crucial components with known failure data under control. However, there are drawbacks to choosing the appropriate amount of time interval for doing maintenance activities.

As previously noted, O&M management of OWT has become increasingly important as the volume of wind energy capacity deployed in electric power networks has grown. Experts have created a number of maintenance solutions aimed at lowering costs. Although it is critical to know a wind turbine's dependability to develop an effective maintenance strategy, OWT failure statistics are not readily available because of commercial limitations. Spinato published results of subassembly-level reliability analysis based on publicly available information from Germany and Denmark in his work (Zhou and Yin, 2019).

2.5.1 Condition-Based maintenance (CBM)

CBM is sometimes discussed as a maintenance strategy and is a subtype of preventive maintenance. Its main purpose is to provide or recommend different maintenance approaches based on the operation of CM. As a result, the accuracy of the monitoring process determines the effectiveness of CBM choices. CBM attempts to manage equipment failure modes, according to (Tian *et al.*, 2011). As a result, when CBM is implemented, all possible failure modes that might result in financial losses should be evaluated. CBM is based on the concept that most breakdowns do not happen at the same time and that they may be detected early in the deteriorating process. The key problem is determining when maintenance should be conducted and what action should be taken at that time. A system's reliability gives useful information for planning maintenance operations at a lesser cost. To this goal, a predictive model must be built that generates a warning early enough to execute the necessary maintenance before the failure occurs. Predictive maintenance is the common name for this method. Predictive maintenance, according to (Zonta *et al.*, 2022) is a component of a wider notion of CBM that arose from the gradual implementation of novel resources to assist the maintenance function, such as skills, technologies, procedures, and processes.

Condition-Based Maintenance (CBM) reduces needless maintenance actions and schedules preventative maintenance to save maintenance costs. Condition monitoring, in particular, is the primary source of data during routine inspections, which is utilized to determine the optimal time for effective maintenance (Tian *et al.*, 2011). The CBM is employed in a variety of sectors, including aerospace, mining, petroleum (Wu, Tian and Chen, 2013a), and power generation (Tian et al., 2010).

2.5.2 Optimization Approaches of CBM

(Goyal *et al.*, 2017) came up with an optimization for the CBM that was based on the proportional hazards concept for the wind industry (PHM). PHM is the model that is used and referenced the most often in other sectors. It blends a baseline hazard function with a covariates component that brings into mind the condition data. Both of these components take into consideration the information. PHM helps enhance the failure prediction by using the values that are supplied for the covariates and the relevant parameter. The latter provides an indication of the degree to which each covariate contributes to the hazard function. The goal function for minimizing the expected average cost may be used to establish the threshold hazard rate, which can then be used accordingly. As a consequence of this, if the anticipated risk is higher than the optimal value, it is worth replacing the component in question. (Lucente, 2008) brought attention to the fact that the PHM may have applications in the construction of wind turbine components. As per her, there are restrictions since there is a shortage of data and determining which confounding factors are significant continues to be a challenging task. In this area's body of research literature, PHM as well as other CBM methodologies have received little attention. In contrast, a number of research have come to the conclusion that CBM is unquestionably advantageous in contrast to other forms of maintenance in terms of enhancing O&M management. (Saeed, 2008) analyzed the life cycle costs of a wind farm with 26 wind turbines of 600 kilowatts each, using a CBM maintenance schedule and a 6-monthly scheduled maintenance schedule. All of the pertinent cost data was easily available. They arrived to the judgment that CBM is the most effective strategy in all and all circumstances.

Because of its influence on costs, hazards, and performance, optimization of maintenance is a critical problem for sectors that use physical assets. (Fischer, 2012) suggested a method for selecting an appropriate maintenance plan based on Reliability Centered Maintenance and Asset Life-Cycle Analysis. (Zhou and Yin, 2019) explored quantitative maintenance optimization and offered a methodology for determining the appropriate inspection interval for wind turbine drive trains. It was suggested that an optimization model for the schedule be used in order to benefit of wind speeds and opportunities for corrective repairs to carry out preventive maintenance at a reasonable cost. (Sainz and Sebastián, 2013) looked at the options for transporting vessels and the advantages of using an internal crane for OWT systems. (Tong, Qian and Liu, 2022) explored quantitative maintenance optimization and offered a methodology for determining the appropriate inspection interval for wind turbine drive trains.

2.5.3 Condition-based maintenance implementation

The selection of parts to be monitored, definition of monitoring methodologies and technologies, implementation of the needed technical means, and development of acceptable data analysis procedures are all common requirements for CBM deployment. As a result, the financial commitment may be substantial. The procurement of measurement instruments, hardware, and software, as well as the provision of specialist expertise and training, are the most significant costs. As a result, the organizational, financial, and technological aspects of CBM deployment should all be considered. According to (Brink, Madsen and Lutz, 2015), the viability of CBM investments should take into account the importance of the equipment, its technical qualities, and the surrounding environment's complication. Technical reasoning that illustrates the potential of CM systems and CBM policies to fulfil the company's strategic objectives is required, according to (Al-Najjar, Algabroun and Jonsson, 2018). CBM helps to enhance the performance of the maintenance function when it is well planned. However, (Goyal *et al.*, 2017) and (Lu *et al.*, 2018) underline that the advantages of CBM adoption are greater when CM is done at the system level in an integrated way.

2.5.4 Maintenance of Offshore Wind Farms

Wind turbines are complex electromechanical devices that are designed to have a life cycle of somewhere between 20 and 30 years (Goudarzi and Zhu, 2013). Studies indicate that the expenditures associated with wind turbine repair and maintenance account for anywhere between 25 and 30 percent of the overall cost (Fischer, 2012). In reality, numerous studies have focused on wind power system maintenance and dependability. For example, several of them have studied and defined the failure frequency (Yurdusev, Ata and Çetin, 2006). Others have offered maintenance solutions to increase dependability (Andrawus *et al.*, 2006), while others have attempted to optimize maintenance by lowering the total cost (Zhang, Dwight and El-Akruti, 2015). (Tian, Ding and Ding, 2011) recently employed CBM and Constant-Interval maintenance to optimize wind farm maintenance during lead time (2010). The authors established two failure probability at the turbine level in particular. They also took into account the fact that the farm only has one type of turbine and a consistent lead time. The authors demonstrated significant results when compared to previous studies, as the CBM lowered total maintenance costs by 44.42 percent more than CI maintenance.

According to studies, the cost of operations and maintenance accounts for 14 percent to 30 percent of the entire cost of an offshore wind farm (Wilkinson, Spianto and Knowles, 2006). Regulations, condition monitoring systems available on the market, and their related expenses control O&M

activities (Shafiee, Finkelstein and Bérenguer, 2015). According to estimates, proper maintenance may save 40-70 percent on direct O&M costs and increase turbine availability by 7%.

2.5.5 Wind Turbine Blades Condition-Based Maintenance Optimization

Francois Besnard came up with a strategy for maximizing the effectiveness of component maintenance that included categorizing degradation according to the level of damage. A simulation strategy was provided as a means of analyzing expected life cycle maintenance expenses. This technique was applied to maintenance techniques that relied on inspections, and also maintenance methods that were based on online condition monitoring. The method allows us to optimize maintenance decisions for each maintenance strategy while comparing them in a single framework. The model was validated by the use of an example that included optimizing and comparing three different techniques to maintaining wind turbine blades: visual inspection, inspection with condition monitoring, and online CBM (Wu, Tian and Chen, 2013b).

(Nilsson Westberg and Bertling Tjernberg, 2007) evaluated the risk-based operation and maintenance of floating wind components. They took into consideration the lifetime expenses involved with all life cycle activities. Wind turbine operators routinely implement preventive maintenance (PM) practices, such as periodic inspections, risk-based maintenance, age replacement, and condition-based maintenance, in order to reduce the likelihood of random failures and reduce potential losses in wind farms. Examples of PM practices include periodic inspections and age replacement. On the other hand, a cursory look through the available research shows that there have only been a handful of papers published on the topic of enhancing the maintenance procedures for rotor blades. An Artificial Neural Network-based approach for defect prediction and automatically creating warning and alarm for wind turbine main bearings using on recorded SCADA data was proposed by (Pazouki, Bahrami and Choi, 2014). This methodology was proposed by Garcia et al (ANN). After the ANN model of the typical behavior of the turbine main bearing was built, the difference between the actual values of the parameter and the simulated results of the parameter was computed. In addition, a method was developed by (Wu, Tian and Chen, 2013b) in order to provide advance indication and alerts based on the deviation, as well as to prevent false warnings and alarms from being generated. As a consequence of this, operators of wind farms will have more time to organize repairs, which will result in less unscheduled downtime and cheaper operation and maintenance costs. In their study on the optimization of quantitative maintenance for wind turbines, (Andrawus *et al.*, 2006) employed Monte Carlo simulation in conjunction with the Delay-Time Maintenance Model (DTMM). Wind turbine performance management system employing condition monitoring systems was investigated by (Zonta *et al.*, 2022). The authors focused on life cycle cost (LCC) analysis and methods for improving maintenance strategy for a single onshore wind turbine as well as an offshore wind farm. They conclude that CMS is useful in the process of wind power system maintenance. (Gray and Watson, 2009) proposed a technique for the CBM of wind turbines that was based on the physics of failure. A novel technique for the continuous, on-line computation of damage accumulation is presented here. This method makes use of the standard turbine performance information and the methodology of the Physics of Failure. Evaluation of the wind turbine system is performed in order to ascertain the primary reasons behind key failure modes, and theoretical damage frameworks are developed in order to evaluate the relationship between the operating environment of the turbine, the loads that are applied, and the rate at which damage accumulates. After that, a precise real-time estimation of the probability of certain failure types and component failures is possible. This method has the potential to considerably improve the entire wind turbine maintenance approach, and it can be implemented at a very cheap cost. (Byon and Ding, 2010) developed models and tools for finding solutions in order to figure out which maintenance practices are the most effective. They take into consideration a multi-state degradation model for wind turbines, which is necessary since these machines are prone to a variety of failure mechanisms.(Besnard and Bertling, 2010) proposed a mathematical method for optimizing the inspection interval and condition monitoring methods for a wind turbine blade the degradation of which is graded according to the degree of the damage.

