UiT The Arctic University of Norway

Department of Engineering and Safety

Wind Turbine System Performance and Reliability Trend Analysis

Analysis of WT availability, capacity factor and Reliability Data

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Abstract

In the last decay grid level wind energy has contributed to the growing electricity demand and observed as great potential for future energy solution in Norway. Currently many European countries including Norway are investing in renewable energy as the preferred future energy solution. Both onshore and offshore wind energy has a great potential to become a key player in energy production, specifically in Europe's renewable energy future. Wind farm technology is known for generating electrical energy from aerodynamic force using wind turbine blades.

Modern wind turbines are complex aerodynamics that are built with mechanical and electrical machines incorporating sophisticated control systems. In recent years WTs are getting more advanced and complicated, to improve productivity and availability. With the increment of electricity generation from wind turbines, the cost reduction is at the top priority for many WF owners. Operational and maintenance uncertainties are one of the main challenges to run a cost-effective energy generation. Specifically unpredicted operational downtime and unscheduled maintenance tasks can be the key drivers for excessive operational expenses. So extra procedures must be implemented to tackle, the economic impacts that sourced from unplanned maintenance tasks and operational downtime. To that end the most critical components that contributed to unplanned maintenance and downtime must be identified, in order to plan the necessary resources.

System performance and reliability analysis are some of the key tools to improve productivity and operational performance. The analysis is highly depending on plant operational, failure and maintenance data. There are a number of wind turbine reliability data sources that have been published by different researchers. Most of these reliability data has been derived from different operational environment or WT design. These types of reliability data sources may not be qualified for every design and operational conditions, as the data may not consider the actual operational uncertainty [6]. Wind turbines operating in the arctic environment are exposed to harsh weather and winter challenges that contributes to failure frequency and operational downtime. The actual data which is gathered from the field operation represents to measure system performance, and directly related to the financial aspects of the WT. This thesis will produce and demonstrate performance and reliability data using field operational data that gathered from local plant owners.

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Notations and abbreviations

WT	Wind Turbine
WF	Wind Farm
MTBF	Mean Time Between Failure
MTTR	Mean Time to Repair
MTTF	Mean Time to Failure
MTBE	Mean Time Between Events
FMEA	Failure Mode and Effect Analysis
HAWT	Horizontal Axis Wind Turbine
SCADA	Supervisory Control and Data Acquisition
CP	Capacity Factor
CREW	Continuous Reliability Enhancements for Wind
CWEA	Chinese Wind Energy Association
NEDO	New Energy and Industrial Technology Department Organization
WMEP	Wissenschaftliches Mess- und Evaluierungsprogramm

1. Introduction

Over the past decades, the wind energy investment has been growing significantly and electrical generation from wind turbines is still an unreliable energy source as it requires frequent maintenance. Improving wind turbine productivity, reliability and maintenance resource allocation are the main performance goals of wind farm asset managers. This could be managed by using reliable components and maintenance approaches [2]. Alongside with the performance goals, the wind turbine owners should also satisfy strict governmental regulations on health, safety and environmental issues. All these requirements can be achieved by keeping all structural components in the acceptable design values.

The Arctic region has special environmental conditions for any industrial activities, such as a vulnerable environment, a rough and unstable climate and remote distances that contribute to significant challenges for all industrial operations in the region. Grid level Wind energy investment in the region is under research development and contributions from different parts of researchers is important for future energy sustainability in the region. The operational conditions and environment in which wind turbines operate often contribute to system maintenance frequency. Power generation from the system is highly unpredictable as the turbine continuously operates to variation of wind loads. In addition to wind load variation, the operational environment can be the main contributor to failure frequency. Experience from oil industry shows reliability analysis is the key to the success on improvements of machine/equipment performance and productivity. Poor levels of reliability data could result in multiple operational downtimes, which reduces productivity, increases operational expense and reduces total revenue. In contrary, good levels of reliability can reduce downtimes and improve production by reducing maintenance frequency.

Breakdown maintenance expense is the most significant part in operational and maintenance expenses on wind farms. Scheduled or unscheduled wind turbine maintenance affects overall system performance and energy output, which results in extra costs from lost revenue [3]. Wind turbine technology has been advanced to minimize failure rates of components; however, failures of some parts are continually occurring as a result of harsh environmental conditions. The component failures can be critical as it causes downtime and prevents the primary function of power generation. So those critical components with frequent failures must be identified and addressed properly for better maintenance approach.

Wind farm reliability data gathering is an important tool for engineers and manufacturers on analyzing plant productivity and design. The background of wind farm operational failure Data gathering and Analysis is to show the system reliability and serve as a reference for improved maintenance approach and minimize downtime of turbines [4]. Component or system reliability analysis approach is designed to give better understanding for wind farm owners and operators on wind turbine component failures. The efforts of reliability data can give a clear picture where to be focused to resolve these component failures and mitigate the consequences, which result in improved operations and reduced maintenance costs. In addition to Operational and maintenance improvements, reliability data is key reference for future component and system design improvements. In general, the goal of reliability data gathering and analysis actions are to minimize financial and technical challenges for wind farm owners.

Basically, component or system reliability data can be predicted from component operational failure frequencies data. Usually, failure data can be collected from wind farm owners' maintenance reports. I have experienced that; most companies are reserved opening their maintenance data as a result of profit related computation. That is one of the main reasons that maintenance and reliability related researchers use generic data for reliability analysis. Reliability analysis using simulated failure data or engineering judgement can't represent most operational conditions, so it may not be qualified as a reference for maintenance or design improvement. So, it is very crucial to consider real field operational data for better representation and improvement reference.

This thesis summarizes the maintenance and operational downtime data in order to analyze life cycle reliability for wind farm subassemblies in the Northern Norway region specifically Fakken wind farm. The analysis will apply the idea of failure mode and effect analysis (FMEA) and some graph related modelling to show the effect of changing maintenance approach on the life cycle cost of the turbines. The analyzed results can be used to recommend the optimum maintenance schedules and preventive measures.

1.1. Research Problem

There are a number factors that contributes wind turbine operational availability and reliability. These factors must be addressed properly by identifying the key operational parameters to achieve profitable energy production. The main problem that arises in this thesis is:

How to make wind energy more sustainable by applying availability and reliability analysis?

1.2. Research Questions

As it described above reliability data are vital tools for measuring effectiveness of system production. These data are important as a decision-making tool for operation and maintenance management teams. Reliability analysis aims to identify critical components/parts that have big impact for improving the overall system availability.

Based on the basis of the research problem, this thesis will attempt to answer the following questions:

What is operational, technical and production availability of WT system using partner's failure, maintenance and production data?

What is the capacity factor in of WT system using energy production data?

What is the expected failure frequency of most critical subsystems based on reliability data?

What is the average downtime for the most critical subsystems by using reliability data?

What is the average time between two successive failures for each subsystem and event type?

1.3. Objective of the thesis

The main objectives of this thesis are to improve availability, minimize Operations and Maintenance expenses, and maximize the productivity of the existing wind turbines. In order to reach these vital goals, it is important to produce applicable analyzed reliability, availability and maintenance data. These data support operation and maintenance management team;

- ❖ To identify critical subsystems that needs special attention for system improvements.
- ❖ To analyze the expected operational time before failure happens of each subsystem and event type.

- ❖ To evaluate the performance and reliability of the WT system.

Using the analyzed data, one can recommend, the best fitted maintenance and inspection strategy based on maintainability and reliability analysis.

Based on performance and reliability data, the plant owner can improve overall system energy production.

1.4. Project Outline

This project is written the following sequential order:

Chapter 2, describes basics of relevant WT subsystems and their structural integrity.

Chapter 3, explains the key factors that are used to measure WT operational performance and productivity.

Chapter 4, shows the finding from previous WT performance and reliability researches from different publishing research papers.

Chapter 5, discusses the project data gathering approach, data definition and data formatting to correspond with relevant software's.

Chapter 6, explains performance and reliability analysis methods that are specifically applied to this project.

Chapter 7, presents data related analyzed availability, capacity factor and reliability results.

Chaplter8, discusses project achievements, challenges and possible future work related to this project.

2. Basics of Wind turbine (WT)

Wind turbines are built to convert the kinetic energy in the wind into electric energy [1]. The mechanism is achieved by allowing the wind energy to generate aerodynamic mechanical energy using turbine blades. Low speed shaft which directly connected to the rotating blades, transforms the geared up rotational energy to high/speed shaft using gearbox. High speed shaft is directly connected to generator rotor and then the generator is responsible to transform mechanical energy to electrical energy. The electricity that generated from the generator then connected to the grid system.

The process of winning wind base electrical energy seems a straightforward but in practice, it is a complicated mechanism. Specially in the recent years, the development within wind power has come extra miles and advanced new technology designs expands to new level. High demands on safety, protection and energy, boost the number and size of subassemblies or components within the entire structure. However, the basics of transforming wind energy into electrical energy using conventional generator is still unchanged.

2.1. Modeling of the Turbine System

Modern wind turbine assemblies are a combination of a massive complex components that are designed to contribute in reliable energy production process. For any qualitative or quantitative system analysis can be achieved by modeling the system into a manageable fashion. The best approach to model WT assembly is subdivide the system into subsystem or subassembly based taxonomic structure. Normally, Modern horizontal axis wind turbine (HAWT) assemblies include tower which carries the nacelle and rotor subassemblies to a certain height from the ground such that turbine blades can gain enough wind power to produce electrical energy. Usually, HAWT has three rotor blades that located upwind of the nacelle and the tower as shown in Figure 1 On the top of nacelle external surface, placed anemometer and windvane that are designed to measure wind speed and wind direction [38]. The Nacelle accommodates the key turbine subassemblies such as the drive shafts, generator, gearbox, brake system and yaw system.

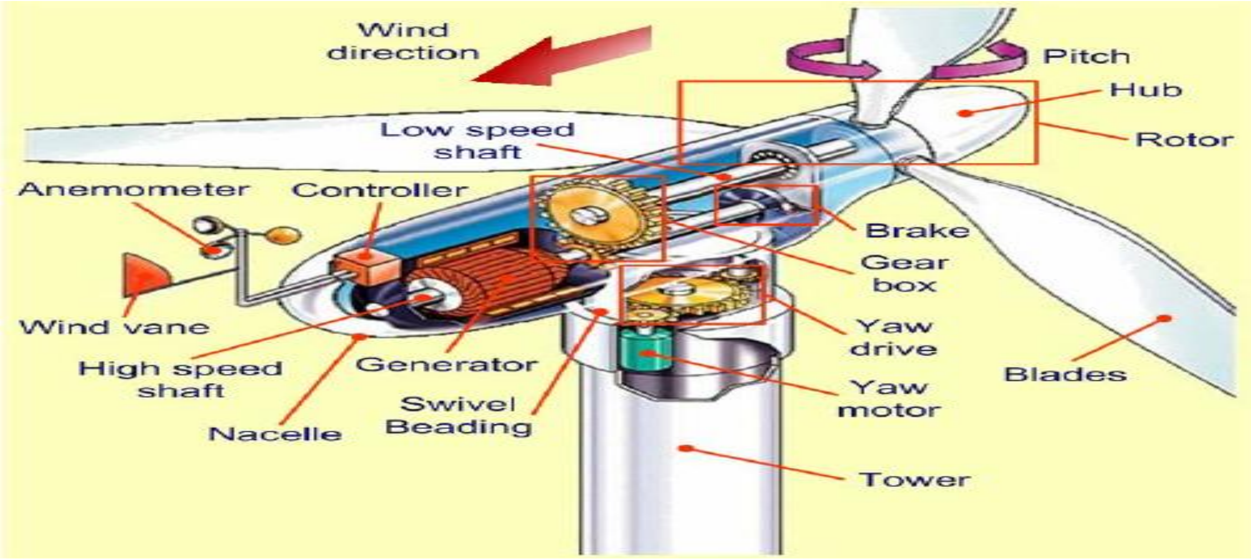

Figure 1:Basic Horizontal Wind Turbine Components **[38]**

2.2. Selection of Subsystem or Component

The selection of WT subsystem is not just a random, but a selection is based on practical application or data accessibility. So, the selection approach can be classified either based on functionality or information accessibility (data availability).

Subdividing WT assembly in a component level could be a complex task, as the system has huge number of components. To that reason, it is recommended to analyze in subsystem level in order to minimize the complexity of analysis task. functional based classification of subsystem is the most common approach to explain the system. This can be breaking the system into a reasonable number of subsystems by their features as shown on table 1.

At a times, subassembly or component can be selected for analysis. This can be applied if failure data is reported in a component level. In this case it only components that are exposed to failure or downtime can be considered in the analysis.

2.3. Typical WT Subsystem Classification

Wind turbine contains large number of small and large components that are assembled to a system. Failure or under performance of each component affects the regular operation to the entire system. However, covering each individual component failure or downtime is beyond the scope this paper. To that end, turbine assembly classified in to simple subsystem and subassembly taxonomy as shown on Table 1 The taxonomy of turbine structure helps to minimize massive failure data into a smaller group.

Subsystem	Subassembly
Structure	Tower structure Foundation Tower equipment’s Crane Internal environment
Balance of grid	Grid connection Collection and distribution Substation Converter
Electrical system	Wiring and connections Transformer Power converter PFC system Electrical protection and switchgear
Control system	Controller Ups Sensors Communication system Metrological equipment’s
Yaw system	Hydraulics Brake and clutch assembly Bearings Damper Gear system Cable twist/untwist system Drives
Generator	Cooling system Stator Rotor Housing Bearings
Gearbox	Bearings Gears Lubrication system Housing Torque arm system
Drive train	Low and High-speed Shafts Bearings Mechanical brake
Rotor	Blades Hub slipring Pitch system Aero-dynamic brake

Table 1 : Wind turbine taxonomy classification used widely by IEEE members [12]

2.3.1. Tower & Foundation

The tower is usually conical tubular structure, made of steel that are painted with anticorrosion material and it from ground foundation to nacelle. The tower should be strong enough to withstand the heavy parts on the top of the tower including environmental and operational loads. The tower attached strongly to a solid concrete and iron foundation [13].

2.3.2. Yaw System

Yaw system is attached on the tower that is designed to keep the turbine nacelle towards wind direction. The system includes bearing system and six electrical gears with motor brakes that works for directional movement. Yaw gears placed in an oil sump with lubrication oil that aimed to lubricate the yaw gears continuously. Wind sensor sends wind direction formation to the control system and yawing operation carried out automatically.

2.3.3. Generator

The V90 turbine has equipped with a 4-pole asynchronous generator that can generate up 3MW (3000kw). The generator is fitted with OptiSpeed system that helps the rotor to run at variable speed to improve aerodynamic efficiency of the rotor [7].

2.3.4. Drive Train

The turbine has two different transition shafts that are the low-speed shaft and high-speed shaft. Low speed shaft transfers rotational energy from hub to the gearbox at low speed. In the contrary the high-speed shaft transfers rotational motion from gearbox to the generator at high speed.

2.3.5. Control and Regulation system

V90 turbines has a number of complicated and advanced control system, which are responsible for various tasks. The control system is built by a number of individual sub controller. These individual sub-controllers have separate operational function that corresponds via an optical-based net-work system. All control and regulation system are managed by microprocessor-based control units that are located in the hub, in the nacelle and at the bottom of tower. The control system is supplied with battery backup system.

Wind turbine manufacturer specifies some of key characteristics of V90, 3MW turbine control system as follows;

- ✓ Follow up turbine's entire operation.

- ✓ Assessing and running the turbine during different operational faults.
- ✓ Harmonizing the turbine with the grid to limit the flow of current during the connection sequence.
- ✓ Self-regulating yaw system in the direction of wind.
- ✓ Auto pitching of the blades.
- ✓ Controlling of system environmental limit (temperature, wind speed and pressure).
- ✓ Controlling of noise emission, smoke detection and lightning strikes.
- ✓ Control for smooth and stable energy production.

2.3.5.1. Data Monitoring Sensors

Data for turbine control and regulation system gathered from various sensors that attached with the turbine components. In addition to that these component sensors are responsible to provide fault alarm data and energy production data.

The sensors are designed to gather various system condition data;

- ✓ System vibrational and lighting detection.
- ✓ Blade movement activities such that speed and pitch movement.
- ✓ Environmental conditions such that temperature, wind direction and wind speed
- ✓ Component/system operational status, for example component temperature, pressure, oil and water levels.

Generator electrical output conditions such as voltage, current, power and frequency values.

DNVGL-ST-0438 standard has described the minimum requirements of for wind turbine control and protection system. The standard is decisive to the design and verify the control and protection systems for the entire system. Turbine protection system is designed by applying descriptive and risk-based approach that each protection system developed according to turbine functional principles or risk-based approach [42]. One's suitable protection system defined and designed; control system develops using suitable software.

The component protection can be monitored automatically by the protection and control system or manually during regular inspection routine. Wind turbine control and protection depends on environmental parameters and construction of the turbine itself. The most recognized monitoring parameters are [42];

- ✓ Wind speed
- ✓ Rotational speed
- ✓ Electrical power output
- ✓ Blade angle or position of the aerodynamic brakes.
- ✓ Hydraulic pressure at the mechanical brakes
- ✓ Torque of the main shaft or driving torque of the rotor

- ✓ Blade angle and root bending moments.
- ✓ Wind direction
- ✓ Nacelle position (Yaw control)
- ✓ Automatic Ice detection

DNVGL-ST-0438 states that, when protection system activated and turbine shut down activated, the control system is allowed to restart the system automatically to a certain number (shown on table 2.).

Activated component or function	**Reset type**	**Reset limit**	**condition**
Rotational speed over operating limit	Automatic	3 in 24hrs	No safety related fault condition
Protection system activated	Manually at the turbine	None	None
	Manually from remote	Customer states	Root cause analysis and investigation of the wind turbine has to be successfully accomplished.
Blade pitch angle exceeded limiting value	Automatic	3 in 24hrs	No safety-related fault condition
Individual pitch operation exceeded limiting values	Automatic	3 in 24hrs	Faulty condition does not exist anymore
Nacelle acceleration exceeds a limit			
Cable twisting exceeded limiting value	Automatic	none	No safety-related fault condition, untwist operation finalized
Self-monitoring of control system triggered	Automatic	3 in 24hrs	No safety related fault condition
Automatic ice detection triggered	Manually at the turbine	None	No safety-related fault condition, visual inspection shows that rotor blades are ice free
	Manually from remote and automatic	None	No safety-related fault condition, sensor shows that rotor blades are ice free

Table 2. List of possible system shut down and reactivating (resetting) approach.

2.3.6. The Brake System

The turbine has two different brake mechanism that allows to stop the system when it is necessary. The first brake mechanism is performed by full-feathering the rotor blades and pitch cylinders serve as brake safety. The second brake is a hydraulic disc brake mechanism that located on high-speed shaft.