2.5.6 ANN applications Wind Turbines

Wind turbines are pre-fitted with a plethora of sensors that measure things like humidity, temperature, and vibration, amongst other things. In order to ascertain the current state of the system, data acquisition systems take readings of all of its variables. The processing of data necessitates the use of reliable algorithms that make it possible to extract as much useful information as possible from the data that is readily accessible. The capacity of machine learning algorithms to analyze massive amounts of data has led to their widespread use; artificial neural networks (ANNs) are one of the most popular approaches now in use. ANNs are intricate structures that are modeled after biological neuronal networks (Shah *et al.*, 2021)v. When it comes to solving issues that cannot be specified analytically, such frameworks provide a useful answer. Neurons, which are basic processing units, make up an artificial neural network (ANN), and weighted connections link these neurons to one another. The multilayer perceptron represents a structure that is representative of the norm. Following the acquisition of a dataset, the ANN initiates a training procedure in order to calibrate the weights of the many interconnections among neurons. In the event when the output cannot be predicted, the training will be referred to be unsupervised training rather than supervised training (Finamore *et al.*, 2016). ANNs are used in a variety of industries because of the multiple benefits they provide. Some examples of these fields include medical, pharmacology, robotics, spatial analysis, and others. ANNs may be used to produce functions that describe a specific occurrence when the data doesn't really enable such characteristics to be built by hand. This is possible because ANNs are capable of learning from their own data. The following are the primary benefits (Malik and Savita, 2016)v: -

- Adaptive learning as they are able to learn how to complete tasks by going through a training procedure.
- Through a process of training, artificial neural networks (ANNs) are capable of self-organization, in which they may develop their own framework to reflect the information.
- Tolerance to failure since the ANN may continue to function even when its structure is broken and distorted, or partial results can be obtained even when the inputs are noisy.
- They may be executed in simultaneously, and they carry out their tasks very quickly. As a consequence of this, they have been particularly developed to carry out procedures that take place online.
- Integration into the system is made simple by the availability of customized chips that make the process of incorporating ANNs into the system much simpler.

ANNs are helpful for finding solutions to a broad variety of issues falling into seven distinct categories (Gray and Watson, 2009).

- Through supervised learning, ANNs have the ability to recognize patterns within a dataset.
- Unsupervised learning is used to determine whether or not there are similarities or differences in the data. The network will place data that are comparable under the same category (or cluster).

- ANNs have the potential to be used in situations when a theoretical model would be ineffective. They are able to provide an approximation of the data input to a function that has a given amount of information.
- ANN may be taught to produce a forecast of the future conduct by using time series as the training data.
- It is possible to locate a solution that either maximizes or decreases the value of a function while adhering to a variety of restrictions.
- Developing an association pattern is one way to use an associative network, which may then be used to recreate data that has been damaged.
- It is feasible to discover the inputs that will lead a system to behave in a certain way that is desired.

Classification structure of the applications of ANN in wind turbines.

Artificial neural networks and wind energy	Forecasting and predictions	Wind speed
		Wind power
		Other parameters
	Design optimization	Wind turbine
		Wind farm
	Fault detection and diagnosis	Gearbox and bearings
		Generator, power electronics and electric
		Rotor, blades and hydraulic
		False-alarm rate reduction
	Optimal control	Maximum power tracking
		Pitch angle
		Speed
		Reactive power
		Converter

Figure 9 Applications of ANN in Wind Turbines (Murugaperumal and Ajay D Vimal Raj, 2019)

The amount of wind that is blowing through an area is a key operating parameter for wind turbines. Long-term wind speed forecasting is most accurately accomplished via the use of physical techniques. The short-term prediction of speed may be accomplished effectively using statistical approaches and models developed using artificial intelligence. An NN-based technique for the creation of prediction intervals was created by (Quan *et al.*, 2020) in order to evaluate the possible uncertainties associated with predictions. With the use of an MLP, (Sainz and Sebastián, 2013) were also able to quantify the uncertainty that are connected with projections. The vast majority of the research papers and methodologies for predicting wind speed are focused on extremely short-term or short-term prediction. Predictions with a time horizon of only a few seconds or less are helpful for applications that involve controlling turbines. As a result, the computational cost of the models that are going to be employed in online applications is a significant consideration. In comparison to an MLP, the findings obtained by (Zonta *et al.*, 2022) using wavelet-based networks and particle swarm optimization were much more precise; nevertheless, the computing costs were significantly higher. (Lu *et al.*, 2018) proposed combining Markov chain models with multi-layer perceptrons. This strategy decreases both the mistakes and uncertainties that were expected while only requiring a minimal amount of computing power. Because of this, the paradigm is suitable for implementation in web-based applications.

An hybrid model based on chaotic phase space rebuilding and NWP-General regression NN was suggested by (Wu, Tian and Chen, 2013b). The use of this strategy lessens the effect that erroneous weather information has. The models that were discussed before came to the conclusion that the combination of ANNs produces superior outcomes than single ANN techniques for the extremely short-term prediction of wind speed. In the context of short-term prediction, (Shah *et al.*, 2021) used three distinct ANNs i.e., a linear element network, an RBFNN, and a BPNN) for predictions made 1 hour in advance. According to the findings of this research, there has not been a single ANN that excels in all situations and delivers the best possible outcomes. The BPNN that was created by Palomares et al. (Palomares-Salas et al., 2014) may also be used for predictions that are made 1 hour in advance. This strategy not only enhanced the findings of the tenacity model but also indicated that data acquired from conventional agricultural observations might be beneficial in accurately forecasting wind speed. An artificial neural network (ANN) feed-forward technique was presented by for a coastal area with a highly complicated topography. They showed that this model is correct by using the capacity of the ANNs to take into account the erratic properties of the wind that are caused by the geography. (Carta and Velázquez, 2011) devised a system based on MLP for estimating the wind speed at various sites inside a wind farm. They demonstrated that this model, when applied to an actual wind farm, generates minimal values for the mean absolute error. The findings of all of these research show that the majority of the models based on ANN are more accurate than techniques that do not use artificial intelligence. The kind of data and the criteria for the estimate both play a role in determining which model is the most appropriate for a given scenario. ANNs are also used to construct algorithms for medium-term wind speed predictions. This is another application for their use. When the time horizon is expanded, it tends to result in less accurate predictions. Wavelet decomposition and artificial neural networks (ANN) are both components of the hybrid model that (Xing *et al.*, 2019) shown can accurately predict wind speeds. In comparison to other empirical mode decomposition approaches, the predicting performance of our method was much better.

In order to do a multi-resolution study for the purpose of forecasting wind speed time series, (Doucoure, Agbossou and Cardenas, 2016) use an adaptive wavelet artificial neural network (ANN). (Ak, Vitelli and Zio, 2015) trained an MLP using a multi-objective genetic algorithm, and as a result, they were able to acquire a valid assessment of the prediction intervals. Adaptive linear element, BPNN, and RBFNN were examined via the lens of (Li and Shi, 2010) comparison. They came to the conclusion that the accuracy of the estimate was affected by a variety of parameters, including those relating to the inputs of the model and the training rates. Because of how inaccurate the long-term wind speed estimates are, there is not a lot of published research on the topic. (Malik and Savita, 2016), for instance, provided a BPNN that was trained using data from a total of 22 cities. The goal of this work is to achieve the highest possible level of precision by minimizing the total number of hidden neurons. A strategy for the medium-to-long term prediction based on a multi-layer perceptron (MLP) and the spatiotemporal development of weather was given by (Finamore *et al.*, 2016). The model produced several intriguing findings, namely that it was able to mitigate the impact of climatic outliers. The findings of this model give an accurate prediction that might be helpful in assisting with the activities that are associated with maintenance. (Tong, Qian and Liu, 2022) have created a long-term prediction model that uses a feedforward BPNN to forecast the trend of the next year. This model was used to predict the trend of the upcoming year.

CHAPTER 3 Methodology

3.1 ANN life percentage prediction mode

3.1.1 OWTs ANN prognostic approaches

According to the findings of a number of studies, the adaptability, nonlinearity, and arbitrary function approximation qualities of ANN make it an exceptionally astute prognostic tool, especially when it comes to the prediction of health conditions (Huang et al., 2007). In order to simulate the connection between the age of OWT blades, the data from condition monitoring, and the percentage of component life remaining, an ANN is used. The temperature and vibration data from the OWT were selected to be used as measures in the construction of the ANN model. A feedforward neural network model has a structure with four layers: one input layer, one output layer, and 2 hidden stages. The input layer is the visible layer. The input layer is comprised of six neurons, each of which correlates to component age and condition monitoring measures acquired at the current and prior inspection points. The neuron in the output layer acts as a representation for the percentage of the component's life that can be predicted based on its current state at the time of inspection. The logsig function is used as the transfer function in the hidden layer, whereas the purelin function is used in the layer that outputs information. The inputs of the six neurons that make up the input layer are taken into consideration by the ANN prediction model, which then makes a prediction on the component's learnt current life percent.

3.2 Proposed Framework

For the purpose of determining the anticipated probability of failure of OWT blades, which is a decision variable, an ANN prognostic approach for predicting the life percent of a component in the recommended CBM method is utilized. The ANN model, which is reliant on condition monitoring, provides the anticipated component life %. This percentage may be found in the table below. Uncertainties about the predicted failure time continue to exist regardless of the result. These uncertainties, also referred as ANN life percentage prediction errors, are gained during the training, and testing of the ANN, and they are utilized to create the expected failure-time distribution.

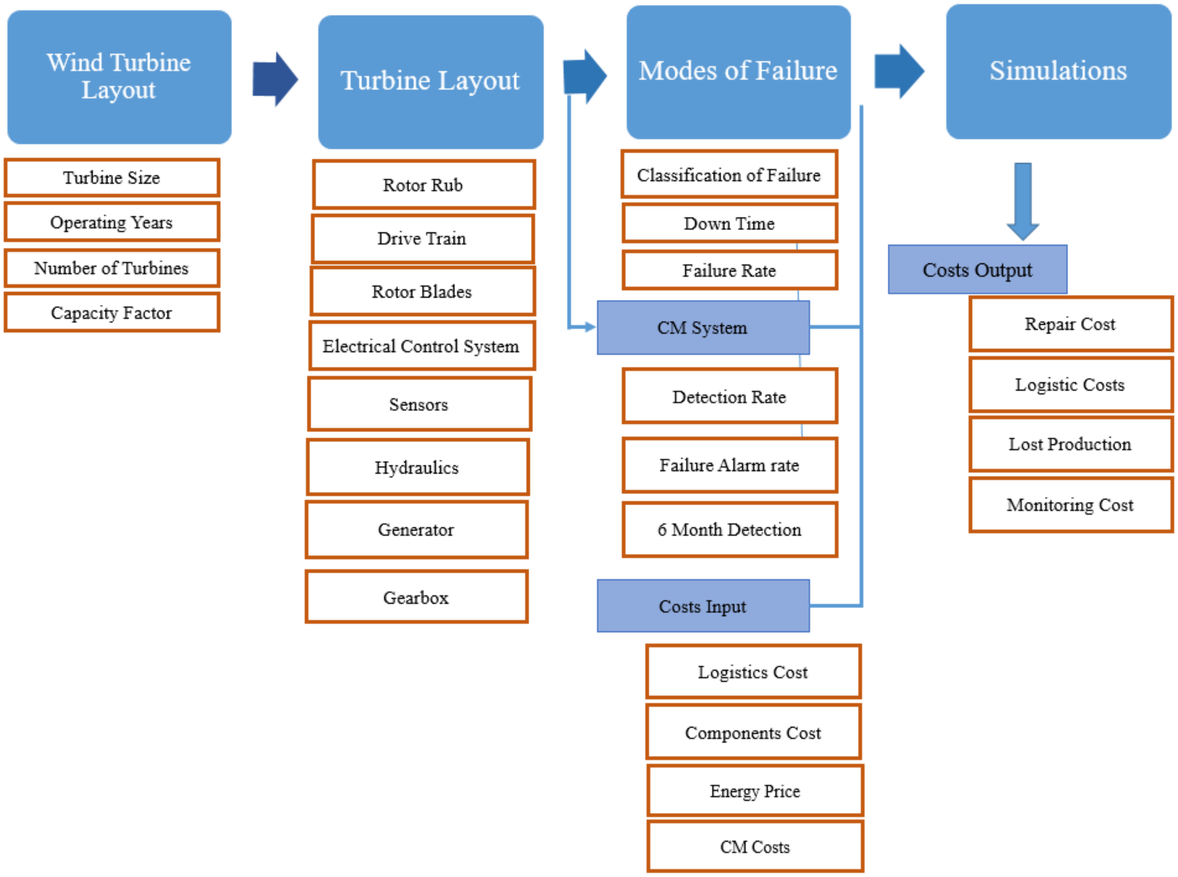


Figure 10 Proposed Framework Using ANN

3.2.1 CBM optimization for Turbines based on ANN life percentage prediction.

CBM optimization is being used to strike a balance between the resources needed for maintenance and the needs based on the data collected from condition monitoring. The purpose of this procedure is to determine the optimal moment to perform preventative maintenance or component replacement in order to cut down on the expenditures that are anticipated to accrue over the long run. By using an ANN health prediction model, one is able to derive the anticipated failure-time distributions for every inspection point, and the condition failure probability Pr_i^* represents the component deterioration. We define the suggested opportunistic CBM approach by utilizing a threshold with two-level failure probability, and the ideal thresholds, designated by "Pr_1^*" and "Pr_2^*" may be found by carrying out the CBM optimization. The opportunistic CBM approach for OWTs, which is based on ANN life percentage prediction, is thus carried out in the following manner:

(1) Inspections are performed on turbine components that are currently undergoing condition monitoring at consistent intervals. To determine the conditional failure probability of OWT components, the predicted failure-time distribution for every element is estimated at every inspection time by using ANN life % prediction model. This is done before the conditional failure probability is computed.

(2) When the conditional failure probability Pr_i^* of the turbine component hits the first-level threshold value, Pr_1^*, a PM is carried out on this component.

(3) In the event that a component of the turbine fails, a failure replacement will be carried out on that component.

(4) When a failed replacement or PM is done on any OWT component, the OM is performed on any additional components whose Pr_1^* values concurrently exceed the threshold value of the second level concurrently.

3.3 CBM optimization model

By rearranging the two choice variables Pr1* and Pr2* in the CBM approach that has been suggested for OWTs, it is possible to derive a variety of maintenance methods, as well as the projected costs associated with each strategy. The optimal thresholds of the failure probability demonstrate when upon which turbine element the failure substitution, PM, or OM will be conducted, and they have the potential to reduce a predicted long-term increase in the cost of maintenance. The following is an expression that may be used to describe the optimization method for the CBM approach described above:

min $C_r\,(Pr_1^*, Pr_2^*)$ s.t. $0 \le Pr_2^* \le Pr_1^* \le 1$

where the first-level failure probability threshold Pr1* and the second-level failure probability threshold Pr2* are the first and second-level failure probability thresholds that are used as the decision variables for this approach, respectively.

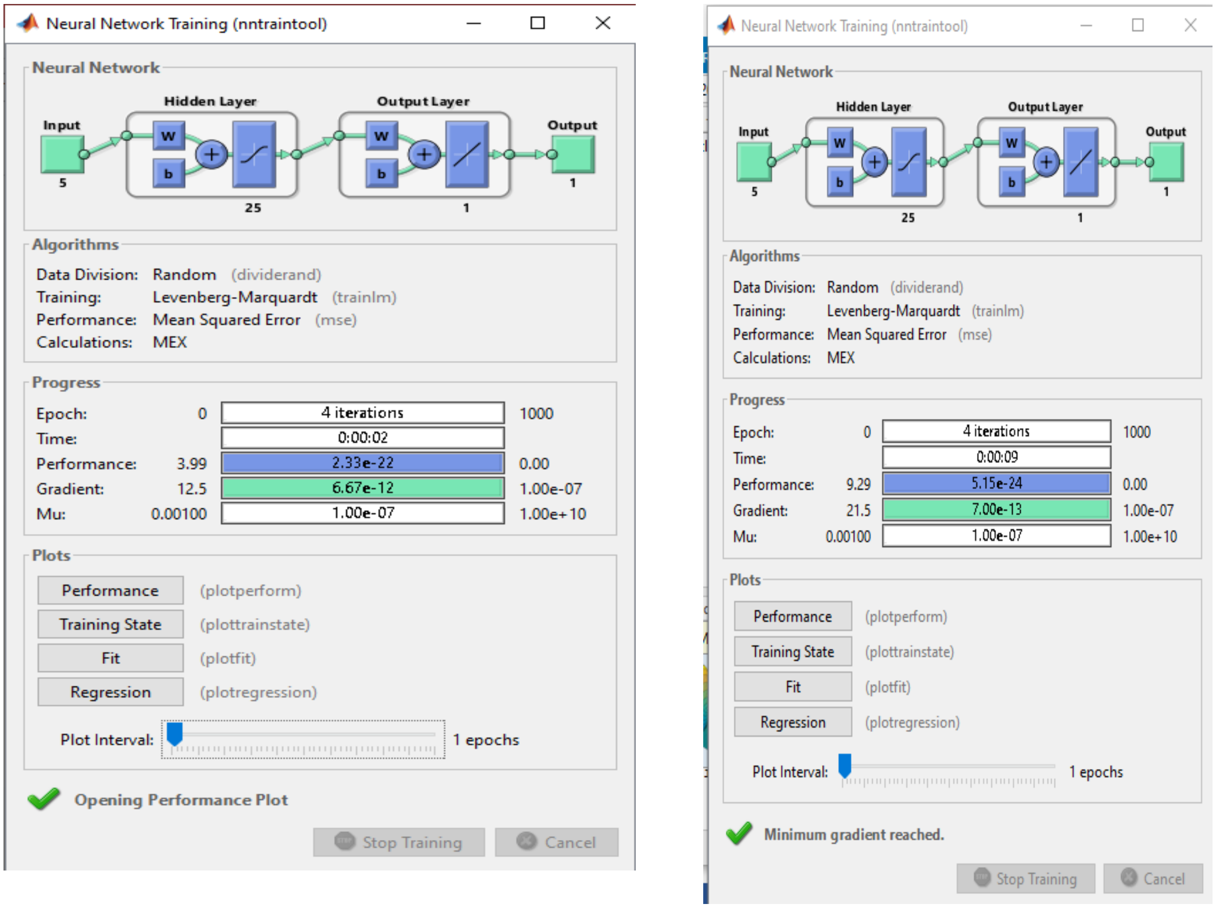
Through the use of simulation optimization in MATLAB, the total estimated maintenance costs for turbines are determined in this investigation. By simulating several scenarios, one may determine the ideal failure probability threshold value, which, in turn, can be used to calculate the predicted minimum cost of maintenance. Fig. 9 is an illustration of the process that is involved in the simulation optimization approach, and the in-depth explanations of this method are addressed in the upcoming sections:

Step one: Define the maximum number of iterations

Indicate the iteration number that should be used for the simulation using the notation NT. For instance, if there were 100 inspection points, it would mean that the inspection point began at 0 and went all the way up to 100. The inspection interval is now set at 10 days, which enables us to get reliable results while maintaining a level of computing efficiency that is acceptable. In our particular instance, we decided to make the value in MATLAB equal to four iterations.

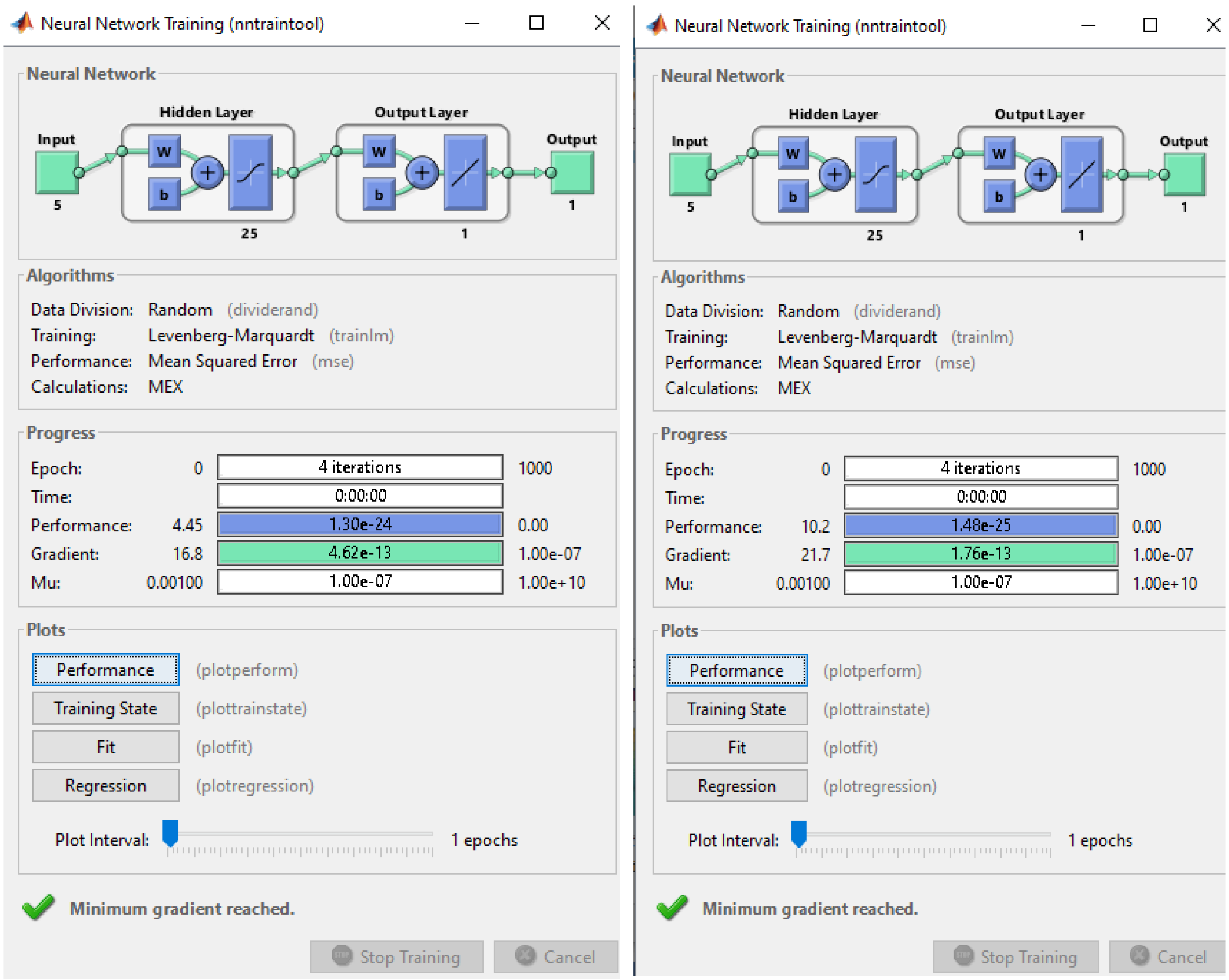
Neural Network training

The neural network (NN) training is starting with the choosing of input and target choices which the human operator can handle through the simple listdlg function. The program is then using these choices along with some options chosen at the start to train the NN with the inbuilt MATLAB functions. The trained program is continuing this process until a limit is reached or a high enough degree of fitting has been achieved and is then saving the NN as a separate function that can be used by the program later for this input data or another run of the program with different data.