2.3.7. Rotor

The rotor includes both the hub and the blades. The blades are normally attached to the hub, which converts wind energy to rotational mechanical energy (rotational) and then transfers the rotational mechanical energy to the gearbox via the low-speed shaft. Each turbine blades are 44m long and made of fiber glass reinforced epoxy and carbon fibers [7]. The blade bearing is a double raced 4-point ball bearing bolted to the blade hub.

2.3.8. Blades

The turbine blades are produced from fiberglass and carbon fiber reinforced epoxy that are designed to maximize output and minimize noise [7]. They are attached with double raced 4-point ball bearing on the blade hub. The blades are equipped with lighting protection system.

2.3.9. Pitch System

The turbine is equipped with a microprocessor-controlled pitch control system called OptiTip [7]. The pitch mechanism is located in the hub, which is designed to regulate the blade pitch angle by hydraulic cylinders. The turbine pitch control system is responsible to regulate the blade pitch angle in order to keep the rotor speed within operational design limits as the wind speed varies. All the idea of pitch system is to protect the generator from overloading when the amount of wind speed is high. The pitch system is equipped with a hydraulic system that produces hydraulic pressure for the pitch mechanism. The system is also equipped with backup accumulator to regulate pitch angle in case of hydraulic system failure.

2.3.10. Gearbox

The main function of gearbox is to convert slow rotational speed from turbine blades to relatively high speed that needed to generate electrical energy [7]. The gearbox is equipped with forced feed oil lubrication system. Gearbox is one of turbine subassemblies that exposed to operational hardship which failure on bearings could lead for longer turbine down time and breakdown maintenance. Gearbox gears wheels and bearings are lubricated by oil which collects from separate oil tank by pump.

2.3.11. Nacelle Assembly

Nacelle subassembly is a part of turbine system that locates on the top of the tower (Figure 2). Nacelle houses all of the components that designed to exchange mechanical energy to electrical energy. The subassembly contains all the drive train components, gearbox, brake assembly, generator and controller. The assembly has flap valves that can open to the outside air in order to regulate internal air temperature when a temperature exceeds a certain given level.

Figure 2. Typical V90 Vestas Nacelle Assembly with Anemometer [63]

2.3.12. SCADA System

Supervisory control and data acquisition (SCADA) is a computer data gathering system that collects logs data from turbine sensers and sends to the central location. The system helps to simplify operational supervision and data logs tracking approach. Alle the operational or maintenance activities that shuts the system down registered and gathered in the system [4]. Furthermore, the system summarizes periodic energy production reports. The system is regularly used in order to update operators for preferable maintenance activities [4].

3. Basics of WT Operational performance and Reliability theory

In this chapter, it is going to be presented the relevant theoretical background for the research. Initially, description of the most important terms used are provided. The chapter further outlines the basics of WT Operational availability, productivity, and reliability performance theory.

3.1. Basics of Failure, Availability, Maintainability and Reliability Characterization

Failure:

Failure is the state in which a system or a component that fails to perform its intended functionality or doesn't meet its designed functionality under a given condition. When a system or a component failure appear for a several times and failure can be analyzed statically by its average value. The key failure parameters that are usually used in failure analysis are:

- MTTF (Mean time to failure)
- MTTR (Mean time to repair)
- MTBF (mean time between failure)

Mean Time to Failure (MTTF):

Mean time to failure (MTTF) is defined as the mean time to failure for the component or subsystem that is normally non repairable [34]. If a component or a system can't be repairable, then the entire operational time is equal to expected life time of the item [30]. MTTF analysis can guide to preventive maintenance in case that regular maintenance procedure can extend the life of the component and a system. In addition to that, MTTF helps to give the whole picture about spare part purchasing and reserve. As the chart representation shown Figure 3, MTTF is measured the expected span of time from time to end repair to the first or next failure.

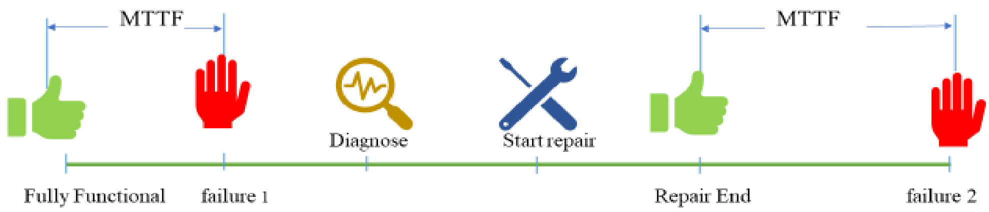

Figure 3: Detailed graphical demonstration of MTTF metric **[31].**

Generally, MTTF can be calculated by taking the total number of item operational hours and dividing them by the total number of components changed [33].

$$\text{MTTF} = \frac{\text{Total hours of operation}}{\text{Total number of component changed}} \qquad (2.1)$$

Mean Time to Repair (MTTR):

If a failed item is qualified to be maintained or repaired, then it is important to register amount time spent on repair which helps for future time allocation management. As shown Figure 4, the entire process represents the system recovery time, however repair doesn't include the notification time [34]. When a system has a number of maintenance work and repair time, then average repair time can be analyzed statically that is known as Mean Time to Repair (MTTR). MTTR analyzed as, the total amount of time used to achieve all types of maintenance work divided by the total number of the repairs [34].

Figure 4: Graphical representation of Time to recovery and time to repair.

$$MTTR = \frac{Total\ maintenance\ time}{Total\ number\ of\ repairs} \qquad (2.2)$$

MTTR calculation, determines the repair plans and the ability of organization to figure out repair issue.

Mean Time Between Failure (MTBF):

MTBF the average expected time span between two subsequent failures under normal operating conditions [35]. MTBF is generally determined over duration of time that includes several failures of a system, so that mean or average time between disruptions can be calculated. MTBF is a metric that applied for repairable systems [36].

Figure 5 illustrates brief graphical representation of MTBF of a system. MTBF can be calculated from empirical data (Eq 2.3.) or from reliability function (Eq 2.4.) [35] as;

$$MTBF = \frac{Total\ Operational\ hours}{Total\ number\ of\ failures} \qquad (2.3)$$

$$MTBF = \int_0^\infty R(t)dt \qquad (2.4.)$$

Where R(t) is reliability at a time t.

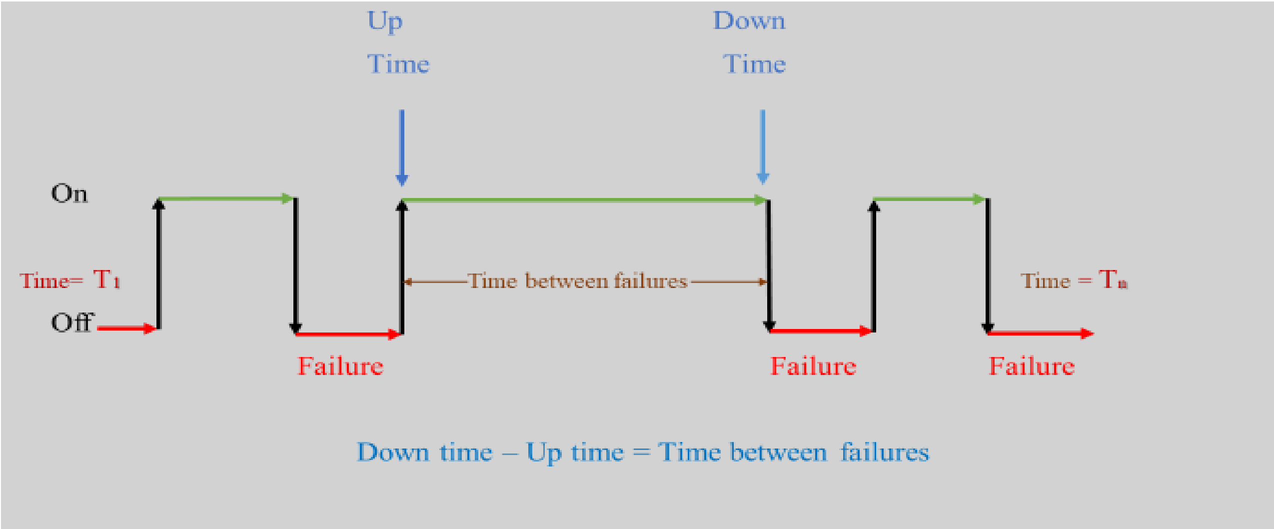

Figure 5: Simple graphical representation of MTBF metric **[32]**.

Failure Rates:

A failure rate is normally a measure of system failures over period of time. Failure rate function can be used to predict the number of expected failures in a given future time period which is represented by λ(t). When the time to recover neglected from failure rate, then the probability of failure remains constant with respect to time, so failure rate is simply the mathematical inverse of MTBF [39] (eq.2.5). The failure function expresses, the probability of failure per unit time, t, given that the component has survived to time t. Analytically, the failure rate function is given in a conditional form of failure distribution function [37], as shown in the equation (2.6);

$$\lambda = \frac{1}{MTBF} \qquad (2.5)$$

$$\lambda(t) = \frac{f(t)}{R(t)} \qquad (2.6)$$

Where f(t) is the time to failure distribution(pdf) and R(t) the components reliability at a time t.

Reliability:

Reliability is described as the probability that a device or system performs its designed function under a given conditions for a specific period of time [28]. Reliability concept is a probabilistic approach that associates a device operational plan, operational environment and operational time. The key factors to express of reliability statement are illustrated by hierarchy chart on Figure 6.

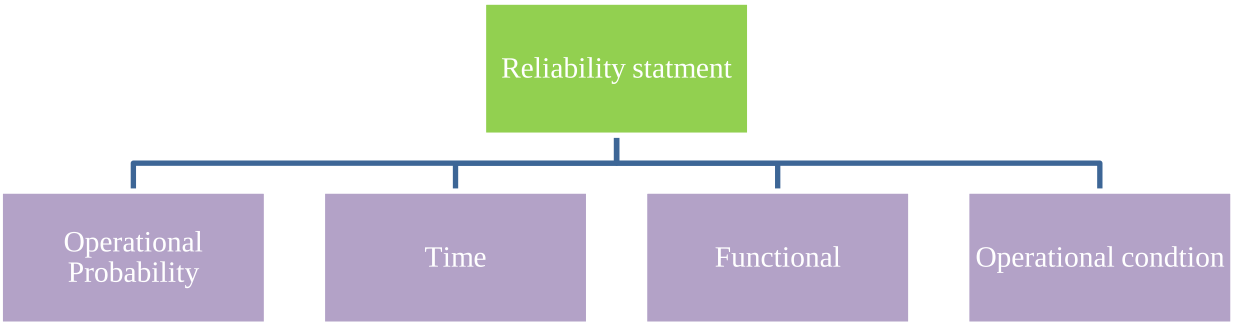

Figure 6: The key elements that describe Reliability statement.

In wind energy industry turbine lifetime is expected 20 years [28]. So, the reliability of the turbine is the probability that the turbine will perform within designed function during appropriate environmental condition for a 20-years.

Generally, life cycle of any device or product can be described by graphical representation called the bathtub curve which represents the reliability of the product in three different stages shown in Figure 7. The first stage of bathtub curve is called an infant mortality period with a decreasing failure rate followed by a normal life period with relatively low constant failure rate and at the last stage with a high wear and tear period that defines as a higher failure rate (decreasing reliability).

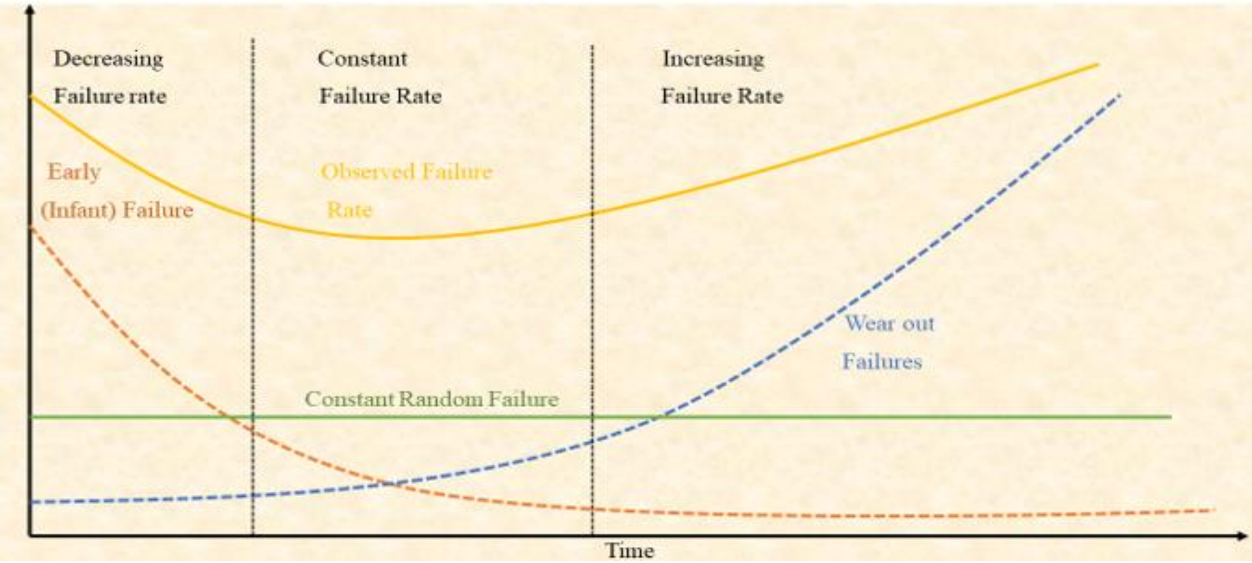

Figure 7: Bathtub curve showing early (infant mortality) failures, Normal life and wear-out failures **[29]**.

Maintainability:

Maintainability is the ability of a failed system or component to return to its normal operational status and how fast failed system can be fixed in order to restore its normal functional status. Maintenance could be breakdown, corrective or preventive depending on inspection routine and management decision. Generally, maintainability is the probability that a successful maintenance action at a time t which the probability distribution function is defined by Weibull distribution as:

$$M(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}} \qquad (2.7)$$

Where:

$t = time$, β= $shape\ parameter$ & η= $scale\ parameter$

Maintainability using exponential distribution analyzed as:

$$M(t) = 1 - e^{-\mu t} \qquad (2.8)$$

Where

t =*point of time*

μ=*repair time*

Availability:

Availability is often defined as the amount of time that a system or component is operational or ready for use divided by that total amount of time in the period of operation. A system is available when it is functional status or ready to function. In contrary the system is unavailable when it is impossible or unable to operate or to produce. The total time is defined as the total amount of time that the system is available and unavailable (downtime). Availability is directly proportional to reliability and maintainability a system [27]. All reliability, maintainability and availability relate each other in a way shown by chart on Figure 8. Generally, availability is defined by the formula shown in eq 2.9.

$$Availability = \frac{Uptime}{Uptime+Downtime} \qquad 2.9$$

The uptime is the time that the system is functioning or technically ready to function, where down time is when the system isn't in functional stand (it can be technical or environmental conditions) [11].

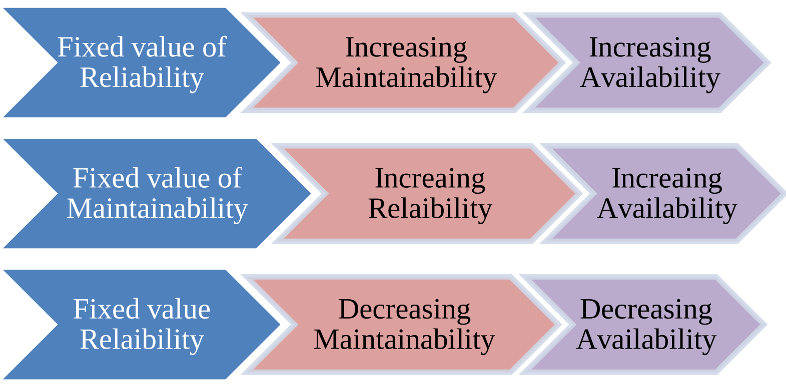

Figure 8: Basic relationships between reliability, maintainability and availability [27].

Capacity Factor:

When evaluating WT energy production performance, there are a number quantification approach that are normally taken into account. Capacity factor is one of them that measures WT production performance over period of time. Capacity factor of wind turbines is defined as the percentage of the actual annual energy production E(kWh) over the rated annual energy production from a WT [1]. Therefore, many different factors that affect the capacity factor values, these includes wind speed, maintenance and repair downtime, etc.

$$Capacity\ factor = \frac{E}{Rated\ power \times 8760} \times 100\% \qquad (2.10)$$

3.2. Wind Turbine Failure and Downtime

It is well known that the biggest challenges having wind energy is power production inconsistency, these challenges mainly come from turbines technical stand and undesirable environmental impacts [17]. These challenges should carefully study for accurate prediction of system availability and reliability. The primary approach on analyzing system downtime is acknowledging the possible system failure modes [12]. For every potential failure is identified by damaged component, possible failure mode, cause and consequences on the system safety and productivity.

3.2.1. Wind Turbine Failure Modes

Failure Modes and Effect Analysis (FMEA) is mainly to analyze or determine the critical subsystem and the effects on the system productivity [14]. Wind turbine are exposed to harish environments that the uncertainties from environmental loads could predominantly contributes on production losses.

The system fails when it is no longer functioning the way it designed. In a complicated system assembly like wind turbines, there can be numerous failure modes that contributes on availability and reliability value of the system. These failure modes can cause complete or partial loss of power production. To that end it is important to illustrate system failure tree diagram that shows the relationship between subsystem and system functional failure as shown on Figure 9.

Figure 9: Fault tree analysis diagram for wind turbine assembly **[16]**.

3.2.1.1. WT Failure due to External Loads

High wind and low wind speed are considered as one on the main environmental induced downtime factors. In most cases, wind turbines stop running, when the wind speed exceeds maximum rated limit. Most wind turbines have a maximum rated wind speed around 25m/s where wind speeds more than the rated level can generate a significant load that can cause a serious damage on the generator [18]. In contrary Low rated speed, 4 m/s in most cases, is not enough wind power to run the turbine blades.

Ice accretion around the turbines and anemometer on the top of nacelle may shut the turbine down [18]. Ice on the turbine can cause aerodynamic and mass imbalance on the turbine blades that leads to vibration on driveshaft and gearbox [19, 20]. Icing on measurement instruments like anemometer may leads to measurement and data uncertainties that alters with control and sensor operation [20].

Wind turbines are designed with certain range of safe operational temperature. The turbines may shut down, if the operational temperature goes out from the rated value [18]. DNVGL-RP-0363 [21], states that as a standard, the normal operational temperature ranges from -10°C to +40°C, however in an extreme condition, the operational temperature range goes from -20°C to +50°C.