(a) (b)

Figure 11 (a) Neural Network Model for rotor (b) Neural Network Model for Gear box



(a) (b)

Figure 12 a) Neural Network Model for Generator b) Neural Network Model for pitch

There are four iterations in neural network of each component, levenberg-marquardt is the training model. The performance and gradient for each component is given. The thought is to train the NN with a whole year of historical data and then use this NN to test days and weeks continuously with a fast already finished and trained NN. The selections in the start of the training is saved in a separate file so that the program automatically can choose the correct variables when used on another data file. This is important as the trained program only works with the same inputs and targets.

Step two: generate the “actual failure time”

The Weibull distribution is an excellent method for examining and making predictions on the actual lifespan of a component, and the lifetime may be expressed in the following format (Brink, Madsen and Lutz, 2015):

$$f(t) = \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1} \exp[-(\frac{t}{\alpha})^{\beta}]$$

When a failed replacement or preventative maintenance procedure is done on any turbine component, a new life cycle starts. The random failure time, denoted by FT_i is subject to a Weibull distribution, with and serving as the parameters (see Figure 8, Label 1), and it is possible for this value to be created whenever a new lifetime begins for component i. The actual lifespan of the turbine element is represented by the value that is stored in the FT_i variable.

Step three: generate predictive failure-time distribution for a component

Establish the anticipated failure-time distribution for element I relying on the ANN pre-diction error of life % by utilizing condition monitoring data at inspection point k (k = 0,..., NT). This should be done at inspection point k (k = 0,..., NT). The normal distributions are as follows for the anticipated lifespan of turbine component I at inspection point k, represented by PT_{ki}

$$PT_{ki} \sim \mathrm{N}(\mu, \sigma^2) \text{ (k = 0, ..., NT; i = 1, ..., N),}$$

where μ = FTi , $\sigma = \sigma_p \times FT_i$, with a standard deviation of prediction error σ_p by an ANN.

Step four: calculate conditional failure probability

It is possible to compute as follows the lifespan conditional failure probability Pr_{ki} for component i at inspection point k (Tian, Ding and Ding, 2011):

$$Pr_{ki} = \frac{\int_{t_i}^{t_i+l} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t_i-\mu)^2/2\sigma^2} dt}{\int_{t_i}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t_i-\mu)^2/2\sigma^2} dt} \qquad (k = 0, \dots \dots NT; i = 1, \dots \dots N),$$

where L and t_i denote constant inspection interval and time of component *i*, respectively; μ and σ_p are the predicted failure timesbased on the predicted life percentage by ANN and the standard deviation of prediction error; and $\sigma = \sigma_p \times FT_i$.If the conditional failure probability of a turbine component Pr_{ki}reaches the first-level threshold Pr1∗, then a PM at inspection point k for this component is performed. If no PM is performed during the lifetime of component i, then a failure replacement should be arranged at the inspection point pastFT_i . The OM for other components should be simultaneously conducted if their Pr_{ki} values reach the second-level threshold Pr2∗when a failure replacement or PM is performed on any turbine component

Table 1 Turbine Failure Model

Component	Distribution	α(day)	B
Rotor	Weibull	3000	3
Gear Box		2400	3
Generator		3300	2
Pitch		1858	3

To calculate the total cost of maintenance for the turbines in the following manner, two variables that each indicate the status of component I in the turbines are brought into play:

$$\Delta PK_i = \begin{Bmatrix} 1\ Component\ i\ is\ preventively\ maintained\ in\ the\ point\ time\ k \\ 0\ No\ preventive\ maintenance\ on\ component\ i\ in\ the\ point\ time\ k \end{Bmatrix}$$

$$\Delta fk_i = \begin{Bmatrix} 1\ Component\ i\ is\ replaced\ in\ the\ point\ time\ k \\ 0\ No\ failure\ replacement\ on\ component\ i\ in\ the\ point\ time\ k \end{Bmatrix}$$

If ΔPK_i= 0 & Δfk_i= 0, then the regular operation of component *i* continues.

Step five: start a new life cycle

In the event that a preventative maintenance or failure replacement is carried out on component I a new life cycle has to be initiated. Proceed to Step 2 and begin counting from 0. (set the cumulated inspection time ti, if necessary). The iteration of the simulation will proceed as usual until it reaches its maximum value.

Step six: calculate total expected maintenance cost

After the last inspection point has been performed, the following formula may be used to determine the anticipated cost of maintenance for turbines (Guangqian *et al.*, 2018):

$$CE = \frac{\sum_{K=0}^{Nt} CT}{NT * L}$$

where CT is the cumulative maintenance cost at inspection point k, NT is the total inspection point for the simulation optimization process, and L is the inspection interval. These values are specified in the equation.

$$CT = CF_i * \sum_{i=1}^{N} \Delta f K_i + CP_i * \sum_{i=1}^{N} \Delta PK_i + \Delta k_i * C_o$$

where Δk_i= 0, when $\sum_{i=1}^{N} \Delta PK_i$ = 0 & $\sum_{i=1}^{N} \Delta PK_i$= 0; otherwise$\Delta k_i$ = 1. N is the number of turbine components under condition monitoring, CF_i is the failure replacement cost, CP_i is the PM cost, and C_o is the fixed cost of sending a maintenance team to wind farms.

Table 2 Cost parameter of critical component OWT

	Cost of failure replacement C_{fi}	Cost of preventive maintenance C_{pi}	Cfi+Cpi=C_0
Rotor	215000	10500	225500
Gearbox	260000	10000	270000
Generatar	90000	11000	101000
Pitch	44000	9400	53400
			Sum = 649900

Step seven: determine the optimized CBM method for Turbines

In this opportunistic CBM technique for OWTs, the decision variables are the two-level failure probability threshold values. With the failure probability threshold values of Pr1* and Pr2*, the CBM approach has been optimized to the point where it is possible to achieve the least estimated cost of maintenance.

CHAPTER 4 Results and Discussion

4.1 Maintenance optimization using the proposed CBM method

In order to demonstrate the effectiveness of our CBM approach for wind turbines, we collected failure statistics and the costs of maintenance from published studies. The cost aspects of the turbine are outlined in Table 1, which includes the costs of replacing components in the case of failure and the costs of performing preventive maintenance on wind turbines. The facts pertaining to the expenditures were used in the process of calculating the costs of maintenance. The failure-time distributions may be predicted using the ANN pre-diction approach by using the failure incidences and condition monitoring parameters of the WT sections with an inspection interval of 10 days.

Table 3 failure history with best result of rotor

S.NO.	TIME	VIBRATION VELOCITY	TEMPERATURE
1	1617	8.241	71.3
2	2049	9.582	72.7
3	1922	8.296	72.9
4	1148	8.491	69.3
5	1489	9.419	64.2
BEST DATA RESULT	2049	9.582	72.9

Table 4 failure history with best result for gearbox

S.NO.	TIME	VIBRATION VELOCITY	TEMPERATURE
1	1340	15.711	77.4
2	1598	17.561	78.5
3	1051	14.626	76.8

4	931	11.741	75.5
5	1267	13.892	76.7
BEST DATA RESULT	1598	17.561	78.5

Table 5 failure history with best result for generator

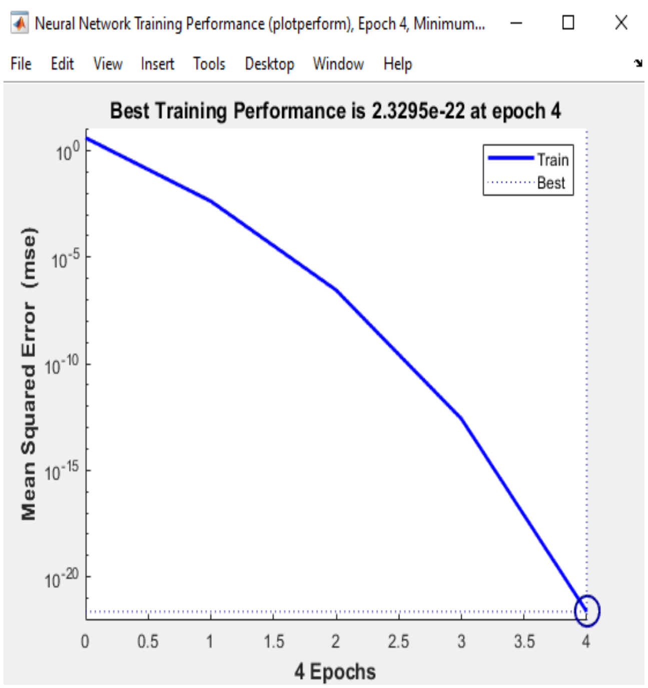
S.NO.	TIME	VIBRATION VELOCITY	TEMPERATURE
1	1417	6.356	81.3
2	1782	6.964	83.2
3	1008	6.081	77.2
4	1351	6.273	80.2
5	1426	6.472	81.8
BEST DATA RESULT	1782	6.964	83.2

Table 6 failure history with best result for pitch

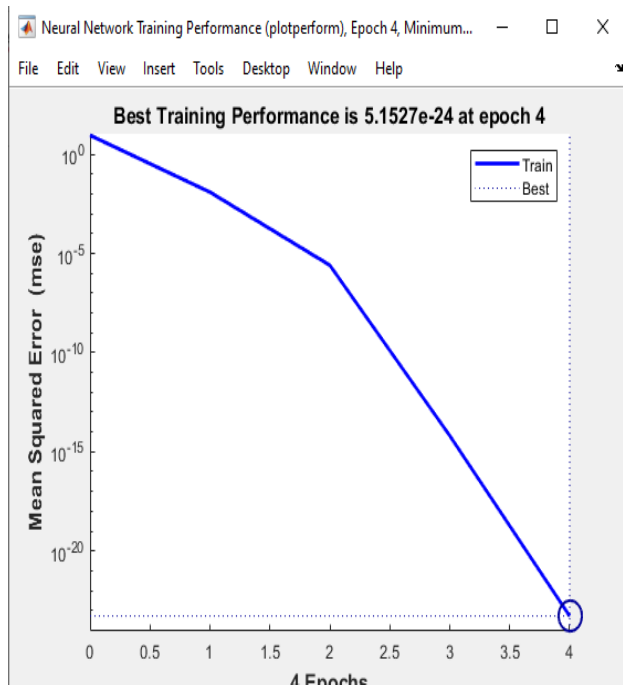
S.NO.	TIME	VIBRATION VELOCITY	TEMPERATURE
1	1009	8.802	64.5
2	1268	9.314	66.6
3	911	8.271	62.7
4	969	8.419	65.9
5	752	7.692	60.5
BEST DATA	1268	9.314	66.6