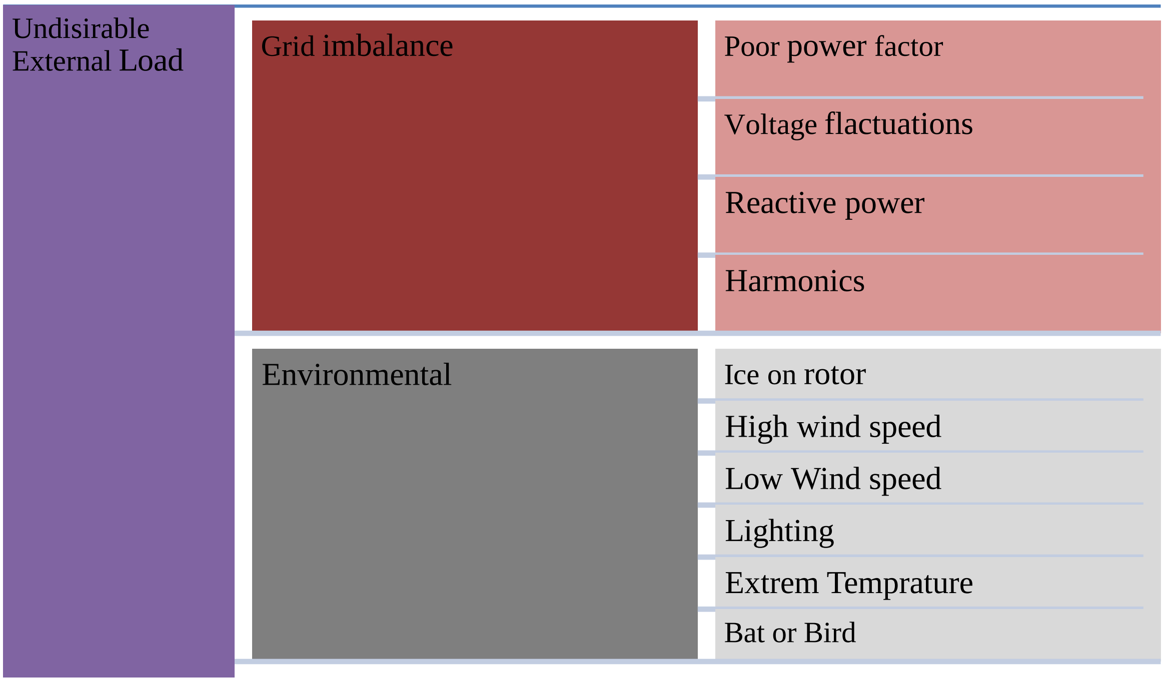

Figure 10: Fault tree analysis for wind turbine undesirable loads **[19,20,22]**.

As number of wind turbines growing, there are some challenges related to the quality of the electrical power delivered to the grid [24]. The challenges are primarily appearing in current harmonics, responsive power, and power factor [22][23][24]. As illustrated, Figure 10, these grid related challenges can be one of the reasons for production downtime or weak power quality in the supply line. The factors like voltage fluctuations, reactive power, poor power factor, and harmonics distortion are some of uncertainties for production of sustainable wind energy production.

3.2.1.2. WT System Technical Failure Modes

Modern wind turbines are getting larger, complicated and contain large number of components that contributes to a higher failure rate. The failure rates vary with the operational condition and plant location. Wind turbine system failure modes can be analyzed by the failures that occurs in the various main subsystems as illustrated in Figure 11.

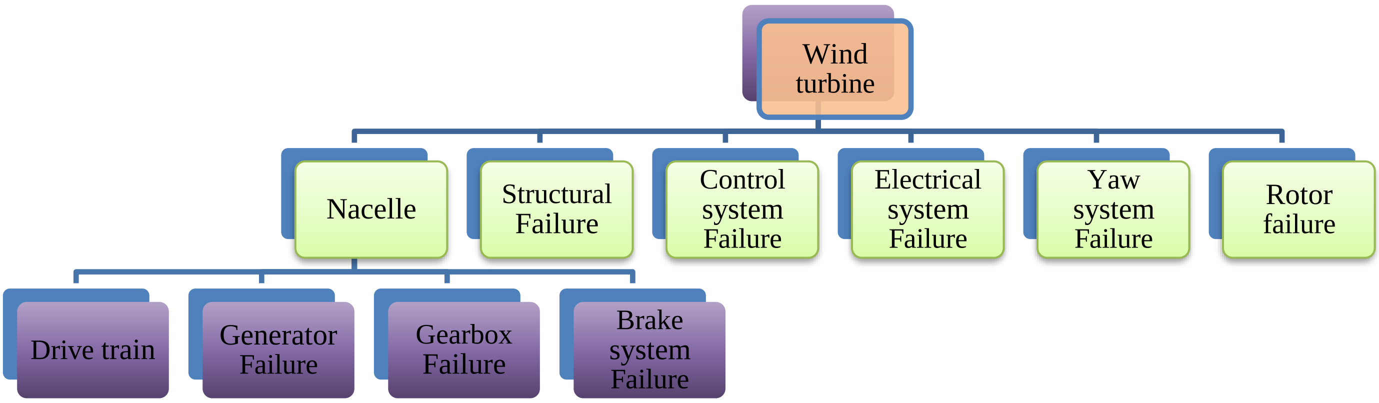

Figure 11: Fault tree for WT with its basic subsystems.

3.2.2. WT Failure Causes

The most recognized wind turbine system failure causes are component wear or damage, loosing parts, fault on control system, excessive wind load, grid malfunction, icing, lighting, other causes and unknown causes [25]. The database has analyzed the possible failure root cause for different wind turbine components as shown on Tables 3,4,5.

Failure mode	Cause	Mechanism
Too low magnetization and demagnetization	Underestimated operating temperature on design level Magnet estimation error in design level.	Overheating and material failure
Magnet Detachment	Manufacturing error	
Electrical failure of windings or Loss of insulation in the winding	Poor winding insulation quality in design and manufacturing level. Insulation degradation due to service time and overload Vibration on structural elements holding winding coils.	Electrical or insulation fault Mechanical failure (mainly bearings) Material degradation due to service time.
Insufficient cooling	Poor ventilation capacity	Various reasons.

Table 3: Essential failure modes and causes of generator **[40]**.

Failure mode	causes	Mechanism
Wear of raceways	Low lubrication oil	Material failure, fatigue
Wearof roller	Overload	Mateial failure, fatigue
Blockage	Poor lubrication on local area	Material wear out
Material cracking	Poor materail quality or overload	Material failure, fatigue and micro pitting
Insufficient oil cooling	Fualt in lubrication line	Various or temprature related effects

Table 4: Essential failure modes and causes of gearbox **[40]**.

Failure Mode	Cause	Mechanism
Leakage from the hydraulic system	Poor fittings either from design or manufacturing stage	
Electrical related fault	Overheating	Overheating drives to high deterioration rate on insulation and other parts. Defect other electrical parts
Leakage from lubrication system	Fault couplings	Crack or breakage
Signal fault	Sensor misalignment	External impacts on sensor

Table 5: Essential failure of yaw system.

3.3. Wind Turbine Standards

The International Electrotechnical Commission (IEC) has promoted the IEC 61400 document that specifies the minimum design requirement for wind turbines. The document indicates key design requirements to ensure the technical integrity of wind turbines. Its aim is to contribute for a standard level of safety and protection against all damage during turbines life time. In addition to IEC 61400, DNV GL standard can be applied in Norway as the technical certification for wind turbines.

Implementation of wind turbine plant is a complex process that needs to consider a number of production and safety uncertainties. Turbine wind class is one of the key factors that determines the type of turbine for the specific location. IEC 61400-1 describes turbine classes by three different parameters that are turbulence/wind class, annual average wind speed and extreme 50-year gust. Turbulence severity specified with the variation of wind within 10 minutes as shown on Table 6. It is well recognized that turbulence is one of the main reasons for fatigue loads and component failure [41].

Wind classes/turbulence	Annual average wind speed at tower height	Extreme 50-year gust
High Wind - Higher turbulence 18%	10 m/s (36 km/h; 22 mph)	70 m/s (250 km/h; 160 mph)
High wind – Lower turbulence 16%	10 m/s (36 km/h; 22 mph)	70 m/s (250 km/h; 160 mph)
Medium wind - Higher Turbulence 18%	8.5 m/s (31 km/h; 19 mph)	59.5 m/s (214 km/h; 133 mph)
Medium wind – Lower turbulence 16%	8.5 m/s (31 km/h; 19 mph)	59.5 m/s (214 km/h; 133 mph)
Low Wind - Higher turbulence 18%	7.5 m/s (27 km/h; 17 mph)	52.5 m/s (189 km/h; 117 mph)
Low wind – Lower turbulence 16%	7.5 m/s (27 km/h; 17 mph)	52.5 m/s (189 km/h; 117 mph)

Table 6: Turbine wind class intensity level **[43]**.

3.4. WT Maintenance methods

As any types of equipment or machinery, WTs requires the standard maintenance procedures. Maintenance approach can be either corrective or preventive. Corrective maintenance can be achieved after breakdown or failure is identified. In contrary, Preventive maintenance can be carried out either in prior to failure or manufacturers maintenance requirements. In general, three different types of maintenance approaches are known in WT industries, these are corrective, condition-based and scheduled maintenances (shown on Figure 12).

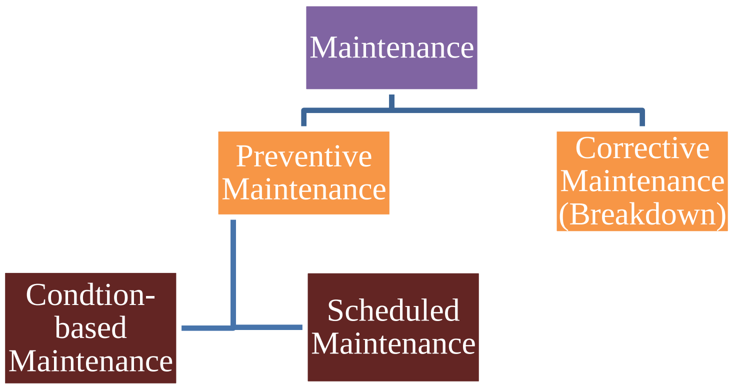

Figure 12: Classifications of maintenance approaches **[8]**.

3.4.1. Corrective Maintenance

Corrective maintenance associates with the replacement or repair of equipment after recognition of component or system failure [65]. Corrective maintenance aims to bring the system or the component back to its normal operational status. This type of maintenance is the most prioritized type as it influences directly to safety and production of the equipment.

As a times Corrective maintenance strategy is applied, when [66];

- ✓ There is no significant functional failure to the system operation.
- ✓ There is no harm to the safety of the system or operator.
- ✓ The expense of breakdown maintenance is less than the preventive maintenance.

Usually, breakdown maintenance requires production loss as a result of unexpected failure related downtime and repair time.

3.4.2. Preventive Maintenance

Preventive maintenance refers as an ordinary, routine maintenance to keep a system in proper function and prevent unexpected downtime and expense related accidental component failure [14,65]. Preventive maintenance is applied regularly in order to extend component failures or stop failures occurring. There are two most common types of preventive maintenance [14];

- ✓ condition-based maintenance.
- ✓ scheduled maintenance.

3.4.2.1. Condition-Based Maintenance

Condition based maintenance is a maintenance approach based on routine inspection or sensors that gathers data about component/system status (e.g., vibration sensors, temperature sensor, number of particles). The components are supposed to operate to a predefined condition of wear and fatigue. Generally, the physical Inspection or sensor information that guides for maintenance task if a component or a system requires functional improvement.

Monitoring the functional status of components used to support for planning maintenance work, prior to failure that will minimize operational downtime and maintenance expenses [14]. In addition to that the statistical data of condition-based system is vital to gather reliable data about the lifetime of the key components in the system.

Figure 13 illustrates an example of condition-based maintenance along with corrective and scheduled maintenance graphically.

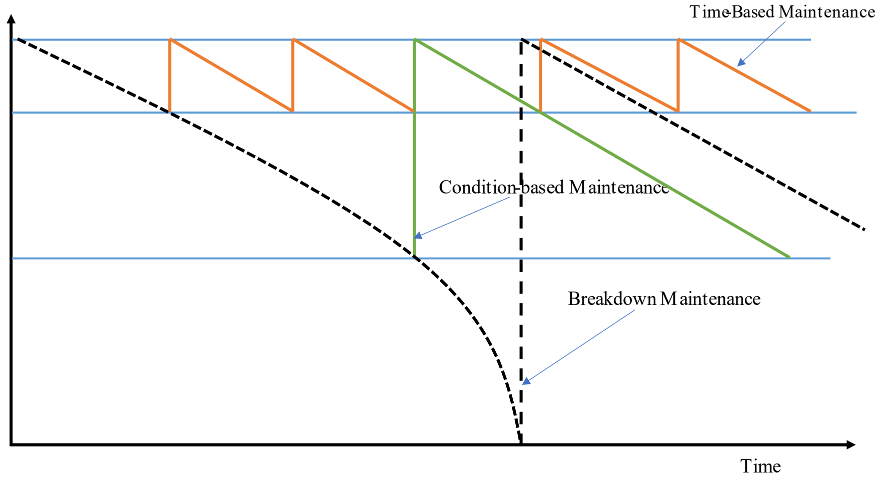

Figure 13: Condition based maintenance compared to Time-based and Breakdown (corrective) maintenance [62].

3.4.2.2. Scheduled Maintenance

Scheduled maintenance is one of preventive maintenance approach, performed based on a fixed time schedule. Often, this type of maintenance approach is periodic based that complies manufacturers instruction, for inspecting, changing and cleaning that helps to keep the system in good functional condition. Sometimes maintenance schedule can be defined by the operator depending on the criticality of the system to the owner or preferable timeline (such that during low production time or less needed time).

4. Existing WT performance and Reliability Researches

This section covers the previous research's and finding related to wind turbines availability and reliability results. The existing results are important to deepen the knowledge on operational characteristics in respect to installation site, turbine type and other types of uncertainties in the wind energy sector. To that end a number of relevant data collected from different researches. The result doesn't need to be similar or can't compared due to their diversity on [44];

- Installation location: location can be onshore or offshore.
- Country: Data observation location and responsible institution.
- Number of wind turbines: Number of wind turbines owned.
- Turbine Operational years: Turbines active years.
- Survey period: Data collecting time period.

Initiative	Country	Number of WT	Turbine location	Start of Data survey	End of data survey	reference
CREW data	USA	900	Onshore	2011	2013	[45]
NEDO data	Japan	780	Onshore	2014	2018	[58]
CWEA	China	751	Onshore	2010	2012	[46]
Garrad Hassan	Internatio nal	250	Onshore	1992	2007	[48]
Muppandal	India	15	Onshore	2000	2004	[50]
WMEP	Germany	1593	Onshore	1989	2008	[55]
WinD-Pool	Germany	456	Offshore	2013		[54]
Round1 offshore	UK	120	Offshore	2004	2007	[51]
SPARTA	UK	1045	Onshore	2013	Ongoing	[52]
Elforsk/vindstat	Sweden	786	Onshore	1989	2005	[47, 49]
VTT	Finland	96	Onshore	1991	Ongoing	[53, 59]
CIRCE	Spain	4300	Onshore			[60,61]

Table 7: An overview on the existing research reviewed in this paper.

A brief description of every researching institution and initiative can be found in Section down.

4.1. CREW-Database

The CREW-Database (Continuous Reliability Enhancements for Wind) and Analysis program was initiated in 2007 to compile operational data and update onshore WT data. The program is based in USA and run by Sandia National Laboratories. The recent data survey that was analyzed and published is from 2012. The General data survey covers from10 different WF that includes up to 900 WT with total power production 1400MW [56]. The results were generated from the collected alarm logs, however the maintenance data was neglected, to that reason the failure rate and mean down time may not qualified to correlate with other initiatives [56, 57]. CREW [56] analyzed WT system performance using the survey data and compared the result with earlier results as summarized on Table 8.

Performance measure	2012 Benchmark	2011 Benchmark
Time-Based Availability	97.0%	94.8%
Capacity Factor	36.0%	33.4%
MTBE (Mean Time Between Events)	35 hrs.	28 hrs.
Mean Downtime	1.6 hrs.	2.5 hrs.

Table 8: CREW WT performance measurement results.

WT reliability can be represented by two basic conditions of downtime [56];

- The rate of downtime events that how often operational downtime occur.
- The downtime duration that the amount of time the system is operational unavailable.

Valerie et al. has illustrated (figure 14) there finding on downtime in subassembly level that shows their overall contribution to system failure frequency and downtime duration. The unit of downtime frequency is given by the Annual Number of downtime events per calendar Year per Turbine. Down time duration is given by Mean Downtime per Event, which is the average time of a single downtime event, in hours.

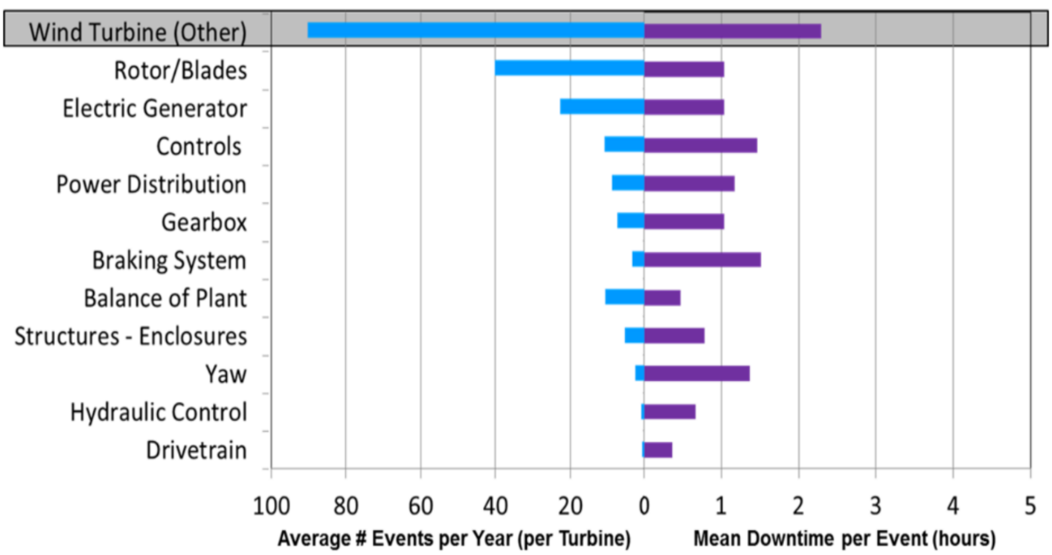

Figure 14: Unavailability contributors, system event frequency and downtime **[56]**.

4.2. NEDO-Database

New Energy and Industrial Technology Department Organization (NEDO) is Japanese based initiative, that collects WT failure, repair cost and downtime data since 2004 within the country [58]. Kikuchi et al. was provided the data for fiscal years 2014-2018 for availability and LCOE (Levelized cost of Energy) analysis purposes. A total of 780 WT are represented by 1663 failure and downtime reports. The purpose of analysis was to investigate the characteristics of WT failure rate and downtime between Japan and Europe. Failure data are gathered by categorizing system subassemblies as such as (blade, hub, grid connection equipment, main shaft/main bearing, gearbox, brake, electrical system, control system, yaw, pitch, hydraulic, foundation, general, no failure assembly, unknown). Failures that are categorized as general, no failure assembly and unknown are excluded from the analysis to make the discussion clear. Kikuchi et al. predicted capacity factor and technical availability as it summarizes on Table 9. and they found that maintenance time in Japan is longer than that in Europe, this is due to Japan's WT industry immaturity [58]. As a result, it is obvious that low availability expected in Japan.

Performance metric	**Average performance value**
$T_{Downtime}$ (hours/turbine)	970 h/turbine
$T_{Scheduled}$ (hours/turbine)	135 h/turbine
T_{Total} (hours/turbine)	1105 h/turbine
Technical Availability	87 %
Capacity factor	22 %

Table 9: LCOE performance parameters using NEDO failure data.

4.3. CWEA-Database

CWEA (Chinese Wind energy Association) is originally from China generated a data on performance and reliability based on the information on total number of failures per sub assembly [46]. Total of 751 WT failure data surveyed between 2010 and 2012 in collaboration with a number of wind turbine manufacturers, developers and spare part suppliers. Lin et al. points out the lucking of detail information about the subassemblies can make the result immature. In addition to that, there was a missing data about system structure, failure severity and downtime information [46]. Using CWEA data, Lin et al. predicted technical availability 97%.

4.4. Garrad Hassan

Garrad Hassan has gathered and analyzed hundreds of operating wind farms worldwide for the 10 years. Hassan et el. has presented their research regarding operational (time based) availability of wind farms at AWEA wind power conference in Houston. The research was performance-based assessment for 14 GW of functional wind farms. The availability data includes for more than 300 wind farms located worldwide with a rated power between 300KW and 3MW [48].

The assessed data shown in Figure 15 is the distribution of annual availability. This distribution illustrates the rate of occurrence of different levels of availability that have been observed periodically, and comparing related with the industrial standard availability (97%). [48]

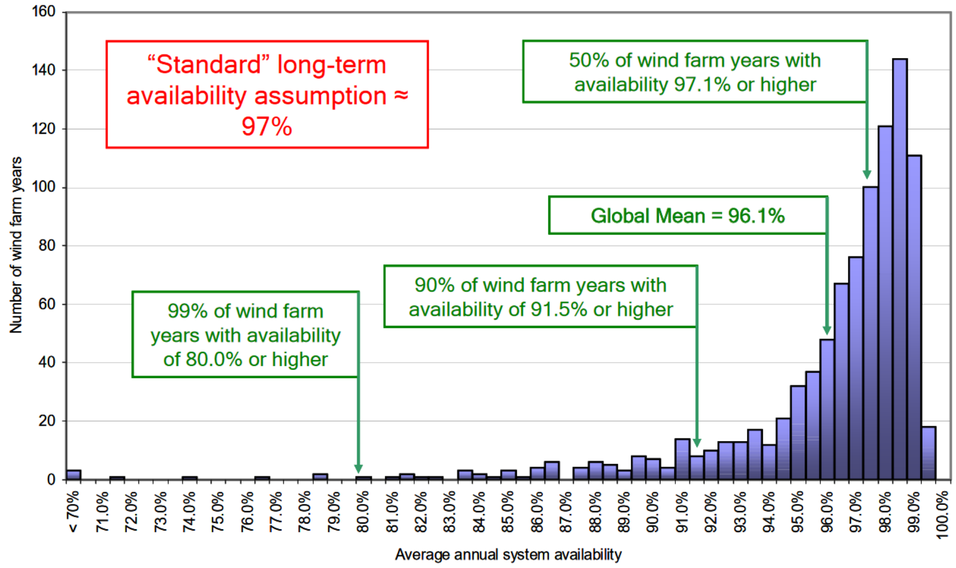

Figure 15: Garrad Hassan's distribution of average annual availability [48].

4.5. Muppandal Wind Farm

Herbert and his partners presented a paper on analysis of failure, spare parts, performance and reliability for wind farm that includes 15 WT. The wind farm is located at Muppandal, Tamil Nadu, South India area and each WT has a rated capacity of 225 Kw [50]. Using five years failure, maintenance and production data (Table 10), Herbert et al has analyzed mean performance value such as technical availability, time-based availability and capacity factor for the wind farm were 94%, 82.88% and 24.9% respectively as illustrated on Figure 16.

Performance data of 3.735 MW wind farm.

Year	2000	2001	2002	2003	2004	Total
Generation (kWh)	7,246,119 (19.7%)	7,215,905 (19.6%)	7,480,740 (20.3%)	7,430,162 (20.2%)	7,480,229 (20.3%)	36,853,155
Generation Time (hrs.)	103,943 (20.1%)	101,625 (19.6%)	106,558 (20.6%)	100,694 (19.5%)	104,574 (20.2%)	517,394
Grid Failure Time (hrs.)	5924 (20.4%)	5963 (20.5%)	4796 (16.5%)	6165 (21.2%)	6216 (21.4%)	29,065
Low Wind Time (hrs.)	20,188 (20.0%)	20,126 (19.9%)	19,179 (19.0%)	23,409 (23.2%)	17,986 (17.8%)	100,887
Control panel failure Time (hrs.)	39 (10.9%)	91 (25.4%)	63 (17.6%)	107 (29.9%)	59 (16.5%)	358
Electrical Failure Time (hrs.)	736 (31.3%)	634 (27.0%)	233 (9.9%)	268 (11.4%)	477 (20.3%)	2349
Mechanical Failure Time (hrs.)	381 (7.5%)	2280 (45.1%)	216 (4.3%)	352 (7.0%)	1826 (36.1%)	5056
Preventive Maint. Time (hrs.)	547 (21.0%)	679 (26.0%)	354 (13.6%)	404 (15.5%)	621 (23.8%)	2607

Table 10: Muppandal Performance data of 3,735 MW wind farm **[50]**.

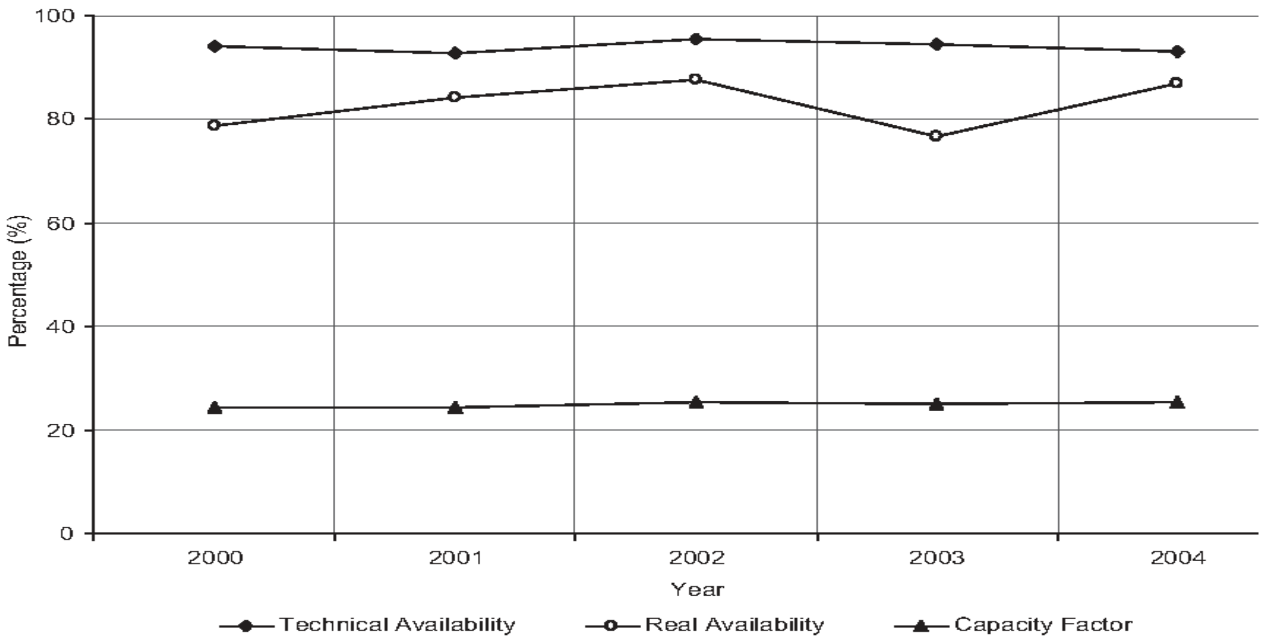

Figure 16: Comparison of Muppandal Technical availability, Real availability (time-based) and Capacity Factor **[50]**.

4.6. WMEP

The WMEP-Database (Wissenschaftliches Mess- und Evaluierungsprogramm) is German based wind power researching group that initiated in 1989. In 2008, WMEP produced a research document for about 18 years (1991-2008) on performance and development of wind power system in the country [55]. The group aimed to produce mathematical proven wind energy generation data in order to evaluate the economics of power generation. The group has studied for 1500 WT with total volume of 350MW power generation since 1996. The group has gathered around 63000 maintenance reports to generate availability, reliability, O&M costs, failure and average downtime. WMEP has published yearly and location based technical availability as illustrated on Figure 17.

WMEP team has used maintenance reports as source of precise information on failures and downtime figures. The annual failure rate (downtime frequency) and downtime duration per failure are drown in the adjacent illustration shown on Figure 18. The illustration shows that in particular, there is a frequent event of failures relating to the electrical system, but excluding generator, relatively quick recovering rate. In case of downtime duration, in most cases average 1 to 1.5 days downtime (repair) duration for each repair activities. However, repair of generator and drive train requires from 5 to 7 days downtime duration at a times [55].

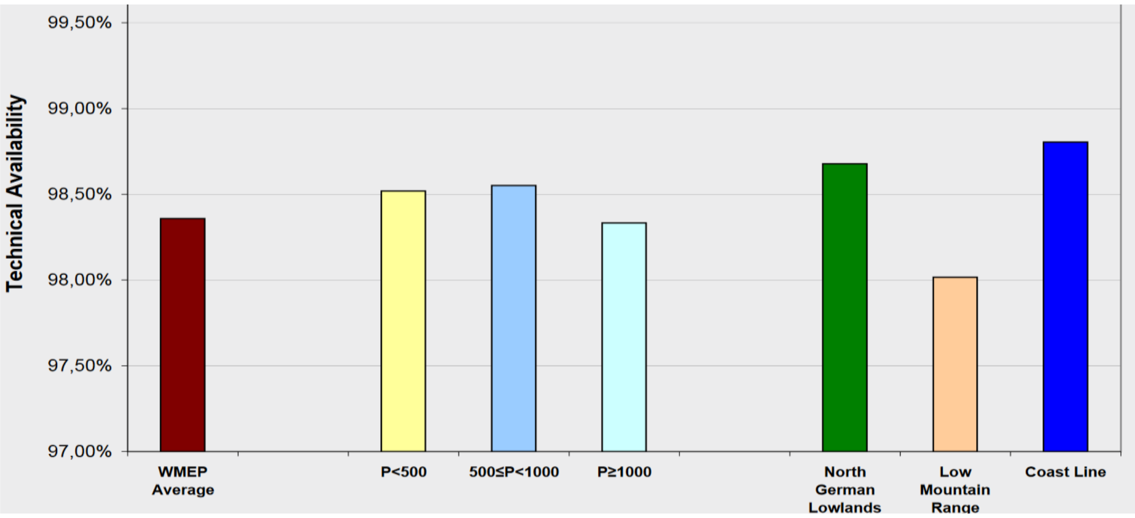

Figure 17: WMEP Mean technical availability for many years and diverse power classes WF site **[55]**.

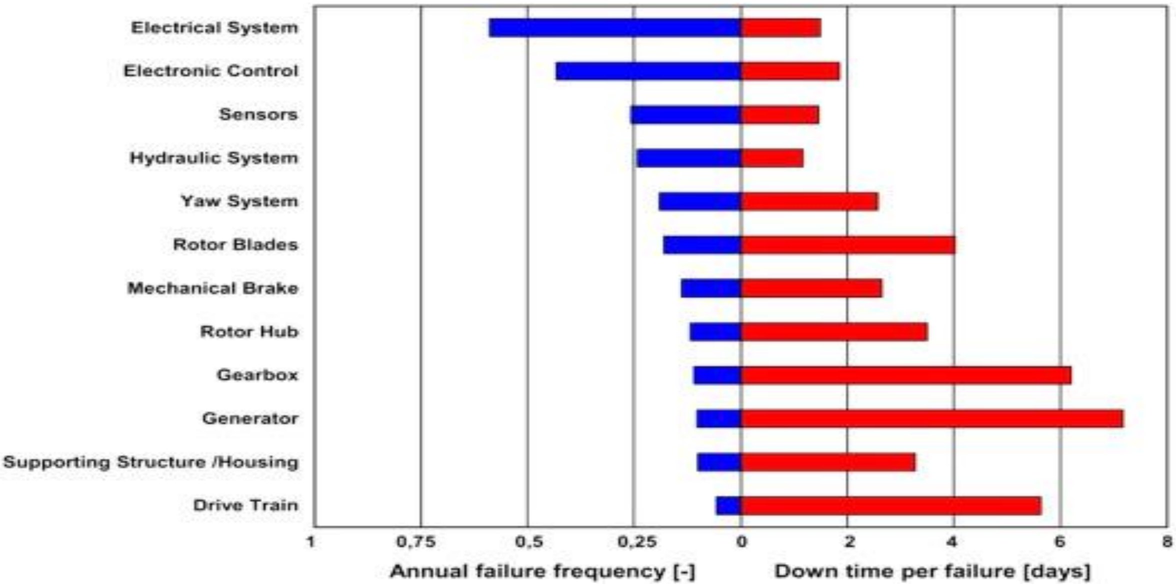

Figure 18: WMEP Failure frequencies for subassemblies and typical downtime duration per failure **[55]**.

4.7. WInD-Pool

WInD-Pool (Wind-energy-information-data-pool) is a joint effort of leading turbine operators and Fraunhofer IWES within Germany and other parts of Europe, that promotes operational experience into knowledge. The group task was collecting operational (SCADA) and maintenance data according the standards. WinD-pool analyzes wind turbine performance and reliability using the collected operational and maintenance data. As an exemplary result, WInD-pool analyzed availability values based on 158 offshore and 200 onshore wind turbines [54] as shown on Table 11. In the evaluation of availability, data gaps are considered as downtime.

Turbine location	Number of WT	Data period	Time based availability	Energy-based availability	Capacity factor
Offshore	158	2011 to 2014	92,2%	88,1%	18,4% for 1610 hours of full load
Onshore	200	2013 to 2014	94,1%	92%	39% for 3422 hours of full load

Table 11: WInD-Pool Operational performance (availability & CF) for onshore and offshore WTs.

4.8. Round 1 Offshore Wind Farms

The round 1 offshore wind farms provided operational reports for the sites initiated in 2001, were funded by the UK Department of Trade and Industry's. The report reviews the performance of four different offshore wind farms during their early operational phase, for the periods 2004 to 2007. Feng et al. published the analyzed results such as cost of energy, capacity factor and technical availability (see Table 12). The performance result was based on failure and downtime data collected from 120 WTs with total rated power 300MW [51].

WF site	Turbine type	Annual average wind speed m/s	Total capacity MW	No of Turbines	Capacity factor %	Technical Availability
Barrow	V90	9,15	90	30	24,1	67,4
North Hoyle	V80	8,36	60	30	35,0	87,7
Scroby Sands	V80	8,08	60	30	27,1	81,0
Kentish Flats	V90	7,88	90	30	27,7	80,4
Annual average					29,5	80,2

Table 12: Operational performance of four different UK round 1 offshore WF.

4.9. SPARTA

SPARTA is a joint initiative of offshore WT owners and operators started in 2013 in order to create WF performance and maintenance database sharing channel within the member. SPARTA is UK based initiative that the name stands for "System Performance, Availability and Reliability Trend Analysis". Through the members common interest agreement (MCIA), SPARTA collects web-based operational data and Key Performance Indicators (KPI) from participating members, that can be used for WT performance improvement activities. SPARTA has published the latest KPI report in august 2019 and the report is based on 12 months data (April 2018-March 2019). The data was collected from 9 operators with 19 WF and 1256WT with total capacity of 4467MW [52]. SPARTA has reported estimated mean performance values such as production (time-based) availability 95,15 % and capacity factor 36,05 % from the given data.

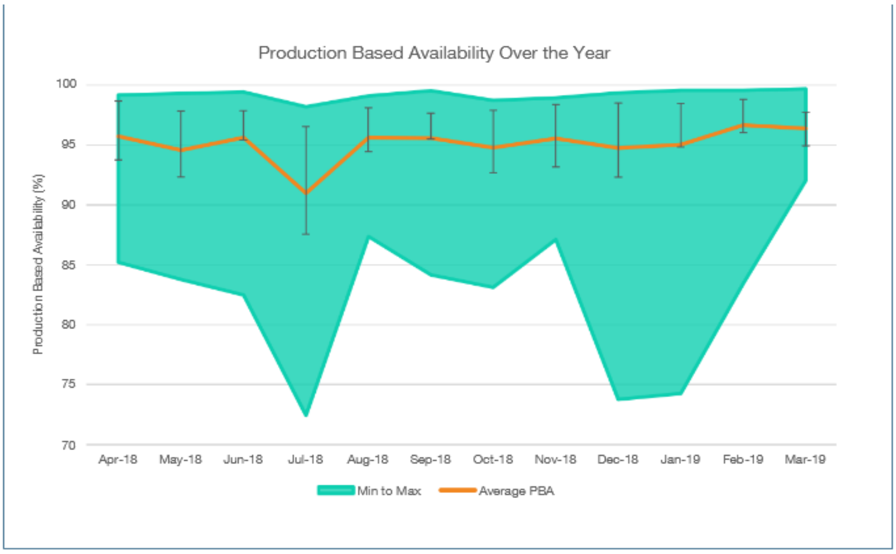

Figure 19: SPARTA production-based availability over the year **[52].**

4.10. Elforsk/Vindstat

Elforsk is an initiative based in Sweden that gathers WT data and analyses operational performance. Reports that cover performance trends over time in terms of efficiency, availability, capacity and geographical distribution publishes annually by Vindstat [47]. The recent publication by Swedish energy authority was 2012 which the study covered for the years 2003 to 2012. For this time of period, they have collected and analyzed data for 1349 WT with the capacity of 2150 MW in 9 different WF. The study shows the average time-based availability value 95% and capacity factor 0,247 [47]. In order to compare system performance over the years, the average availability and CP values calculated as shown on the Table 13 [47].

Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Availability	99.8	99.0	98.7	98.2	95.8	95.5	95.6	95.0
Capacity factor	0.203	0.190	0.238	0.243	0.222	0.212	0.273	0.247

Table 13: Elforsk/Vindstat average wind turbine performance figures over years.

For his master's thesis, J. Ribrant et al. had gathered WT failure data from Elforsk database, which the data was initially collected by Swedpower AB. The data was based on manually prepared failure reports that included for 624 WT in operational periods 2002- 2004 [49]. Using the collected data, Ribrant has analyzed annual failure frequencies and downtime duration per turbine in subassembly level as illustrated in Figure 20. The analysis represented, the average values for all types of turbines and he points out that all turbines may not have hydraulics or gearbox.

The key findings are the annual failure frequency 0,402 and average downtime duration 130 hours and these figures illustrates Yaw system, drive train and gearbox are the most critical subassemblies.

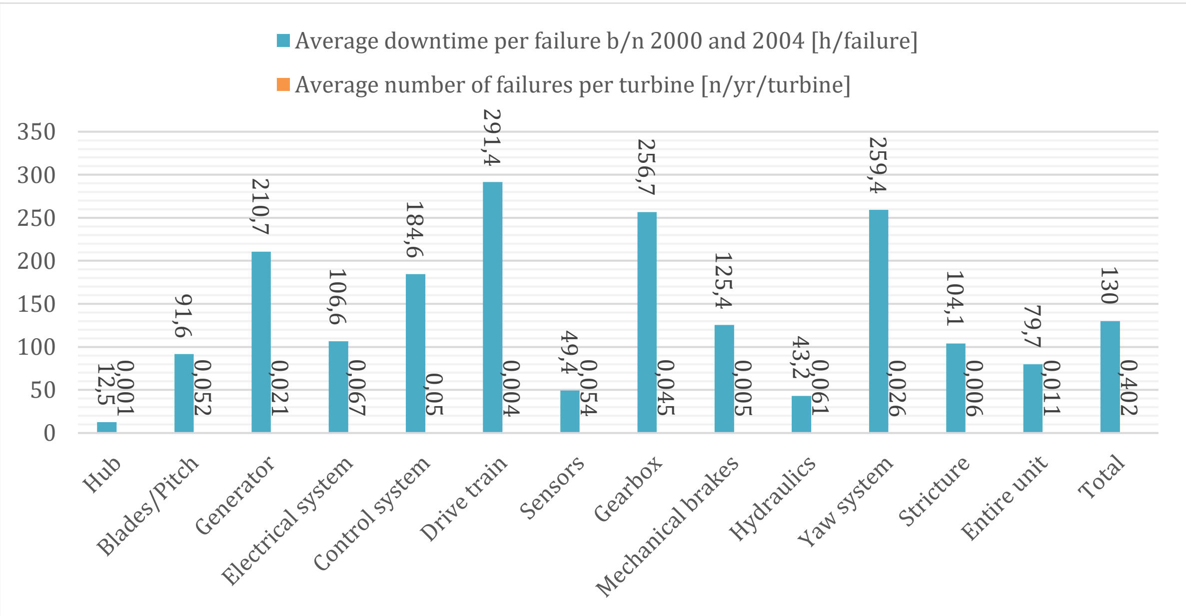

Figure 20: Downtimes and failure frequencies for Swedish wind power plants 2000-2004.

4.11. VTT

VTT as a part of technical research center of Finland, analyzed WT performance using existing wind turbines within the country. Development of Wind Power plant downtime, failure and production data gathering is an ongoing process since 1991 [53, 59]. VTT's recent published study was for the periods 1996 to 2008 which, the analysis includes data from 72 of Finland's 116 wind turbines and corresponds to

a total capacity of 73MW production capacity. The largest turbine power groups are 600 kW, 1,000 kW and 2,300 kW [59]. Holttinen et al. have calculated average capacity factor of wind turbines, which operated the whole year, was 22 % while average technical availability of the wind turbines was 96 % in 2008 [53].

4.12. CIRCE-Universidad de Zaragoza

CIRCE-Universidad de Zaragoza is an initiative from Spain who gathered CM (fault alarm) and Failure Data from different WF around the globe [61]. M D Reder et al. has gathered data from 4300 WTs that associates to 230 WF with total average annual capacity of 5818 MW. The turbines are with a rated capacity between 300kw and 3MW from different manufacturers. In total 440 WTs were analyzed over a period of three years. The various types WT are indicated by their rated power and drive train structure (either direct drive or geared) as shown Table 14. In total 653 failures and 1345036 CM alarms were recorded and processed. There huge amount of data from CM alarm as a result, it was only alarms characterized as problem or failure were considered in the analysis. In total around 7000 failure events/shut downs are considered in the analysis [60, 61]. This task contributes to solve the key issues on WT reliability modeling. Total failure rates and turbine downtime per year, for different turbine capacity and categories shown in Table 15.

WT Make	**Drive Train**	**Rated Capacity (KW**	**Number of Turbine**	**Failures Per Turbines**	**Alarms Per Turbine**
A	Geared	1500	55	0,709	4170,07
B, C	Direct Drive	2000	57	0,632	1120,35
D	Geared	850	77	2,208	2778,78
E	Geared	2000	168	1,780	4704,57
F, G	Geared	1800 &2000	83	1,313	572,14

Table 14: Data used for the CM alarms and failure analysis.

WT Capacity/Drive Train	Failures/Turbine/Year	Downtime/Turbine/Year	Downtime/Failure
Geared < 1 MW	0,46	78,46 hours	151,46 hours
Geared ≥ 1 MW	0,52	44,51 hours	112,67 hours
Direct Drive	0,19	20,50 hours	34,98 hours

Table 15: Total downtimes and failure frequencies calculated for various WT types.

4.13. WT failure Contributing Factors

In order to improve WT performance and reliability, it is essential to understand the failure modes and the root causes. Using a data from WMEP, S. Faulstich et al. analyzed around 64,000 maintenance and repair reports from 1500 for a period of 17 years [25]. To that end the team summarized the possible failure root causes in component level, using chart illustration shown in Figure 21.

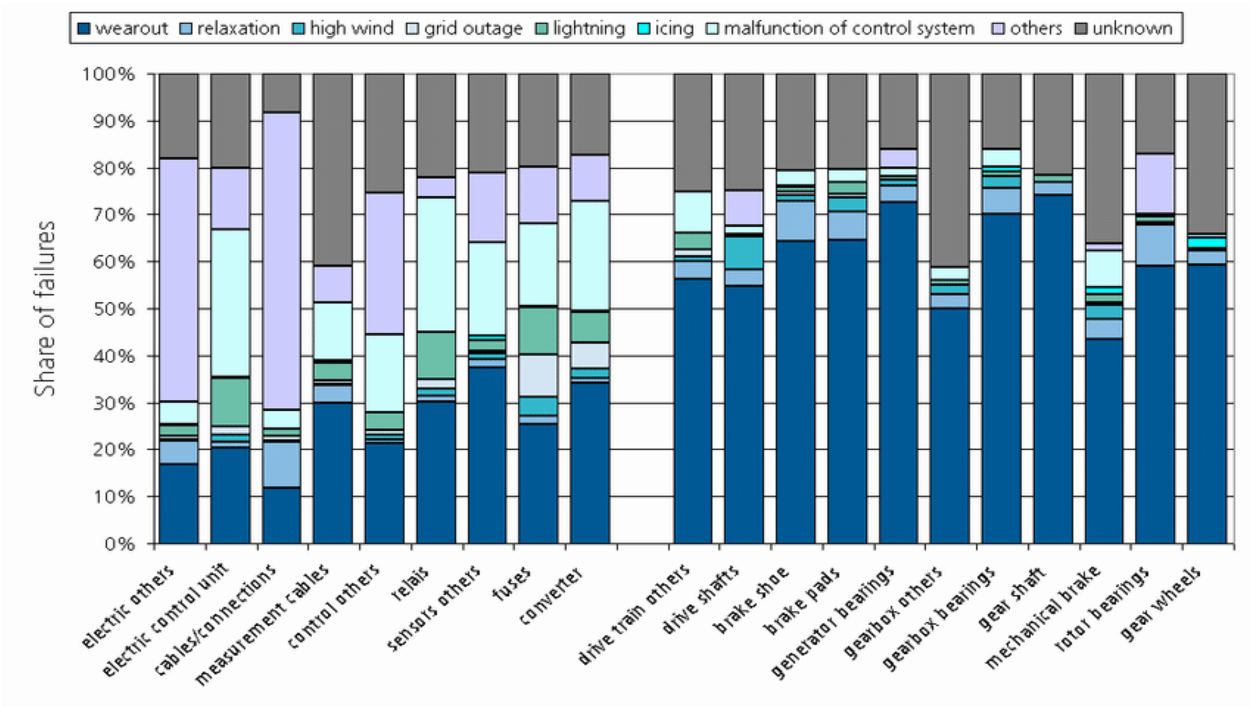

Figure 21: Failure causes for different components WT.

4.14. Discussion about the Reliability of the Statistical Database

All the initiatives shown above has shown WT performance and reliability that gathered from various types of data that covers different design, capacity and time span. However, is the data really decisive or reliable? When performance and reliability data are being analyzed, it important to rise a number of issues:

During major failure event, such that fire incidents on major subassemblies, as a result repair and downtime could be substantial. In this case we can't just consider failure event for a year, but the failure trends have to be examined for many years.

There is a continuous design and reliability improvements within the wind power industry, so the existing database may not be applied for new design wind turbines. For example, new types of WT are accompanied with sensors and self-diagnosing/self-protecting system that protects the system from major failure events, in addition to that early-stage failure incidents might be minimized with design improvement. Therefore, it is important to evaluate database system, if it is relevant to the turbine type or design.

Most initiatives collected and evaluated the data from the wind power production, maintenance and repair reports. In modern turbines with automatic CM system, the turbines have self-protecting and self-starting system that is not included in the maintenance reports. Neglecting alarm data could bring a significant error in evaluating system availability and downtime.

The data collecting body may not understand the importance of data. WT are privately owned by different types of owners with different expertise in gathering data. Some owners perform maintenance and repair activities self, so that the reporting procedure may not be perfect or complete.

4.15. Conclusions on the Existing Database Survey

Table 16 Summarizes availabilities from various initiatives with different values. From the figures, Muppandal data shows a significant gup between time-based and technical availability, this can tell us environmental and grid related downtimes are substantial in India. NEDO-data shows less technical availability in related to the other initiatives, Y. Kikuchi et al justified it as extended failure downtime due to industry prematurity in related to Europe [61]. Offshore WT in UK has showed significant low in technical availability, this is due to the data that were gathered from turbines in early operational period [51].

Figure 20 shows an overview on the outcome of three initiatives that provides data on both, failure rate and mean down time. These figures show the failure frequency of the individual system and subassembly compared to the respective mean down time per failure. The data shows that, there is similarity on failure frequency and downtime duration in Sweden and Spain, however turbines in Germany has higher failure frequency but lower downtime.

Initiative	**Onshore Availability**			**Offshore Availability**		
	Time-Based	Technical-Based	Production-Based	Time-Based	Technical-Based	Production-Based
CREW-Data	97 %					
NEDO-Data		87 %				
Garrad Hassan	97 %					
Muppandal	82.88	94 %				
WMEP		98.3 %				
CWEA-Database		97 %				
WInD-Pool	94.1 %		92 %	92.2 %		88.1 %
Round 1 Offshore Wind Farms					80.2 %	
SPARTA				95.15 %		
Elforsk/Vindstat	95 %					
VTT		96 %				

Table 16: Summary of WT availability values published by different initiatives.

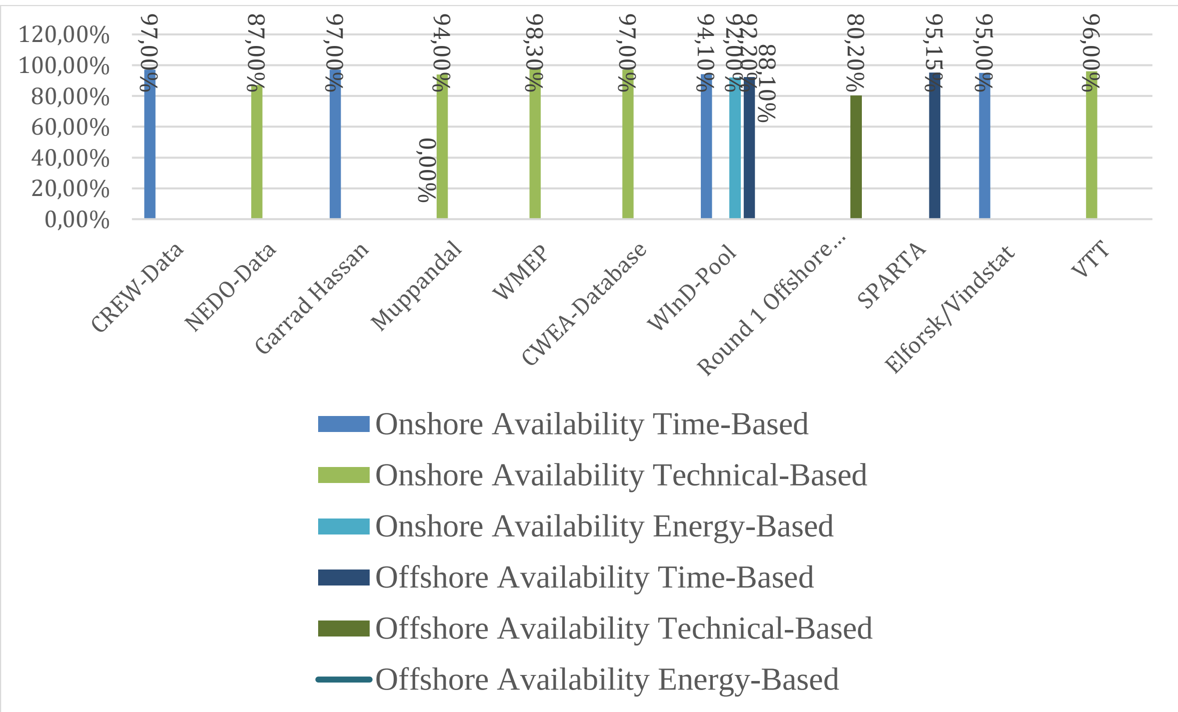

Figure 22: Comparison of WT operational availability from different initiatives.

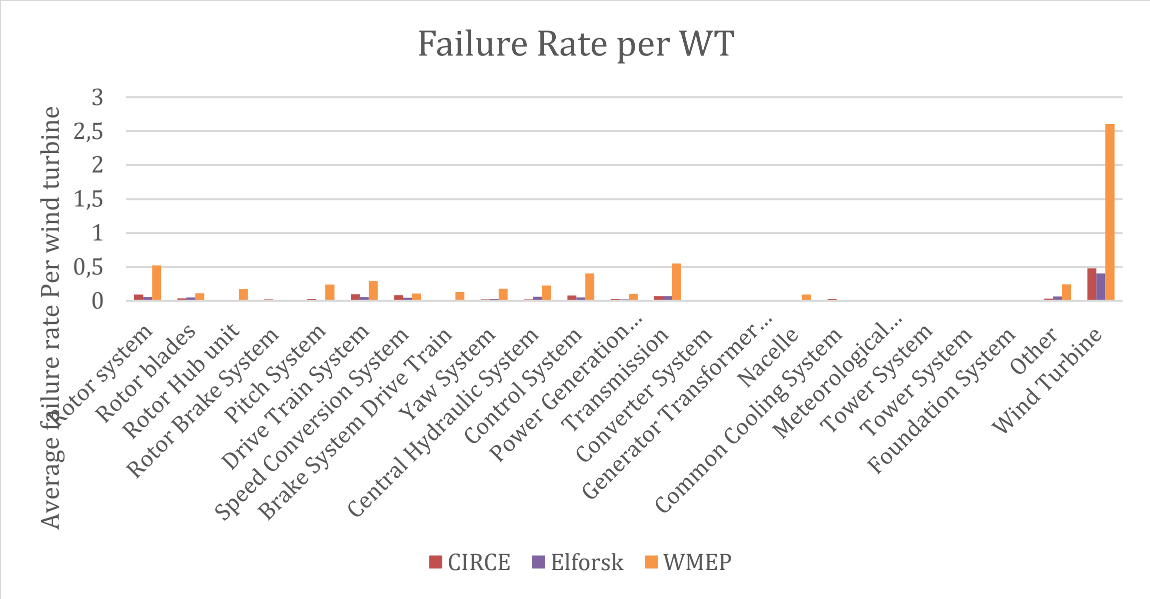

Figure 23: Overview of failure rate per WT from different initiatives.

5. WT Operational Database

In this chapter, explores the type of operational data that can generate from wind turbines. It covers the dataset that is going to be used in this project. In general, this will give an informative explanation on shortcomings and uncertainties on various types of WT operational data.

5.1. General WT Information & Operational Data Processing Procedure

Diverse industrial equipment manufacturers and owners are keen to settle operational databases that plays an important role on system performance improvement. Wind turbine are a part of these industrial equipment that have built database for continuous improvements of availability and reliability by identifying the origin of reduced system availability or reliability. Experience from other industries specially in oil and Gas shows that there are five key steps to achieve fundamental availability and reliability goals. These key steps are explained as [4]

- ✓ Finding data partnership companies related to the project.
- ✓ Data definition and Transfer (what data will be useful, how to transfer it, etc.)
- ✓ Data Formatting and Normalization
- ✓ Analysis
- ✓ Reporting and Analysis Output

5.1.1. Data Partner

The wind turbine operational failure and maintenance data related to this project depends on the existing wind farm throughout the arctic region. The main sources of wind turbine operational database are turbine manufacturers and wind farm owners. It is a complicated process to acquire relevant data from wind turbine manufacturers as they are not located in the country or don’t have any cooperation agreement with local institutions. However, I found two different local wind farm owners that have cooperative agreement with the institution. After a tight conversation with both companies, one is willing to share the required data that is relevant for this paper.

The process of acquiring data from partner requires extensive effort from for both parts as the wind farm owners are highly sensitive on sharing data to externals. Fakken wind farm is one of local wind Farm owners showed interest to share some their operational database after signing companies’ non-disclosure agreements.