RESULT			

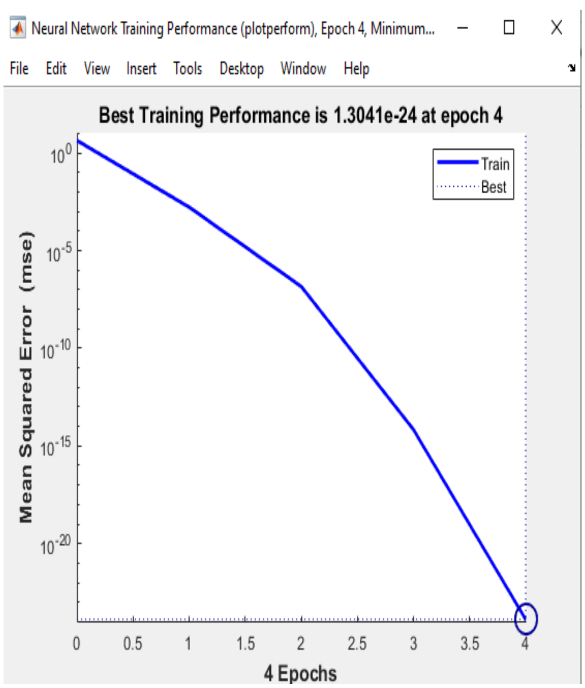
The above result for best training performance is plotted in ANN as below figures:



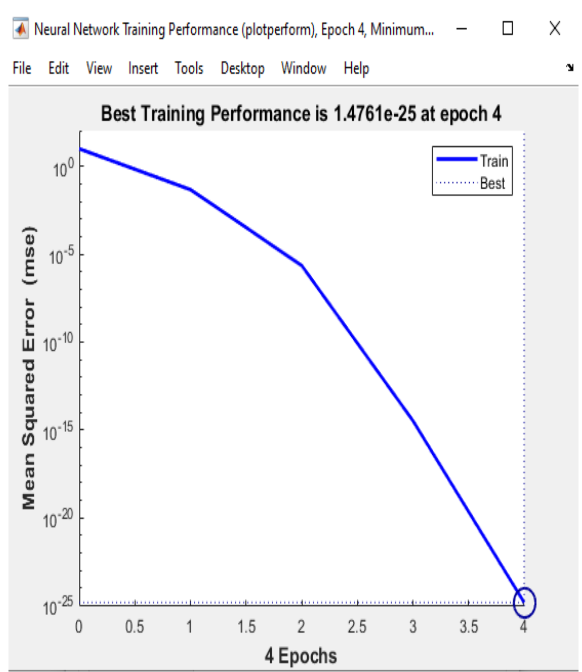
(a)



(b)



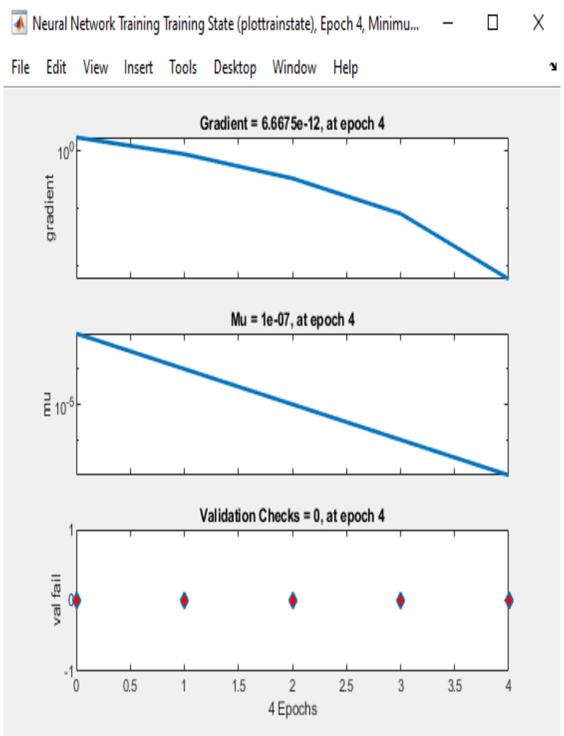
(c)



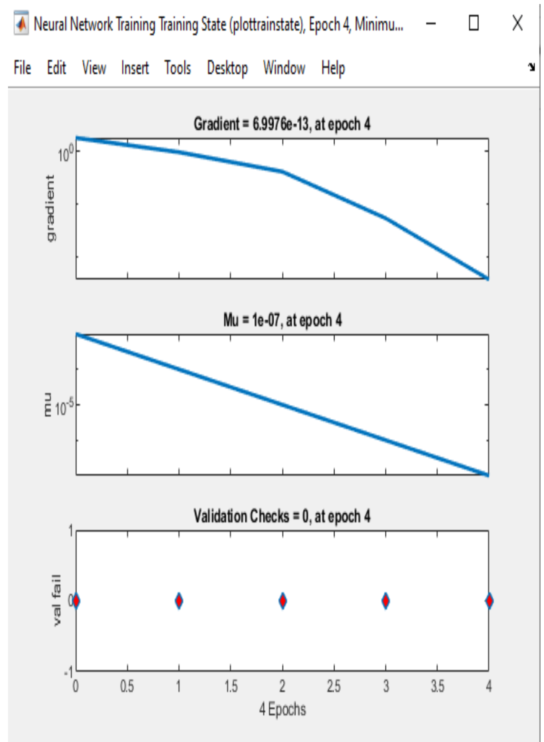
(d)

Figure 13 (a) Best Training Performance for Rotor, (b) Best Training Performance for Gearbox (c) Best Training Performance for Generator (d) Best Training Performance for Pitch

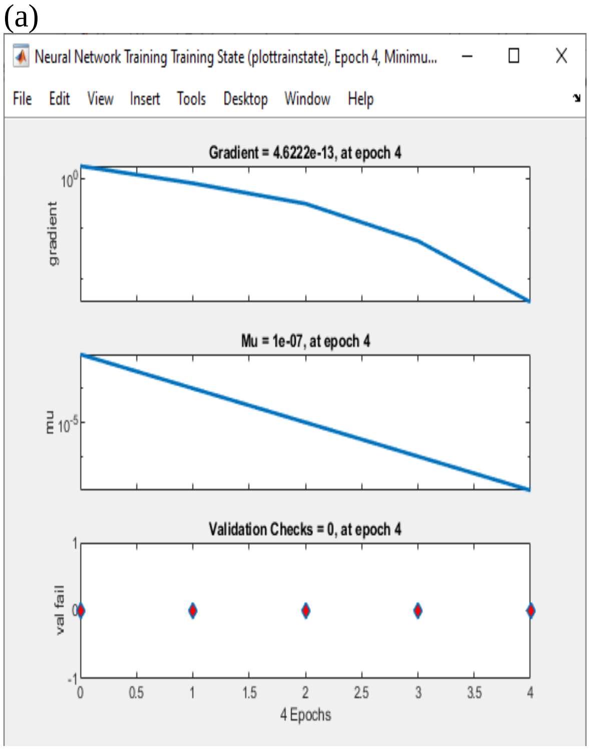
The above tables describe the result from ANN for the variables taken into considerations the vibration velocity and temperature. And the best result means the component will need less maintenance for that variables input.



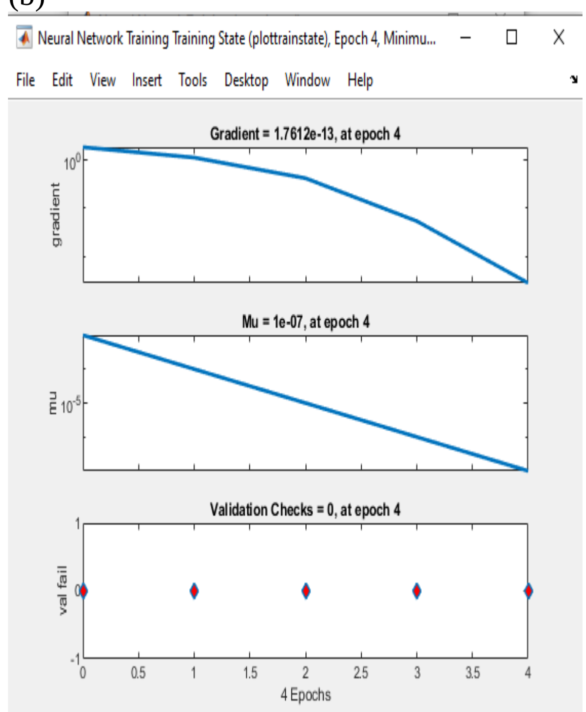
(a)



(b)



(c)



(d)

Figure 14 (a) Neural Network training result for Rotor (b) Neural Network training result for Gear box (c) Neural Network training result for Generator (d) Neural Network training result for Pitch

Our simulation optimization approach may be used to calculate the minimum predicted maintenance cost. The maintenance cost is shown against the interval days under consideration.