5.1.1.1. Fakken Wind Farm

Fakken Wind farm is located at Vannøya in Troms that owned by local energy. The Plant has been in operation since June 2012 with estimated lifetime of 25 years [63]. The WF has equipped with 18 WT from Vestas model V90- 3.0MW and each turbine has 3MW rating power output that gives total plant rated capacity of 54 MW [63]. Tromskraft has informed WF annual production is around 139 GWh which accounts approximately 13% of our total power production. Each individual turbine links to a transformer that increases the low voltage output from 1 kV to higher distribution voltage 22kV. The second stage transformer which increases 22 kV voltage from all turbines to 66kV grid line.

Figure 24: Fakken WF site aerial photograph by Nord24 **[64].**

All wind turbine assemblies in Fakken wind park are horizontal axis wind turbines from Vistas V90-3MW. The turbines technical data is shown on Table 17.

Turbine in operation	Since 2012
Rated power	3000 kw
Wind load cut out	25 m/s
Rated wind load	15 m/s
Wind load Cut in	4 m/s
Rotor diameter	90 m
Number of blades	3
Gearbox	Super 3 stage
Tower height	80 m
Generator voltage	1000v/400v

Table 17: Technical data of V90, 3MW Vestas WT.

5.1.2. Data Definition and Transfer

This paper is to analyze WT performance and reliability by using field operational data. So, it is important to collect relevant data from partner in order to achieve the target. WT performance and reliability investigates mainly the factors that contributes energy production losses or operational downtime. System downtimes and environmental uncertainty are the key factors that are responsible for production losses. Severe or uncomfortable environmental conditions, component failures, maintenance and repair activities are fundamental factors to be considered in WT production performance evaluation. Operational downtime and production losses can be evaluated from energy production data, system or component failure data, maintenance and repair data. Big part of these data is available in plant alarm log data, energy production data, inspection and turbine repair/maintenance reports [4]. Supervisory Control and Data Acquisition (SCADA) is a system that monitors and controls the system or the components from remote sites. The supervisory system collects data from various sensors and sends the information to control system for process [68]. The process requires some database programming software to normalize the information in table form and send to its final destination [67]. Figure 24 shows a basic outline of the data import process.

Inspection personal or automatic control system shuts a turbine down, the shutdown is recorded and stored as alarm log system database. These data can generate the reports that summarize periodic downtime duration that helps to estimate costs of downtime and system failure frequency.

Maintenance/ repair reports are often to generate the type of maintenance, type of component failed, cause of failure, maintenance duration, and human resource used to bring turbine in normal operation status. All these types of reports provide insight into component maintenance downtime, repair expense and component failure frequency.

In general, the details of data collected from partner showed on table 18.

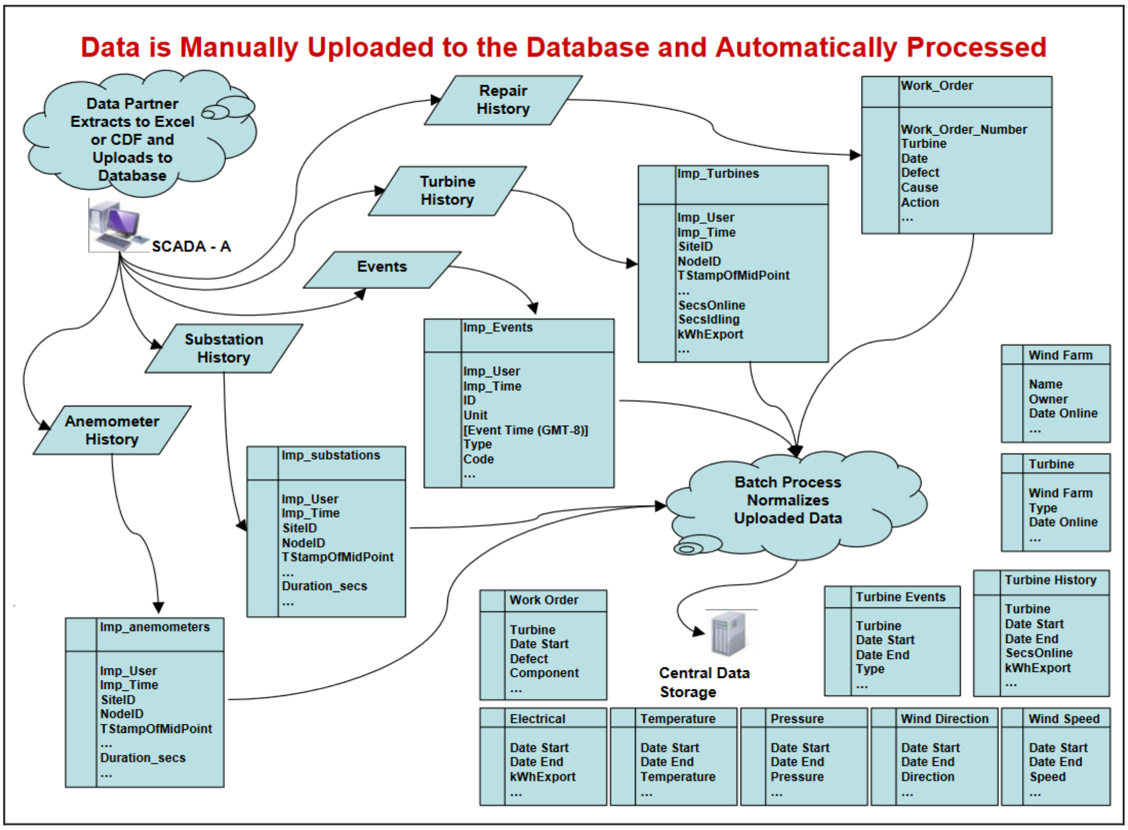

Figure 25: WT Data flow process [4].

Data type	**Data detail**	**Data inconvenience**
2 ½ years maintenance and service report (01.01.2018 – 30.06.2020)	Date and cause of failures Number of hours used to finish the task. Number of personal involved on the task.	Hard to find out the exact time of repair start.
2 ½ years operational fault alarm logs. (01.01.2018 – 30.06.2020)	Fault code and fault description Fault detected date and time Date and time that fault acknowledged and rest. Fault duration	Hard to find proper alarm code description. No info about fault resetting method. Multiple stops for the same fault. Difficult to identify grid and environmental related faults.
Two years energy production data. (01.01.2018 – 31.12.2019)	10 minutes average electric power production. Average wind speed Temperature and wind direction for correspondent energy produced	Time demanding data processing. Hard to find info about data gaps No info about wind power density. No all-production losses associated with fault alarms.

Table 18: The nature and sources of WT production, operation and maintenance data.

5.1.2.1. WT Fault Alarm System

WT alarm system is a part of condition monitoring tool that helps to evaluate the system or component operational state using sensor related data. The alarm data gathered from different parameters monitored by the control system. The alarm parameters include weather parameters such that anemometer measures wind speed and wind direction; machine parameters measures temperature, oil level, pressure, cooling water level and vibration; electrical parameters measure active & reactive power, voltage, current, frequency and Cosφ in generator windings [7].

The turbine alarm system generally characterizes three different levels of severity [68];

- ✓ Alarm massages are normally to inform overall changes in abnormal operating conditions, such that when the wind speed is goes above the rated value or the wind speed is low for energy production.
- ✓ Control system detects when components predefined value exceeds its operational value.
- ✓ Component fault warning alarms generated or acknowledged by the control system.

Table 19 shows a fault related alarm data sample used for this study. Unit and serial number are given to specify the WT.

Unit	Serial no.	Fault Code	Description	Detected	Device acknowledged	Reset/Run	Duration	Event type	Severity	Remark
XX	XX	232	WatchdogReboot	XX	XX	XX	01:59:29	Alarm log (A)	201	
XX	XX	900	Pause pressed on keyboard	XX	XX	XX	01:59:28	Alarm log (A)	201	
XX	XX	3298	Yaw To Cable Twist Reset	XX	XX	XX	01:58:07	Alarm log (A)	201	
XX	XX	5253	GenSlipR SuctionFanOverloaded	XX	XX	XX	11:27:42	Alarm log (A)	413	
XX	XX	144	High windspeed: 25.1 m/s	XX	XX	XX	03:30:50	Alarm log (A)	212	
XX	XX	5644	GearOilInletPresLow 0.0 bar	XX	XX	XX	03:45:59	Alarm log (A)	201	
XX	XX	5663	Emergency lubrication active	XX	XX	XX	03:26:33	Alarm log (A)	201	
XX	XX	5637	GearOilInitialPressLow 0.0bar	XX	XX	XX	01:43:43	Alarm log (A)	201	
XX	XX	5253	GenSlipR SuctionFanOverloaded	XX	XX	XX	05:40:03	Alarm log (A)	413	
XX	XX	5645	Warm gearoil temp : 63 °C	XX	XX	XX	00:42:00	Alarm log (A)	242	
XX	XX	356	Extreme yawerror 5.6m/s 58.5 °	XX	XX	XX	00:01:43	Alarm log (A)	201	
XX	XX	3273	YawUntwistCCW: Code 4, 576 °	XX	XX	XX	00:26:06	Alarm log (A)	201	
XX	XX	163	Low workingpressure : 15.9 bar	XX	XX	XX	11:23:27	Alarm log (A)	413	
XX	XX	3272	YawUntwistCW : Code 4,-000619 °	XX	XX	XX	00:24:43	Alarm log (A)	201	
XX	XX	151	High temp. Gen bearing 2:105 °C	XX	XX	XX	01:40:34	Alarm log (A)	201	

Table 19: Sample of alarm log data used for this paper.

Generally, acknowledged fault alarms can lead the turbine to shut down. When a fault alarm stopped the turbine operation, then there must be some kind of interference to restart the system. Restarting process can be performed in four different ways [67];

- ✓ Automatic restart by the turbine controller system.
- ✓ Manual restart from a remote monitoring control center.
- ✓ Manual by local site operator or technician.
- ✓ If fault requires repair, then restart manually by maintenance technician.

Operational downtime duration for a single fault can be evaluated from the differences between reset time and fault acknowledge time. Alarm code and fault description are originally assigned by manufacturer (Vestas). The severity indicates if the alarm is just an information, warning or fault [68].

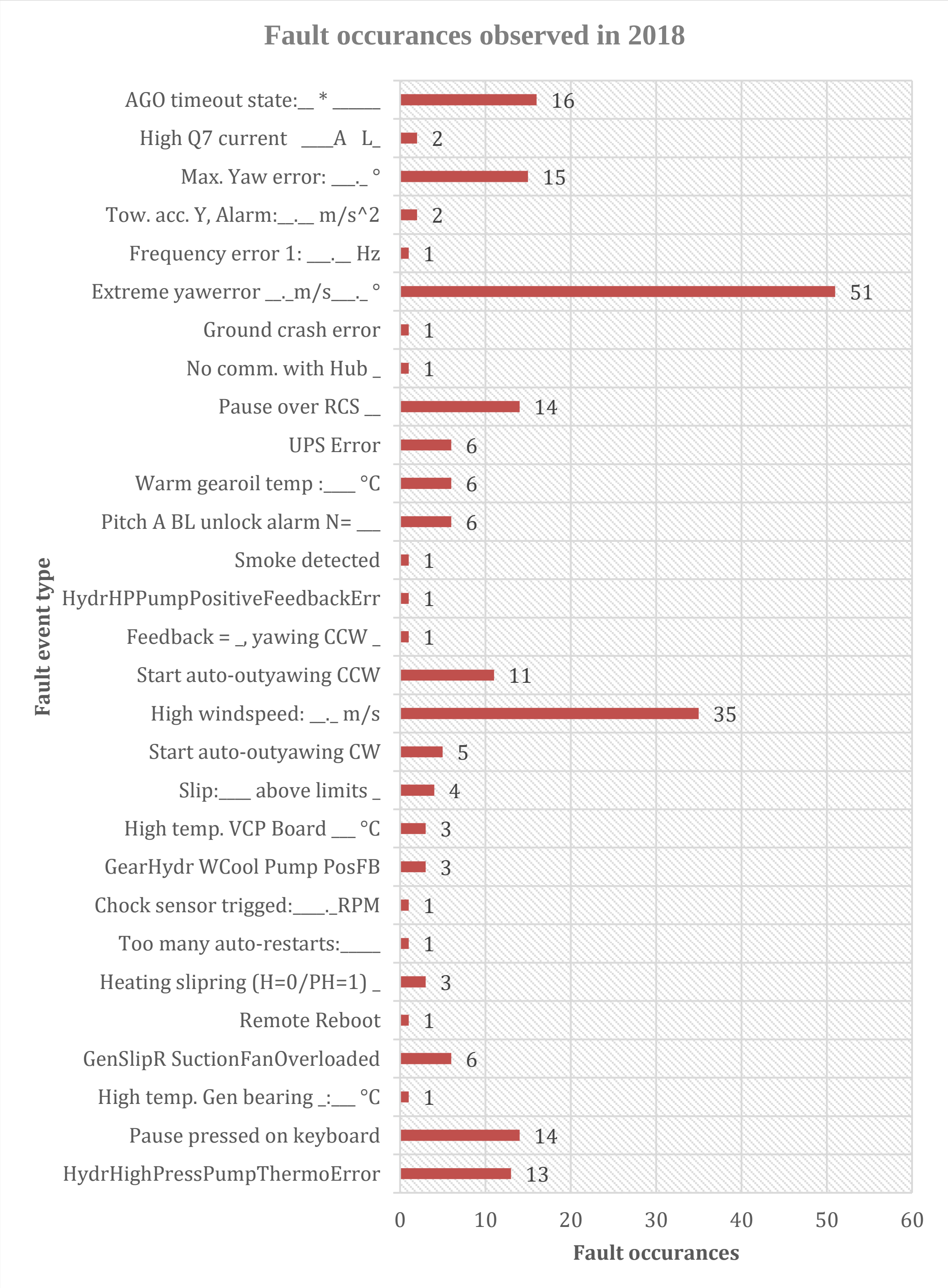

Figure 26: Fault alarm statistics for a single WT in year 2018.

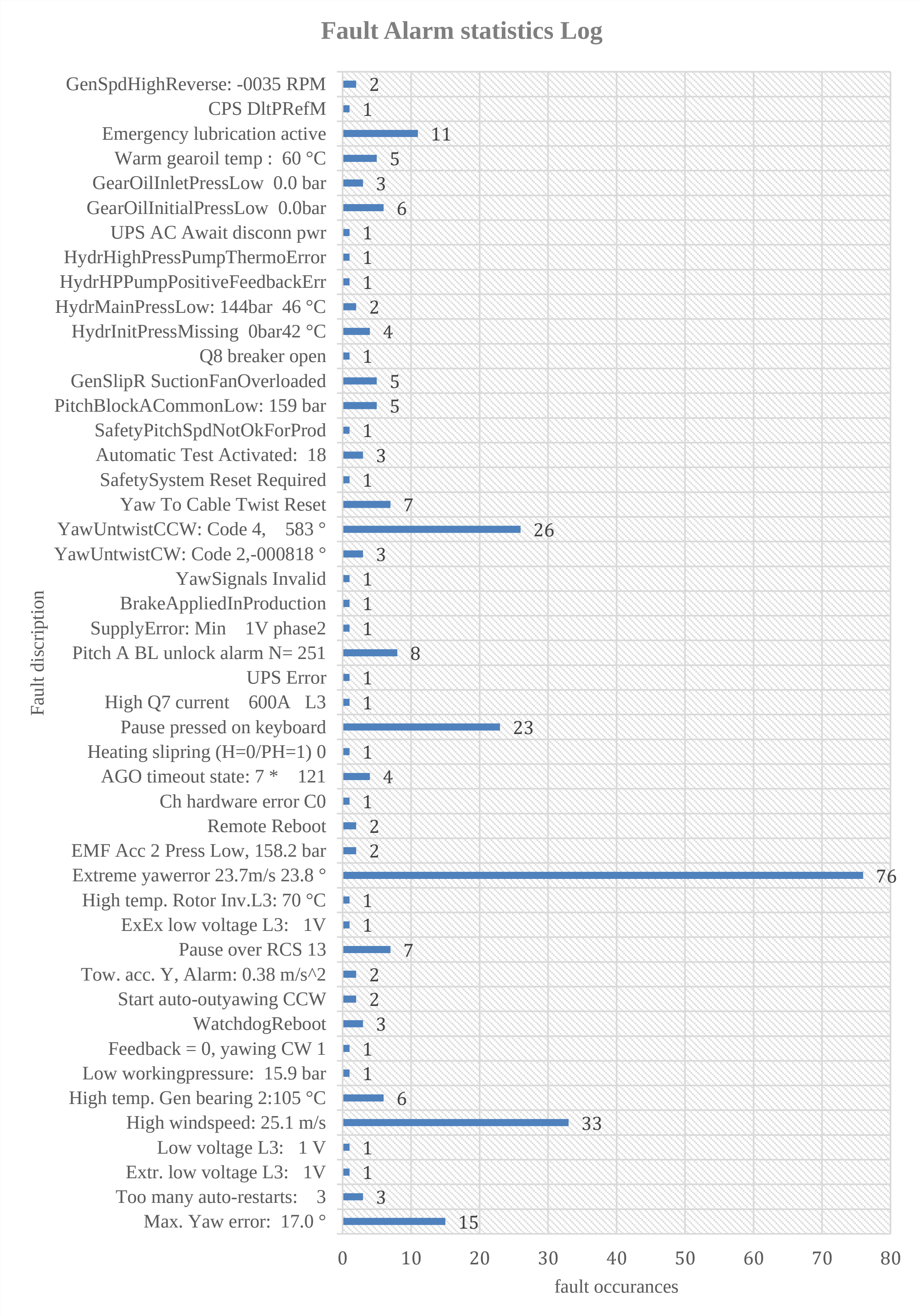

Figure 27: Fault alarm statistics for a single WT in year 2019.

In total, the turbine had around 225 component faults registered in 2018 and 288 faults registered in 2019.

5.1.2.2. WT Energy Production Data

Detailed, accurate and timely energy production data and statistics are essential for the monitoring and evaluation of operational and production system availability. The operational data usually produced from 10 minutes SCADA system. The data includes 10 minutes average wind speed, mean energy output, wind direction and external temperature. Figure 27. Shows a sample of data that collected from data partner.

PCTimeStamp	**Production Power Avg. (1)**	**Ambient WindSpeed Avg. (2)**	**Ambient WindDir Absolute Avg. (3)**	**Ambient Temp. Avg. (4)**
01.01.2018	216,4	5,2	190,0	4,0
01.01.2018 00:10	148,0	4,6	193,9	5,0
01.01.2018 00:20	168,7	4,8	194,6	4,0
01.01.2018 00:30	96,8	4,2	186,3	4,0
13.03.2018 22:50	- 2,6	3,2	121,0	- 3,0
30.10.2018 19:20	1816,7	11,6	154,1	3,0
30.10.2018 19:30	2982,2	16,7	144,0	3,0
30.10.2018 19:40	3000,5	19,9	142,7	4,0
31.12.2018 11:50	- 24,7	19,0	140,2	-
31.12.2018 12:00	- 29,7	13,7	137,5	-
31.12.2018 12:10	- 24,3	11,3	140,3	-
31.12.2018 12:20	- 24,3	11,9	134,2	-

Table 20: Energy production data sample used for this project.