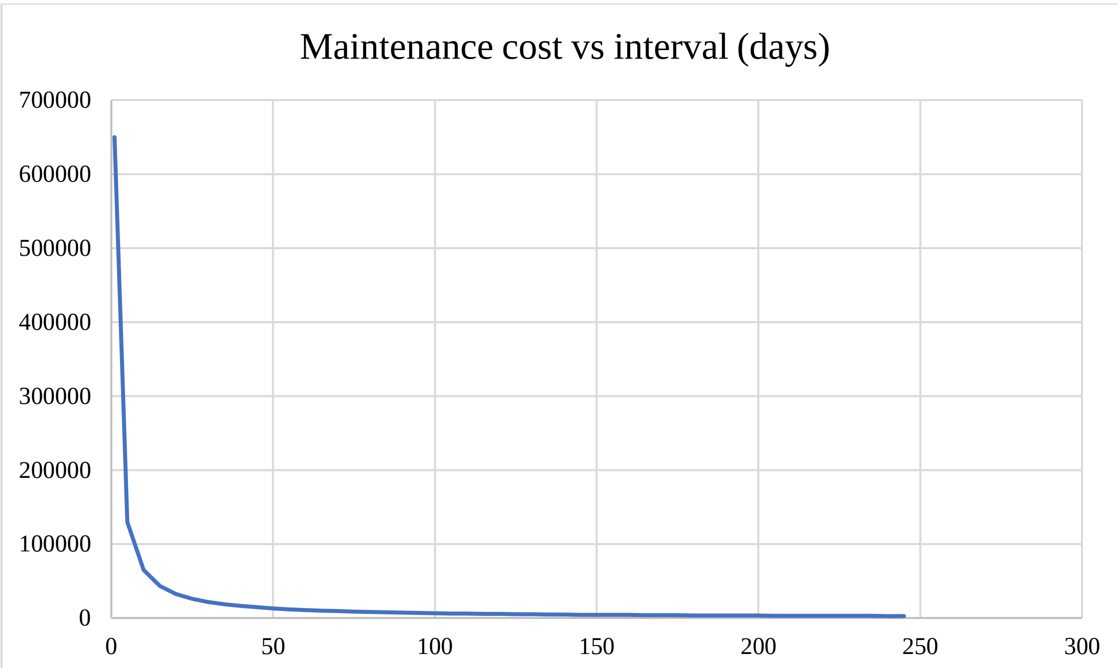


Figure 15 Maintenance cost Vs Interval days

The estimated upkeep expenses are sensitive to the failure probability threshold settings, which may be adjusted at two different levels. The diagram illustrates an appropriate failure probability threshold that corresponds to a lowest estimated cost. Establishing the most effective opportunistic model may be accomplished via the use of simulation optimization with the goal of achieving the lowest expected level of maintenance expense. The optimally predicted cost of maintenance for wind turbines is 256.12 Euros (€) per day and time.

4.2 Comparison of the proposed method with the time-based maintenance method

The time-based maintenance technique is extensively used in the wind energy industry [4]. Components will be subjected to preventative maintenance at regular intervals, and in the event that a component fails, an urgent failure replacement will be carried out. For instance, Goldwind Science and Technology Co., Ltd. has a maintenance strategy that is focused on time and features regular intervals (half a year). In this section, we will contrast the time-based maintenance methodology with the way that we have provided. The time-based maintenance technique's objective is to determine the optimal value for the constant maintenance interval, or Lci, so as to cut down on the total expected maintenance cost. Lci is an abbreviation for "constant maintenance interval." The approach of constant-interval maintenance, which is explained in Ref. [14], may be used to calculate the full expected cost of doing maintenance on the system.

$$C(LCi) = \frac{\sum_{i=1}^{N}[C_{Fi}^{ci} + C_{Pi}^{ci} H_i(L_{ci})]}{L_{ci}}$$

Table 7 Cost parameters for the time-based maintenance method.

Component	Cost of Failure replacement C_{Fi}^{ci}	Cost of preventive maintenance C_{Pi}^{ci}
Rotor	215000	10500
Gearbox	260000	10000
Generator	90000	11000
Pitch	44000	9400

$C_{Fi}^{ci}$and $C_{Pi}^{ci}$are the total cost of component I for a failed replacement and PM, respectively. $H_i(L_{ci})$ is a recurrent function that expresses the expected number of PM iterations for component i in the interval (0, Lci) and may be computed. We use the same failure models and cost data for the components using the time-based maintenance technique for accurate comparison, as shown in Tables 3 and 4. Because the fixed cost C_0 is imposed for every failure replacement, as shown in Table 5, the failure replacement cost C_{Fi}^{ci} in Eq. (5.1) = C_0 plus the failure replacement cost in Table 4. All of the turbine components contribute to the total PM cost, which includes the fixed cost shown in Table 4. As a result, the component i PM cost should be computed as follows:

$$C_{Pi}^{ci} = C_{pi} + C0/N$$

Table 3 also shows the cost of PM estimated using Eq. (5.2). By reducing Eq., you may get the estimated maintenance cost L ci (5.1). Figure 11 shows the cost as a function of the L ci values for the maintenance period. If the cost is low, the best maintenance interval is chosen. The ideal maintenance interval will be 161 days, which is roughly the same as Goldwind Sci. and Tech. Co., Ltd.'s maintenance cycle (half a year), and the minimum cost will be 374.01 € /day.

Table 8 Maintenance times for each component with CBM strategy.

Component	CBM		
	CM	PM	OM
Rotor	0	1	2
Gearbox	0	0	4
Generator	0	4	2
Pitch	0	5	2

Fig. 12 shows the CBM planning outcomes for a wind turbine provided the opportunities based on ANN. Table 6 shows the maintenance schedule and cost reductions for each component using the opportunistic CBM technique. Meanwhile, Table 7 shows the CBM strategy's maintenance times for each component.

The results show that the CM for any part throughout these 1000 days is poor, and this result is the same as the maintenance status of Goldwind Science and Technology Co., Ltd. This is due to the fact that the cost of corrective repair is rather high; this difficulty need to be avoided throughout the maintenance process. The CBM strategy, which is based on data collected through condition monitoring, might be used to reduce the amount of time that a system is down and the number of unexpected failures that occur. In addition, the pitch is the component that needs the greatest upkeep since it has a higher rate of failure in comparison to the other components. When the pitch's PM reaches its first-level threshold Pr1*, it usually offers other components with opportunities for maintenance.

As a consequence of completing all of the gearbox's maintenance duties by using the opportunities offered by the PM of the other parts, the economic reliance of the gearbox has been improved. When the CBM is finished, the maintenance manual states that on the 393rd day, all four parts of a wind turbine system should be serviced concurrently. This results in the biggest cost reduction, which is 26207 €. The total cost reductions over 1000 days are 117892 € when the opportunistic CBM method is followed, and the average daily maintenance expenditures for the wind turbine reduce from 374.01 € to 256.12 € as a result. The consequence of this is that the opportunistic CBM strategy saves more money than the time-based maintenance method does, with a savings percentage of 46.03 percent of expenses. The analysis indicates that the opportunistic CBM method has the potential to be successful and become entrenched in the market for wind energy.

Component failure rates for wind turbines are greater than for other types of turbines. On the basis of the presented CBM approach, we will now describe a contrastive study comparing turbine spreads. a comparison of the maintenance costs of WTs. The cost of WT maintenance falls from 279.92 € per day to 202.71 € per day when the CBM approach is used, suggesting that 38.09 percent of the cost is saved. In terms of the turbines, maintenance costs drop from 374.01 €/day to 256.12 €/day, showing that 46.03 percent of the cost is saved. As a result, the CBM approach is critical from an economic standpoint, particularly for turbines.

4.3 Discussion

The expense of ongoing maintenance is the primary barrier to the development of offshore wind turbines. An additional inventory expenses as well as certain mass transit infrastructure have always been required to supply servicing sites for offshore wind turbines. In relation, the ease of access of offshore wind turbines is grossly inadequate due to the obvious unpredictability of the weather. The operations and maintenance expenses of a wind turbines can make a significant contribution i.e., approximately 30 percent of the leveled price of power of an offshore wind farm. In addition, harsh maritime operating circumstances including typhoons, sea ice, salt deposits, and dampness will result in a greater failure rate than onshore operating conditions, which will in turn result in high cost of maintenance. Because of its influence on costs, risks, and performance, maintenance efficiency is a problem that must be addressed by businesses in sectors that make use of physical assets. As a result of innovations and improvements in sensing technology, the maintenance methods used in contemporary industry have transitioned from the antiquated preventive and corrective one into the condition-based maintenance (CBM). In today's sector, there are a great deal of potential applications. The concept behind condition monitoring-based maintenance is that a maintenance service is planned in accordance with the current state of a component or subsystem that is being monitored for its health. It is necessary to incorporate a condition monitoring system, such as vibration measurements for critical machine elements in wind turbines. The goal of condition monitoring is to assure the continued functioning of wind turbines by means of continuous measurement and analysis, hence improving the availability of turbines and lowering associated costs. Particularly with regard to offshore wind farms, in-depth planning of maintenance that is dependent on the condition of the turbines is an essential necessity.

The influence of differing component lead times on the failure probability at the turbine level is discussed in this section. The farm has a variety of turbines, each of which belongs to a distinct kind. Each turbine has four major components: the rotor, pitch, gearbox, and generator.

We apply the equations presented in the approach to calculate the failure probability for components, then we use the equation to compute the failure probability at the turbine level using MATLAB code with iteration 4, and finally we take the average value for results. The failure probability for the above components are calculated.

According to earlier findings, the lead time of components has an impact on the failure likelihood at the turbine level. The failure probability is lowered since we have components with shorter lead times than in the constant lead time situation. To put it another way, the short lead time decreases the likelihood of failure and the danger of downtime. On the other hand, if the component lead time is longer than the constant lead time scenario, the failure probability rises. According to the findings, the total maintenance cost and time in CBM policy are impacted in a linear and direct proportionate relationship by the total number of turbines in the farm. The entire maintenance cost is impacted by the number of turbines in CBM policy. Furthermore, increasing the number of turbines with increasing the variety of turbine types affects the maintenance time. The overall maintenance cost is affected by the variable lead time, whereas the total maintenance time remains constant. The failure thresholds are also influenced by component lead times, as the failure probability of turbines varies with lead time.

Evaluating the transmission and turbine sub-systems seems to give the significant possible gains for O&M expenses. These systems have considerable DTs that are connected with serious failures, high repair costs, and failure rates that are not negligible. Drive train vibration CM offers the benefit of monitoring these sub-systems in addition to the main shaft at a cost that is comparatively modest. It is possible to monitor all of these subsystems using AE, but doing so will incur a higher cost. However, it is arguable that these systems will have a higher detection rate than their vibration-based equivalents. Oil sensors have the ability to identify a broad variety of problems, including those that are beyond the capability of an AE or vibration CM. The combination of these three technologies provides a greater likelihood of identifying flaws before they cause shutdown.

Additionally, the decrease in replacement parts and LP seems to justify the expenses associated with the investment. Due to the fact that the model is presently unable of specifying the many failure circumstances in which one sensor type is superior to another, it is possible that the ROI for both systems is greater than what was first reported. The failure characteristics of rotor blades and hub systems are similarly comparable, which enables monitoring to decrease operation and maintenance costs.

Failure rates and the suppliers of components prices are also significant factors that contribute to the model's overall results. Even though offshore wind has witnessed notable increases in failure rates or expert judgement, O&M models that have been built for offshore wind employ onshore figures such as Williams et al. It is intended that when more information on the operations of offshore wind farms becomes accessible, a more coherent database of high-quality operational information will become available, which might then be utilized for O&M models such as these. An SHM system seems to only modestly raise expenses due to its excellent dependability (annual failure rates of 0.01 for significant failures) and the minimum intervention associated with tower damage. Both of these factors contribute to the low likelihood of catastrophic failure. However, the strategy that was applied does not take into account the decrease in the risk of failure of the tower and offshore structures, nor does it rely upon a complete structural integrity management approach to calculate the cost savings that would result from fewer inspections.

CHAPTER 5 Conclusion

In this piece of study, we provided a CBM technique for lowering the costs associated with maintaining wind turbines. In addition to this, consideration is given to the economic interdependence that exists between the different components. The ANN prediction model is intended to estimate the component failure-time distribution by making use of the data gathered from condition monitoring. A conditional failure probability value is applied to turbines in order to reflect their level of deterioration. This value may be determined with the use of component failure-time distributions. Our opportunistic CBM technique is characterized by a failure probability threshold that consists of two levels. An optimization via simulation is carried out in order to identify the opportunistic CBM approach. This optimization is used to analyze the cost and establish the ideal threshold settings. When it comes to determining when and which parts of the wind turbine will be maintained, the best CBM choices are made, which ultimately results in the lowest anticipated wind turbine maintenance cost. According to the variables that have been provided, the studied four components of the MATLAB ANN neural network that have the best performance condition have been explained. An analysis of the costs involved reveals how effective the approach that was recommended is as well as how significant the CBM strategy is for wind turbines.

5.1 Future work

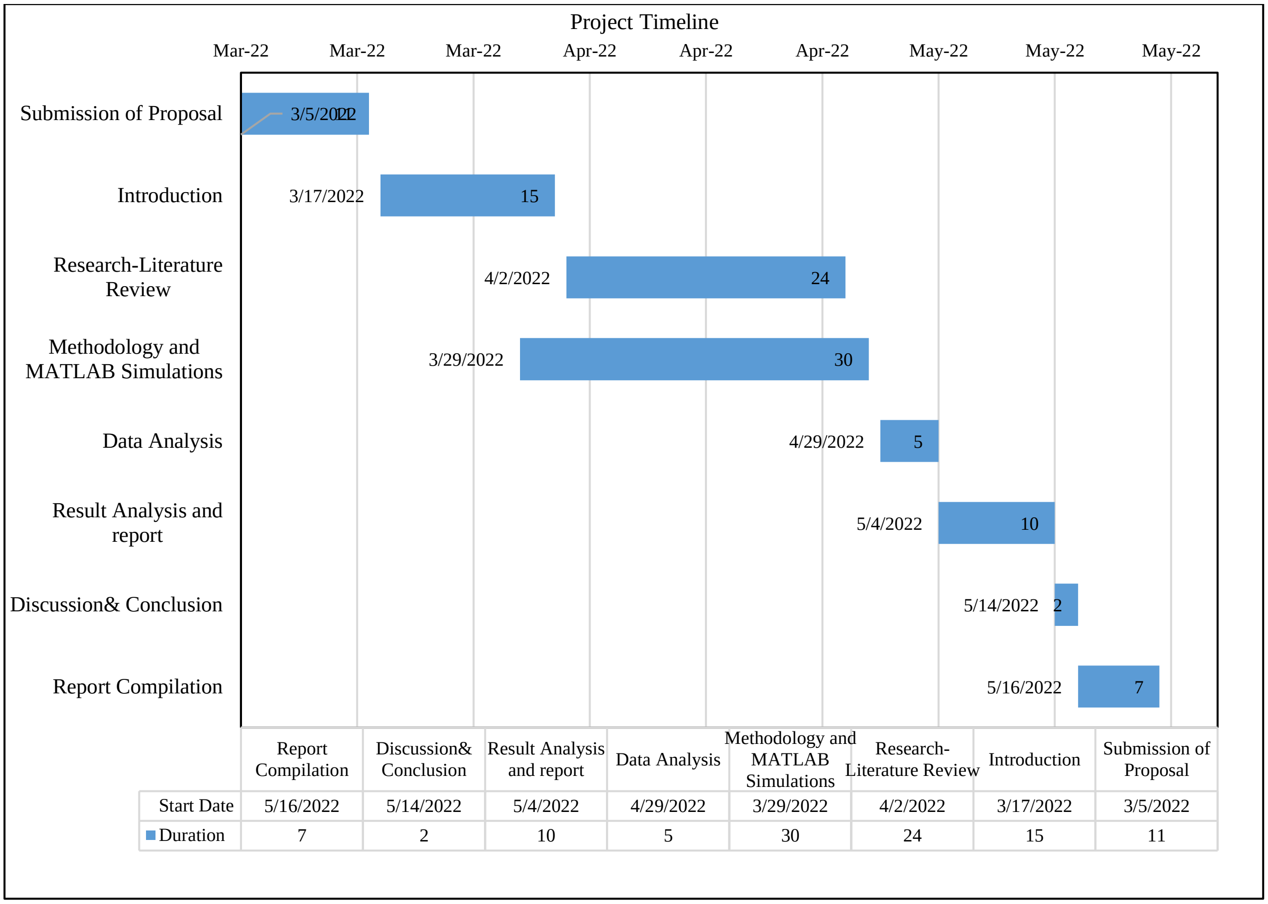
The developed model may provide the most cost-effective wind farm maintenance. Real farms, on the other hand, might be more difficult, with additional circumstances throughout maintenance time. As a result, by taking these factors into account, these approaches can be improved. The following research might be done to expand on the current study:

- Taking into account the likelihood of failure at various seasons. The weather has an impact on wind turbine performance; for example, during the winter, the turbines may freeze.
- Imposing restrictions on the maintenance team's movements in the farms. Because the maintenance personnel sometimes work in locations other than the farm, their availability is limited.

- Counting the quantity of spare parts for each component. The amount of failure components and demand effect the inventory policy for the systems, therefore we may use the failure probability to estimate the inventory for each kind.
- Taking into consideration and improving additional variables.

Real-world wind turbine data is critical for reliability assessments and maintenance planning. Sharing data and a standard report is an excellent way to improve maintenance and maximize research outcomes.

CHAPTER 6 Project Timeline



References

Ahmed, M. and Abdel Gawad, A. (2016) *Utilization of Wind Energy in Green Buildings*.

Ak, R., Vitelli, V. and Zio, E. (2015) 'An Interval-Valued Neural Network Approach for Uncertainty Quantification in Short-Term Wind Speed Prediction.', *IEEE transactions on neural networks and learning systems*. United States, 26(11), pp. 2787–2800. doi: 10.1109/TNNLS.2015.2396933.

Al-Najjar, B., Algabroun, H. and Jonsson, M. (2018) 'Maintenance 4.0 to fulfill the demands of Industry 4.0 and Factory of the Future', *Basim Al-Najjar Journal of Engineering Research and Application www.ijera.com*, 8(11), pp. 20–31. doi: 10.9790/9622-0811022031.

Andrawus, J. *et al.* (2006) 'The Selection of a Suitable Maintenance Strategy for Wind Turbines', *Wind Engineering*, 30. doi: 10.1260/030952406779994141.

Besnard, F. and Bertling, L. (2010) 'An approach for condition-based maintenance optimization applied to wind turbine blades', *IEEE Transactions on Sustainable Energy*, 1(2), pp. 77–83. doi: 10.1109/TSTE.2010.2049452.

Bogaraj, T., Kanakaraj, J. and Kumar, K. M. (2015) 'Optimal sizing and cost analysis of hybrid power system for a stand-alone application in Coimbatore region: A case study', *Archives of Electrical Engineering*, 64(1), pp. 139–155. doi: 10.1515/aee-2015-0013.

Breton, S.-P. and Moe, G. (2009) 'Status, plans and technologies for offshore wind turbines in Europe and North America', *Renewable Energy*, 34(3), pp. 646–654. doi: https://doi.org/10.1016/j.renene.2008.05.040.

Brink, T., Madsen, S. O. and Lutz, S. (2015) 'Perspectives on how operation & maintenance (O&M) innovations contribute to the reduction of Levelized Cost of Energy (LCOE) in offshore wind parks', pp. 1–99.

Byon, E. and Ding, Y. (2010) 'Season-Dependent Condition-Based Maintenance for a Wind Turbine Using a Partially Observed Markov Decision Process', *IEEE Transactions on Power Systems*, 25(4), pp. 1823–1834. doi: 10.1109/TPWRS.2010.2043269.

Carta, J. A. and Velázquez, S. (2011) 'A new probabilistic method to estimate the long-term wind speed characteristics at a potential wind energy conversion site', *Energy*, 36(5), pp. 2671–2685.

doi: https://doi.org/10.1016/j.energy.2011.02.008.

Costa, Á. M. *et al.* (2021) 'New tendencies in wind energy operation and maintenance', *Applied Sciences (Switzerland)*, 11(4), pp. 1–26. doi: 10.3390/app11041386.

Doluweera, G. *et al.* (2020) 'A scenario-based study on the impacts of electric vehicles on energy consumption and sustainability in Alberta', *Applied Energy*, 268, p. 114961. doi: https://doi.org/10.1016/j.apenergy.2020.114961.

Doucoure, B., Agbossou, K. and Cardenas, A. (2016) 'Time series prediction using artificial wavelet neural network and multi-resolution analysis: Application to wind speed data', *Renewable Energy*, 92(C), pp. 202–211. Available at: https://econpapers.repec.org/RePEc:eee:renene:v:92:y:2016:i:c:p:202-211.

Ennis, B. L. *et al.* (2019) 'Optimized Carbon Fiber Composites in Wind Turbine Blade Design', (November).

Finamore, A. R. *et al.* (2016) 'A wind speed forecasting model based on artificial neural network and meteorological data', in *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*, pp. 1–5. doi: 10.1109/EEEIC.2016.7555671.

Fischer, K. (2012) *Maintenance Management of Wind Power Systems by means of Reliability-Centred Maintenance and Condition Monitoring Systems*. doi: 10.13140/RG.2.1.1874.3446.

Foley, A. M. *et al.* (2012) 'Current methods and advances in forecasting of wind power generation', *Renewable Energy*, 37(1), pp. 1–8. doi: https://doi.org/10.1016/j.renene.2011.05.033.

Goudarzi, N. and Zhu, W. D. (2013) 'A review on the development of wind turbine generators across the world', *International Journal of Dynamics and Control*, 1(2), pp. 192–202. doi: 10.1007/s40435-013-0016-y.

Goyal, D. *et al.* (2017) 'Optimization of Condition-Based Maintenance Using Soft Computing', *Neural Comput. Appl.* Berlin, Heidelberg: Springer-Verlag, 28(1), pp. 829–844.

Gray, C. and Watson, S. (2009) 'Physics of Failure approach to wind turbine condition based maintenance', *Wind Energy*, 13, pp. 395–405. doi: 10.1002/we.360.

Griffith, D. *et al.* (2016) 'A study of rotor and platform design trade-offs for large-scale floating vertical axis wind turbines', *Journal of Physics: Conference Series*, 753. doi: 10.1088/1742-

6596/753/10/102003.

Guangqian, D. *et al.* (2018) ‘A hybrid algorithm based optimization on modeling of grid independent biodiesel-based hybrid solar/wind systems’, *Renewable Energy*. Elsevier Ltd, 122, pp. 551–560. doi: 10.1016/j.renene.2018.02.021.