The data is quite big and time demanding to study and summarize. Sometimes the data shows a negative energy production value, this tells us, the turbine is not producing electricity, instead some control equipment’s consume electricity from external sources. In this paper negative values have been considered as zero value, since there isn’t found any documentation to reason out the consumption source and the effect on system operation. Energy production value during operational downtime related to failure, repair, maintenance or environmental uncertainties can be shown as zero or negative value even though wind speed is within the production range. Data Gaps such that no measurement value registered for energy production or its key factors (wind speed, wind direction or temperature) might not be qualified for analysis if there no any details for operational shutdown.

Table 28. shows that Wind speed isn't only that determines the amount of power production values. Indeed, there are other factors that contribute for production fluctuations mainly air density [7].

Figures 27, 28,29 and 30 shows 10 min average energy production in relation to average local wind speed. The figures illustrate seasonal impact on energy production, wind speed and production challenges.

Time stamp	Mean power production	Mean windspeed	Avg ambient wind direction	Ambient temp
XX	1 177,0	9,3	135,2	1,0
XX	1 325,4	9,3	339,1	2,0
XX	1 201,3	9,3	311,3	2,0
XX	1 453,9	9,3	221,8	2,0
XX	1 336,7	9,3	216,2	3,0
XX	1 527,7	9,3	214,7	4,0

Table 21: Variation of 10-minutes average power output related to identical wind speed value.

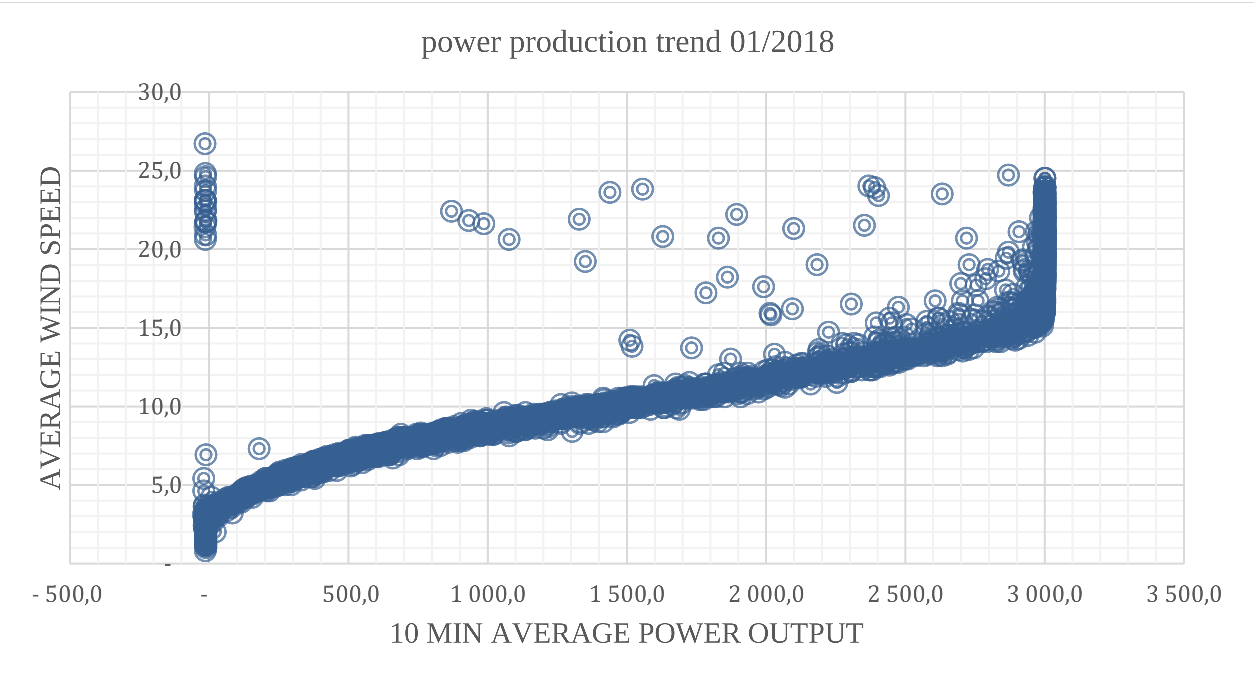

Figure 28: Graphical representation of energy generation observed during winter month 2018.

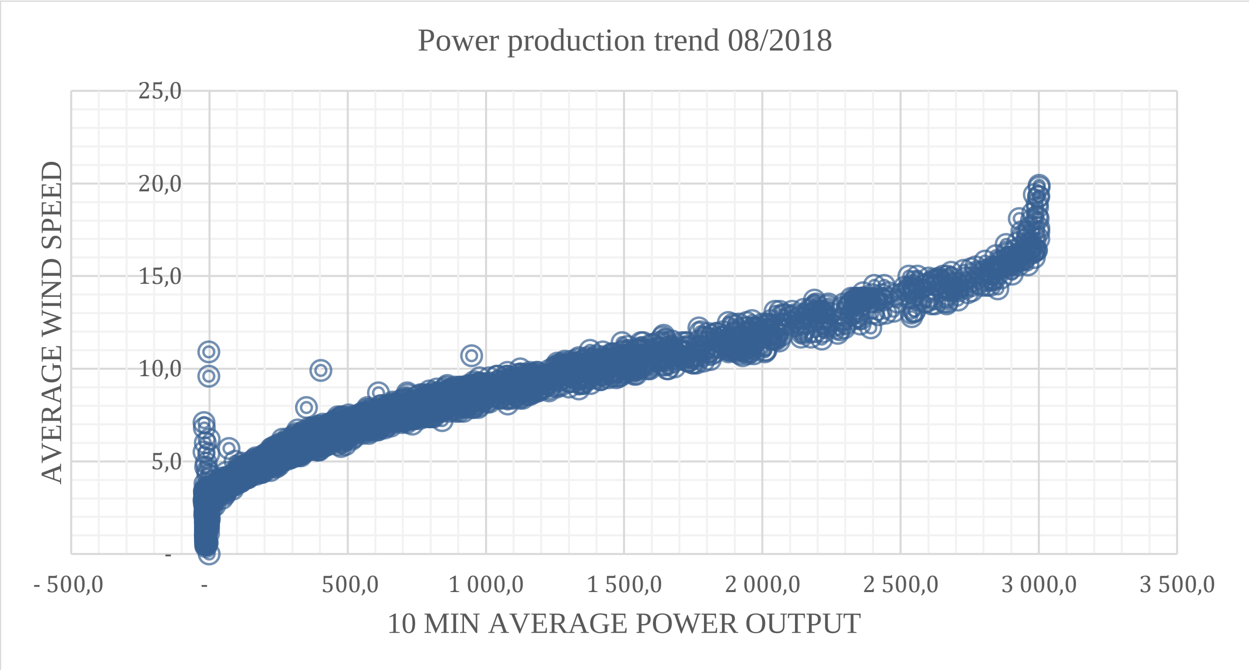

Figure 29: Graphical representation of energy generation observed during summer month 2018.

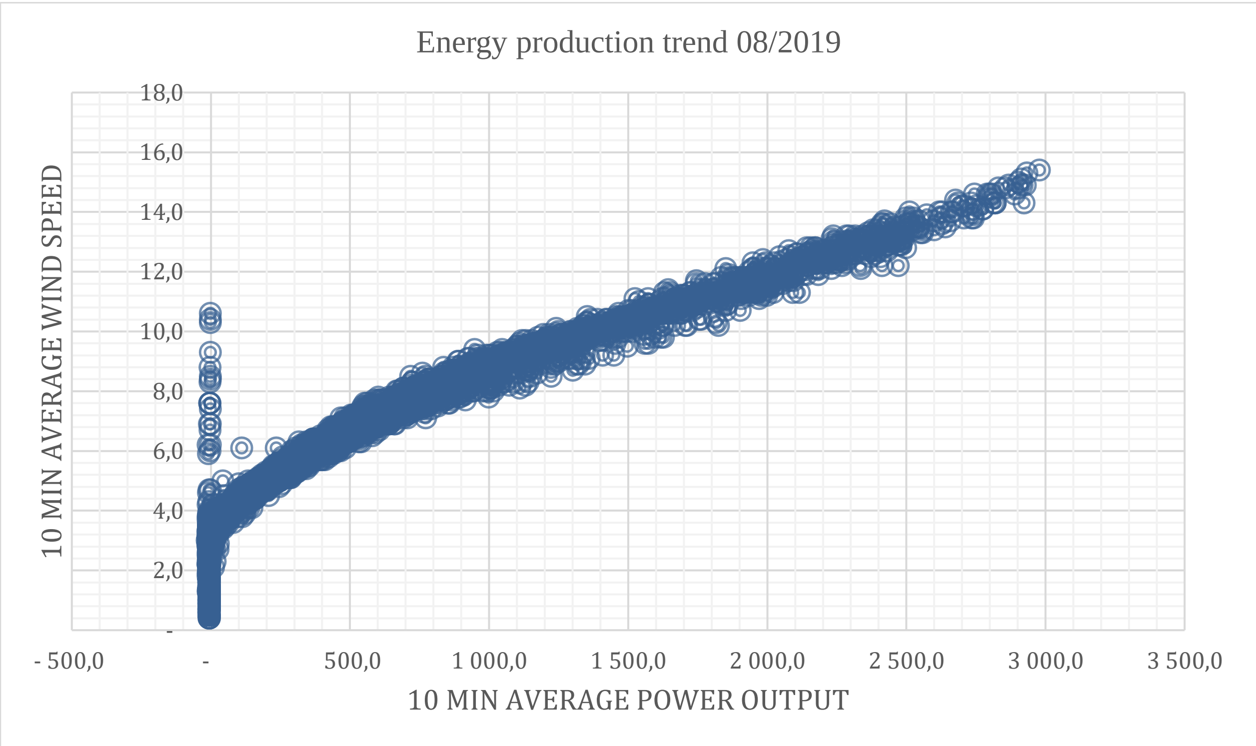

Figure 30: Graphical representation of power generation variation during Summer month 2019.

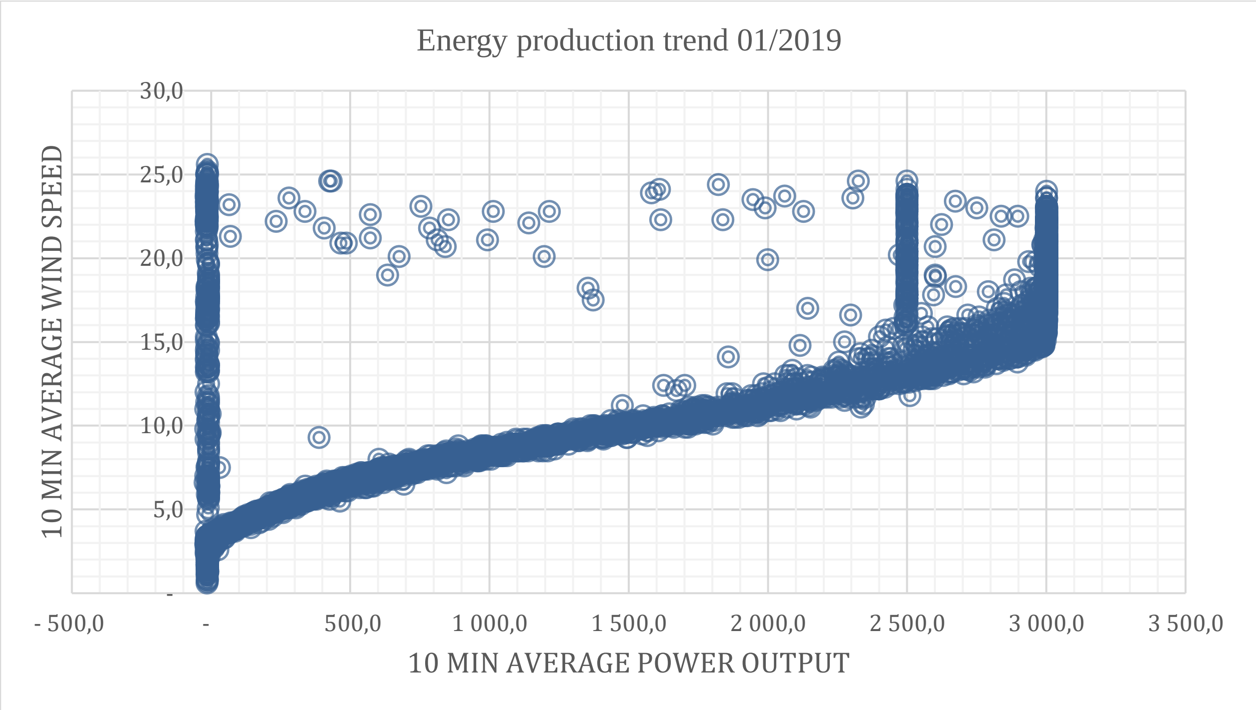

Figure 31: Graphical representation of power generation observed during winter month of 2019.

5.1.2.3. Maintenance and Repair Data

Maintenance and repair data are important to correlate failures and operational downtimes that are registered in SCADA system. To that end 28 service reports for periods between 01/2018 and 07/2020 has collected from partner. From these 28 service reports 26 of maintenance and repair activities have been performed in 2018 and 2019. The report includes the turbine id, date of work order, task starting and finishing dates, maintenance root cause, type work performed, no personals involved in the task and total amount time used to perform the task. From these service reports 5 of them are neglected as they don't show any amount of time used in the maintenance work. Figure 31 shows statistics of maintenance work for a single turbine that are achieved in two years period.

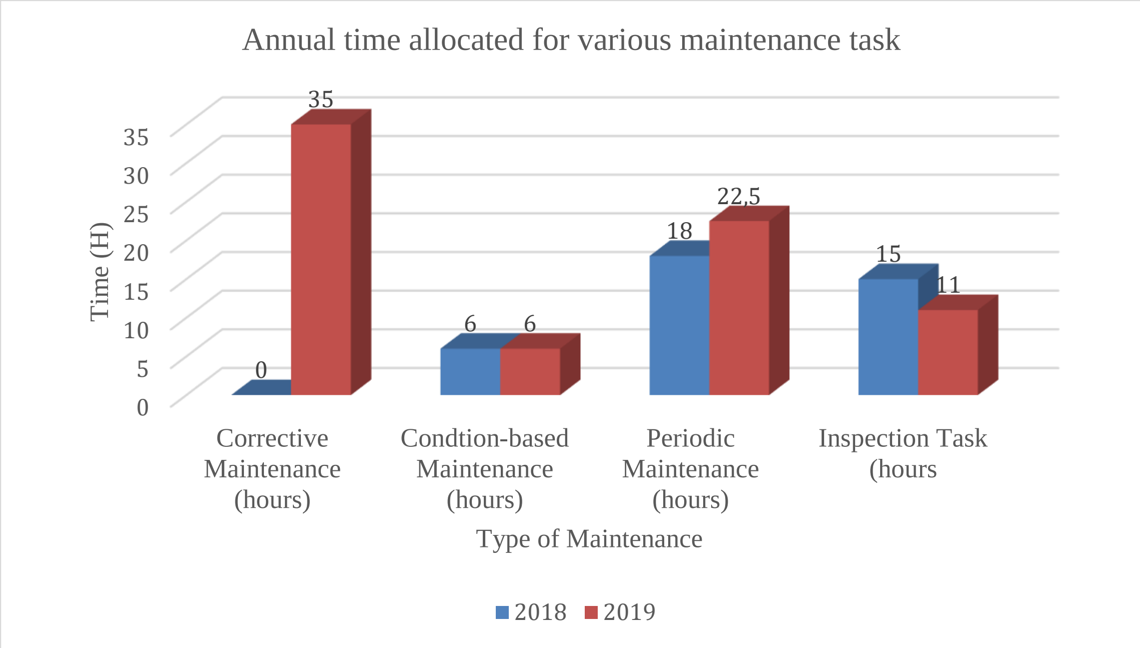

Figure 32: Statistics of maintenance task performed in 2018 and 2019.

5.1.3. Data formatting and normalization

Data normalization is a key element in data analysis process. It allows to compile and compare numbers of different sizes, from various data sources. Partner can only produce a rough maintenance and alarm log, it needs to be studied, understood and rearranged such that the provided data organized in a compatible way for software system and analysis. Wind turbine system has a large number of components which needs to be categorized in a common taxonomy for reliability data assessment. To that reason, it is important to generate physical breakdown of wind turbine structure shown in Figure 32. Reliability data studies often carried out in system, subsystem or subassembly categories [5]. Failure and fault alarm data supplied from partner in component level, that makes the analysis task unmanageable, so it is going to be summarized in system or subsystem level. In addition to that it is going to be categorized as periodic data such that failure and faults analyzed in monthly or yearly bases, this can help compare failure risks related to time.

In addition to failure data, production data that includes wind speed, direction and temperature is provided. The data is average production for every 10 min, with data gaps and production fluctuations with similar wind speed. All these unclear production losses need to be correlate with failure and environmental challenges.

Corelating service reports with turbine operation using fault alarm log data and the total amount of time used in maintenance doesn't always match. Maintenance work doesn't only mean working only mean site related task but also it includes report related task, transport and planning tasks. Therefore, all repair and maintenance can't be considered as an operational downtime.

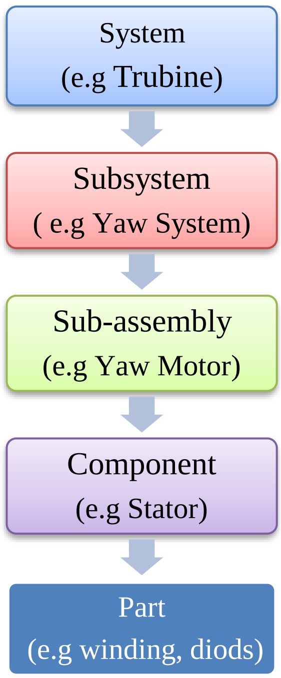

Figure 33: Example of wind turbine breakdown structure.

6. Data Processing and Analysis Methods

This section describes the methodology of data processing and analysis approach that is used for this project. There are a number of performance and reliability analysis methodology, and for this project Norwegian standard like DNV standard applied to analyze availability and CP. CREW reliability methods has applied to calculate reliability data.