Guo, Y., Wang, H. and Lian, J. (2022) ‘Review of integrated installation technologies for offshore wind turbines: Current progress and future development trends’, *Energy Conversion and Management*, 255, p. 115319. doi: https://doi.org/10.1016/j.enconman.2022.115319.

Hiendro, A. *et al.* (2013) ‘Techno-economic analysis of photovoltaic/wind hybrid system for onshore/remote area in Indonesia’, *Energy*. Elsevier Ltd, 59, pp. 652–657. doi: 10.1016/j.energy.2013.06.005.

IEC (2005) *Wind turbines – Part 1: Design requirements This*.

Iqbal, A. *et al.* (2020) ‘Proposed particle swarm optimization technique for the wind turbine control system’, *Measurement and Control*. SAGE Publications Ltd, 53(5–6), pp. 1022–1030. doi: 10.1177/0020294020902785.

Jiang, Z. (2021) ‘Installation of offshore wind turbines: A technical review’, *Renewable and Sustainable Energy Reviews*, 139, p. 110576. doi: https://doi.org/10.1016/j.rser.2020.110576.

Junginger, M., Faaij, A. and Turkenburg, W. C. (2004) ‘Cost Reduction Prospects for Offshore Wind Farms’, *Wind Engineering*. SAGE Publications, 28(1), pp. 97–118. doi: 10.1260/0309524041210847.

Leung, D. Y. C. and Yang, Y. (2012) ‘Wind energy development and its environmental impact: A review’, *Renewable and Sustainable Energy Reviews*, 16(1), pp. 1031–1039. doi: https://doi.org/10.1016/j.rser.2011.09.024.

Li, G. and Shi, J. (2010) ‘Application of Bayesian model averaging in modeling long-term wind speed distributions’, *Renewable Energy*, 35(6), pp. 1192–1202. doi: https://doi.org/10.1016/j.renene.2009.09.003.

Lu, Y. *et al.* (2018) ‘Condition based maintenance optimization for offshore wind turbine considering opportunities based on neural network approach’, *Applied Ocean Research*. Elsevier B.V., 74, pp. 69–79. doi: 10.1016/j.apor.2018.02.016.

Lucente, M. (2008) ‘Condition monitoring system in wind turbine gearbox’, *Master’s dissertation, Stockholm, Sweden*, pp. 43–51.

Malik, H. and Savita (2016) ‘Application of artificial neural network for long term wind speed prediction’, in *2016 Conference on Advances in Signal Processing (CASP)*, pp. 217–222. doi: 10.1109/CASP.2016.7746168.

Miller, D. A., Samborsky, D. D. and Ennis, B. L. (2019) ‘in Wind Turbine Blade Design’, (September).

Murugaperumal, K. and Ajay D Vimal Raj, P. (2019) ‘Feasibility design and techno-economic analysis of hybrid renewable energy system for rural electrification’, *Solar Energy*. Elsevier, 188(February), pp. 1068–1083. doi: 10.1016/j.solener.2019.07.008.

Nilsson Westberg, J. and Bertling Tjernberg, L. (2007) ‘Maintenance Management of Wind Power Systems Using Condition Monitoring Systems—Life Cycle Cost Analysis for Two Case Studies’, *Energy Conversion, IEEE Transactions on*, 22, pp. 223–229. doi: 10.1109/TEC.2006.889623.

Pazouki, E., Bahrami, H. and Choi, S. (2014) ‘Condition Based Maintenance optimization of wind turbine system using degradation prediction’, in *2014 IEEE PES General Meeting | Conference & Exposition*, pp. 1–5. doi: 10.1109/PESGM.2014.6939918.

Quan, H. *et al.* (2020) ‘A Survey of Computational Intelligence Techniques for Wind Power Uncertainty Quantification in Smart Grids’, *IEEE Transactions on Neural Networks and Learning Systems*, 31(11), pp. 4582–4599. doi: 10.1109/TNNLS.2019.2956195.

Saeed, A. (2008) ‘Online Condition Monitoring System for Wind Turbine Case Study’, (October), p. 79.

Saidur, R. *et al.* (2011) ‘Environmental impact of wind energy’, *Renewable and Sustainable Energy Reviews*, 15(5), pp. 2423–2430. doi: 10.1016/j.rser.2011.02.024.

Sainz, J. A. and Sebastián, M. A. (2013) ‘Methodology for the maintenance centered on the reliability on facilities of low accessibility’, *Procedia Engineering*. Elsevier B.V., 63, pp. 852–860. doi: 10.1016/j.proeng.2013.08.279.

Shafiee, M., Finkelstein, M. and Bérenguer, C. (2015) ‘An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks', *Reliability Engineering and System Safety*, 142, pp. 463–471. doi: 10.1016/j.ress.2015.05.001.

Shah, K. A. *et al.* (2021) 'A synthesis of feasible control methods for floating offshore wind turbine system dynamics', *Renewable and Sustainable Energy Reviews*, 151, p. 111525. doi: https://doi.org/10.1016/j.rser.2021.111525.

Tawfiq, K. B. *et al.* (2019) 'Wind energy conversion system topologies and converters: Comparative review', *Energy Procedia*. Elsevier B.V., 162, pp. 38–47. doi: 10.1016/j.egypro.2019.04.005.

Tian, Z. *et al.* (2011) 'Condition based maintenance optimization for wind power generation systems under continuous monitoring', *Renewable Energy*, 36(5), pp. 1502–1509. doi: https://doi.org/10.1016/j.renene.2010.10.028.

Tian, Z., Ding, Y. and Ding, F. (2011) 'Maintenance Optimization of Wind Turbine Systems Based on Intelligent Prediction Tools BT - Innovative Computing Methods and Their Applications to Engineering Problems', in Nedjah, N. et al. (eds). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 53–71. doi: 10.1007/978-3-642-20958-1_4.

Tian, Z. and Wang, H. (2022) 'Wind power system reliability and maintenance optimization considering turbine and wind uncertainty', *Journal of Quality in Maintenance Engineering*. Emerald Publishing Limited, 28(1), pp. 252–273. doi: 10.1108/JQME-03-2020-0017.

Tong, G., Qian, X. and Liu, Y. (2022) 'Prognostics and Predictive Maintenance Optimization Based on Combination BP-RBF-GRNN Neural Network Model and Proportional Hazard Model', *Journal of Sensors*. Edited by M. Xia. Hindawi, 2022, p. 8655669. doi: 10.1155/2022/8655669.

Wilkinson, M., Spianto, F. and Knowles, M. (2006) *Towards the Zero Maintenance Wind Turbine*. doi: 10.1109/UPEC.2006.367718.

Wu, B., Tian, Z. and Chen, M. (2013a) 'Condition-based Maintenance Optimization Using Neural Network-based Health Condition Prediction', *Quality and Reliability Engineering International*. John Wiley & Sons, Ltd, 29(8), pp. 1151–1163. doi: https://doi.org/10.1002/qre.1466.

Wu, B., Tian, Z. and Chen, M. (2013b) 'Condition-based Maintenance Optimization Using Neural Network-based Health Condition Prediction', *Quality and Reliability Engineering International*, 29. doi: 10.1002/qre.1466.

Wu, X. *et al.* (2019) ‘Foundations of offshore wind turbines: A review’, *Renewable and Sustainable Energy Reviews*, 104, pp. 379–393. doi: https://doi.org/10.1016/j.rser.2019.01.012.

Xing, X. *et al.* (2019) ‘Switching Performance Improvement Based on Model-Predictive Control for Wind Turbine Covering the Whole Wind Speed Range’, *IEEE Transactions on Sustainable Energy*, 10(1), pp. 290–300. doi: 10.1109/TSTE.2018.2833634.

Yurdusev, M. A., Ata, R. and Çetin, N. S. (2006) ‘Assessment of optimum tip speed ratio in wind turbines using artificial neural networks’, *Energy*, 31(12), pp. 2153–2161. doi: https://doi.org/10.1016/j.energy.2005.09.007.

Zhang, T., Dwight, R. and El-Akruti, K. (2015) ‘Condition based maintenance and operation of wind turbines’, *Lecture Notes in Mechanical Engineering*, 19(August 2014), pp. 1013–1025. doi: 10.1007/978-3-319-09507-3_87.

Zhou, P. and Yin, P. T. (2019) ‘An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics’, *Renewable and Sustainable Energy Reviews*, 109, pp. 1–9. doi: https://doi.org/10.1016/j.rser.2019.03.049.

Zonta, T. *et al.* (2022) ‘A predictive maintenance model for optimizing production schedule using deep neural networks’, *Journal of Manufacturing Systems*, 62, pp. 450–462. doi: https://doi.org/10.1016/j.jmsy.2021.12.013.

APPENDICES

A.1 MATLAB Code

```
P = [1617 2049 1922 1148 1489; 8.241 9.582 8.296 8.491 9.419; 71.3 72.7 72.9
69.3 64.2];
T = [2049; 8.241; 64.2];
a= [0 0 0 0 0; 0 0 0 0 0; 0 0 0 0 0];

[pn1,PS] = mapminmax(P');
[tn1,TS] = mapminmax(T');
[an1,AS]=  mapminmax(a');
n = 25;
netnew1=newfit(pn1,tn1,n);
[netnew1,tr1]=train (netnew1,pn1,tn1);
y2=sim(netnew1,an1);


P = [1340 1598 1051 931 1267; 15.711  17.561 14.626 11.741 13.892; 77.4 78.5
76.8 75.5 76.7];
T = [1598; 17.561; 78.5];
a= [0 0 0 0 0; 0 0 0 0 0; 0 0 0 0 0];

[pn1,PS] = mapminmax(P');
[tn1,TS] = mapminmax(T');
[an1,AS]=  mapminmax(a');
n = 25;
netnew1=newfit(pn1,tn1,n);
[netnew1,tr1]=train (netnew1,pn1,tn1);
y2=sim(netnew1,an1);


P = [1417 1782 1008 1351 1426; 6.356 6.964 6.081 6.273 6.472; 81.3 83.2 77.2
80.2 81.8];
T = [1782; 6.964; 83.2];
a= [0 0 0 0 0; 0 0 0 0 0; 0 0 0 0 0];

[pn1,PS] = mapminmax(P');
[tn1,TS] = mapminmax(T');
[an1,AS]=  mapminmax(a');
n = 25;
netnew1=newfit(pn1,tn1,n);
[netnew1,tr1]=train (netnew1,pn1,tn1);
y2=sim(netnew1,an1);

P = [1009 1268 911 969 752; 8.802 9.314 8.271 8.419 7.692; 64.5 66.6 62.7 65.9
60.5];
T = [1268; 9.314; 66.6];
a= [0 0 0 0 0; 0 0 0 0 0; 0 0 0 0 0];

[pn1,PS] = mapminmax(P');
[tn1,TS] = mapminmax(T');
[an1,AS]=  mapminmax(a');
```

```
n = 25;
netnew1=newfit(pn1,tn1,n);
[netnew1,tr1]=train (netnew1,pn1,tn1);
y2=sim(netnew1,an1);
```