6.1. Evaluation Methods of WT Operational Availability

When a wind turbine availability is evaluated, then the down time in related to grid or the whole wind farm might not consider or included in the analysis. So, for the single wind turbine availability considers only those downtimes that are directly related to the reliability that specific turbine. Depending the definition of availability, turbine availability can be affected by a number of factors that is directly related to the specific turbine, that includes failure/faults and maintenance activities, high and low wind speed outage, winter related downtimes, lighting and cable unwrapping activities.

There a number of approach that availability of wind turbines can be evaluated directly from turbine alarm log or energy production data (SCADA data). The most common one's that are recognized by turbine manufacturers are:

- ✓ Time based availability
- ✓ Technical availability
- ✓ Energy based availability

6.1.1. Time Based Availability

Time-based availability (A_t) does Inform or provide the fraction of time where a wind turbine system or component is in production or able to produce energy in related to the total time [10]. A number of researchers defines time-based availability in different ways, however the most standard one's is given by IEC 61400-25-1 and DNV GL White Paper EAA-WP-15 [11]. The calculations of time-based availability don't consider the periodic wind speed variation and doesn't consider turbine's energy production during low wind periods. Time-based availability isn't difficult to calculate from given alarm log data of an operating wind turbine. Generally, time-based availability is defined as eq (5.1).

$$A_t = \frac{t_{available}}{t_{consideration}} \quad (5.1)$$

Where A_t = Time based availability

$t_{available}$ = full or partial operational time including low wind speed time

$t_{Consideration}$= total time in consideration

In this paper, the calculation of time-based availability considers all downtimes registered on turbines alarm log system as unavailable. Downtimes due to low windspeed considers as available and all downtimes registered on alarm log system considered as downtime. Data gaps isn't included in the calculation. So, time-based availability is calculated as Equation (5.2) below;

$$A_t = \frac{t_{available}}{t_{total} - t_{data\ gaps}} \quad (5.2)$$

Where A_t = Time based availability

$t_{available}$ = full or partial operational time including low wind speed time

t_{total} = total hours in one year (365 X 60 h = 8760hours)

$t_{data\ gaps}$ = The days energy production or wind speed data unavailable

6.1.2. Technical Availability

Technical availability (A) is similar to the time-based availability, however technical availability provides more information on the amount of time that the turbine is available from on a technical perspective. Turbine owners expects a continuous power generation when local environmental conditions are within the turbines specified operational condition. According to DNV standards [11], technical availability provides more accurate measure to assess suppliers' technological achievement. For this calculations purpose, all down time that the turbine itself isn't responsible considered as negligible or not included in the calculation. For example, production down times due to high and low wind speeds and weather/grid related downtimes are excluded from the total time [11]. Technical availability is calculated as Eq (5.3);

$$A_{tech} = \frac{t_{available}}{t_{available}+t_{unavailable}} \quad (5.3)$$

A_{tech} = technical availability

$t_{available}$ = Full, Partial energy production hours.

$t_{unavailable}$ = All non-production hours that the turbine itself is responsible, excluding downtimes due to environment and grid.

6.1.3. Production based Availability

Production based availability (A_w) is calculated based on turbines production output, which shows evidence about the turbines actual energy production performance in related to the potential production associated with wind speed. It is known that higher wind speed (within the turbines design limit) drives to higher energy production, in contrary lower wind load implies lower production. It possible to consider that some maintenance and repair activities can be achieved during low wind hours. For calculation reason, important to produce time-based energy production data from turbines SCADA system, that includes wind load data and power output data. The actual energy output can be calculated easily from the given data, but the potential power production is a complex task that needs fair estimation for each production losses for specific downtimes. Potential power output includes both actual energy output and production losses as a result of fault and all types of maintenance activities as shown in Eq (5.4) [10]. In this paper Production losses during high wind considers as potential peak power production (3MW). Power production losses during other maintenance and fault related downtimes estimated from standard specifications given by manufacturer on table 23 and from data analogy. Potential production loss below 4 m/s wind speed has been considered unproductive periods. Generally, production or energy-based availability can be calculated as it shows on Eq (5.5);

$$\overline{W}_{potential} = \overline{W}_{actual} + \overline{W}_{losses} \qquad (5.4)$$

Where;

$\overline{W}_{potential}$= Average potential energy output

$\overline{W}_{actual}$ = Average actual energy output

$\overline{W}_{losses}$= Average energy losses due to all types of faults and maintenance excluding low wind and data gaps.

$$A_w = \frac{\overline{W}_{actual}}{\overline{W}_{potential}} \qquad (5.5)$$

Where; A_w = Production based availability

Turbine status	Examples	Technical availability	Time based availability	Energy based availability
Energy production		Available	Available	Available
Outage due to wind speed specifications	High wind	Neglected	Unavailable	Available as full capacity
	Low wind	Neglected	Available	Available
Turbine related outage	Scheduled maintenance	Unavailable	Unavailable	Unavailable
	Corrective maintenance failure/faults Cable untwists Lighting	Unavailable	Unavailable	Unavailable
Weather and grid related downtimes	Plant related Ice removal Bird cutback	Neglected	Available	Available
Data Gap		Neglected	Neglected	Neglected

Table 22: Definitions of three different turbine availability approach applied in this project.

	Air Density kg/m^3											
Wind speed m/s	0,97	1	1,03	1,06	1,09	1,12	1,15	1,18	1,21	1,225	1,24	1,27
4	53	56	59	61	64	67	70	72	75	77	78	81
5	142	148	153	159	165	170	176	181	187	190	193	198
6	271	281	290	300	310	319	329	339	348	353	358	368
7	451	466	482	497	512	528	543	558	574	581	589	604
8	691	714	737	760	783	806	829	852	875	886	898	921
9	995	1028	1061	1093	1126	1159	1191	1224	1257	1273	1289	1322
10	1341	1385	1428	1471	1515	1558	1602	1645	1688	1710	1732	1775
11	1686	1740	1794	1849	1903	1956	2010	2064	2118	2145	2172	2226
12	2010	2074	2137	2201	2265	2329	2392	2454	2514	2544	2573	2628
13	2310	2382	2455	2525	2593	2658	2717	2771	2817	2837	2856	2889
14	2588	2662	2730	2790	2841	2883	2915	2940	2958	2965	2971	2981
15	2815	2868	2909	2939	2960	2975	2984	2990	2994	2995	2996	2998
16	2943	2965	2979	2988	2993	2996	2998	2999	2999	3000	3000	3000
17	2988	2994	2997	2998	2999	3000	3000	3000	3000	3000	3000	3000
18	3000	2999	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000
19	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000
20	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000

Table 23: Standard specifications V90, 3MW turbine power output in related to wind speed and air density at 109.4dB sound level [7].

6.2. Reliability methodology and analysis

Reliability is the probability of a component, subsystem or subassembly to perform its designed function, within a given operational conditions, for an intended time limit. The reliability of most industry equipment’s operating within the arctic region, can be expected lower than those operating in different operating condition. This is due to the fact that these equipment’s are exposed to harsher operational environment. To that reason, the performance evaluation of wind turbine within the region is considered as a vital issue for the system productivity and life time.

Grid level wind power industry is young related to other industries. Many modern turbines are still operating in their early stage as a result failure and maintenance data are not as compiled as in a mature industry. Thinking that modern turbines are big and complicated in design, makes it critical to focus on the subject. However, the current operational evaluation was built based on earlier turbine data that is built in different operational and environmental conditions. This means that evaluating failure and maintenance for the industry couldn't be representative and the evaluation could result high uncertainty. Nevertheless, the previous evaluations are important insights that gives a basic ground for evaluation of wide range of wind turbine installation.

6.2.1. Reliability Model

As it stated above reliability data is the key decision tool for operational and maintenance management as the data gives the general picture for system or component failure and downtime probability. The model is aiming to estimate the values of system/component failure frequencies and failure related downtime. Reliability data helps to estimate future failure occurrences and then plan for operational and maintenance tasks (O&M) from estimated failures occurrences. In addition, the data helps to evaluate production or operational losses due to failure downtime.

There are a number of reliability models that have been used in different researches, as shown above from existing researches. In this paper CREW reliability model will be used.

6.2.1.1. CREW Reliability Model

The CREW team usually uses two different types of reliability models to analyze event Fault frequency and event downtime. The models are known as an individual plant reliability model and Individual plant aggregation into CREW reliability model [45].

Individual plant reliability models the event frequency and downtime for each component event type. The analysis is for each individual component and event type based on overall operational time and total number of events. Equation (5.6) and (5.7) shows the plant model how to calculate the values of event frequency and mean downtime for each component and event type respectively [45].

$$Event\ frequency_{plant,Component+event\ type} = \frac{\sum_{Turbines,events} Event\ count_{compo+event\ type}}{\sum_{turbines} Operating\ hours}$$

(5.6)

$$Mean\ downtime_{plant,component+event\ type} = \frac{\sum_{Turbines,events} Event\ duration_{compo+event\ type}}{\sum_{turbines} Event\ count_{compo+event\ type}}$$

(5.7)

Individual plant models shown above can be aggregated into Crew reliability model. In this case, both downtime events and reserve events are included in the model. The combination considers the number of turbine operational time (days) for the plant. In relative to a simple individual plant model, this one can evaluate for a large number of turbines and larger quantity of data.

Equation 5.8 illustrates the CREW model to evaluate for plant event frequency for each component and event type [45]. In this model, downtime evaluated by the event frequency and turbine operational days as shown on equation 5.9.

$$Event\ frequency_{\mathbf{comp+event\ type}} = \frac{\sum_{plants}(Event\ frequency_{plant,comp+event\ type} * turbine\ days_{plants})}{\sum_{plants} Turbine\ days_{plant}} \quad (5.8)$$

$$Mean\ downtime_{comp+event\ type} = \frac{\sum_{plants}(Mean\ Downtime_{plant,comp+event\ type} * Event\ frequency_{plant,comp+event\ type} * Turbine\ days_{plant})}{\sum_{plants}(Event\ Frequency_{plant,comp+event\ type} * Turbine\ days_{plant})}$$

(5.9)

After the plant level models are aggregated, then the average downtime and event frequency for every component + event type evaluated. Considering the turbine as a series system and assuming a constant failure rate such that the analyst can evaluate the entire turbine event frequency as summation of each event frequencies. Equation 5.10, 5.11, and 5.12 are specifically appropriate to evaluate overall failure frequency, downtime and mean time between failures for a single turbine [45].

$$Event\ Frequency = \sum_{comp+event\ type}(Event\ Frequency_{comp.+event\ type}) \quad (5.10)$$

$$Mean\ Downtime = \frac{\sum_{comp+event\ type}(Event\ Frequency_{comp+event\ type} * Downtime_{comp.+event\ type})}{\sum_{comp.+event\ type}(Event\ Frequency_{comp.+event\ type})}$$

(5.11)

$$Mean\ time\ between\ failures = \frac{1}{failure\ frequency} \qquad (5.12)$$

7. Results

This chapter demonstrates the findings of performance and reliability data (value) that analyzed using partner's operation and maintenance data. The findings are demonstrated using charts with data labels.

7.1. System Availability and Capacity Factor

Both availability and capacity factors are evaluated using the theory and equations shown on section 5.1. Even though the description and the equations are straightforward, the process of evaluation was challenging. In general, there was a limited resource to understand all types of fault codes and descriptions.

In time-based availability, grid or external influence related outage supposed to be included in the evaluation as available, but data related fault code or fault description were not enough to identify external related faults. Data partner informed that they don't have any handbook that describes fault codes and the manufacturer wasn't willing to respond my request. To that end all types of faults registered on alarm log considered to be unavailable. Maintenance and inspection downtimes are normally included in alarm log data as "pause pressed on keyboard".

Referring the results, July month shows lower availability relating to other months, this is most due to longer maintenance and service downtimes. Due to harish external environment, most maintenance and inspection tasks carried out during summer times. Winter season is normally accompanied with higher windspeed and often goes to over the safety limit (25 m/s), so December 2018 and January 2019 showed lower available. Most fault alarms registered during winter season, this is due to lower working temperature and ice load on the rotating blade.

Similar to time-based availability, in technical based availability fault types needs to study carefully in order to reach a reasonable value. Both production and alarm log data were decisive to reach the final value.

Energy availability is a key to identify possible downtime production losses during optimum wind speed. The evaluation is mainly depending on the production data that shows the actual average windspeed during fault and maintenance downtimes. Estimation of production losses was the main challenge to reach to the final result. Even if energy production mainly depends on windspeed, there are other factors like air density, air pressure, temperature etc. In this paper energy production losses estimated using the registered windspeed during downtimes, manufacturers air density standard, production time sequential and temperature. Power production losses due to high windspeed are considered as rated power production (3000kw).

Winter season shows us higher capacity factor as a result of high fault frequency and optimum windspeed.

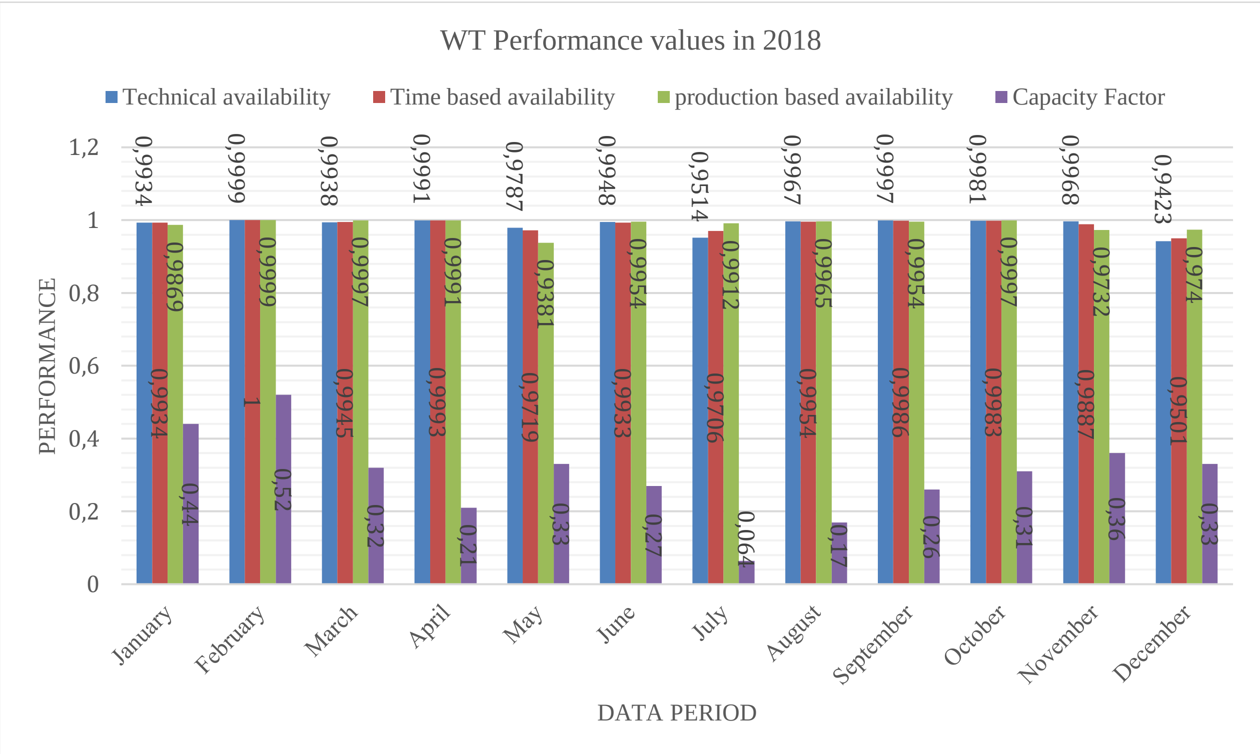

Figure 34: Monthly base WT operational availability and capacity factor analyzed based on partners alarm log and production data for 2018.

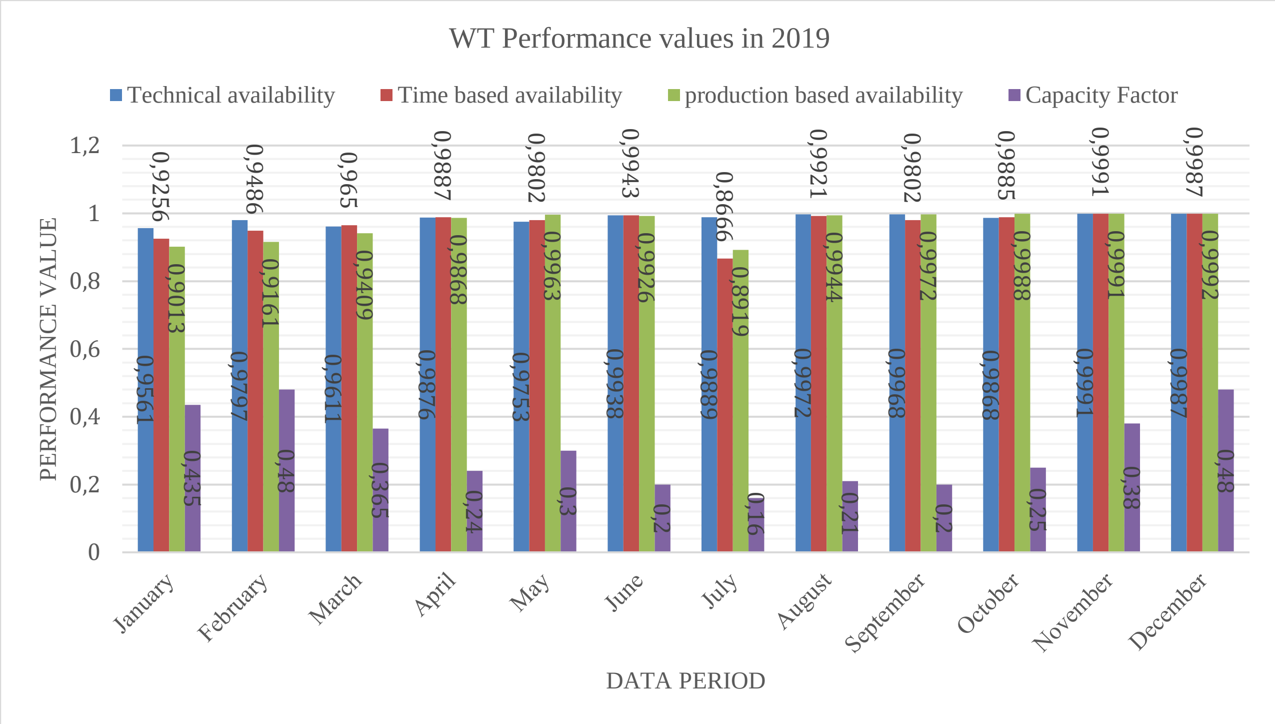

Figure 35: Monthly base WT operational availability and capacity factor calculated based on partners data for 2019.

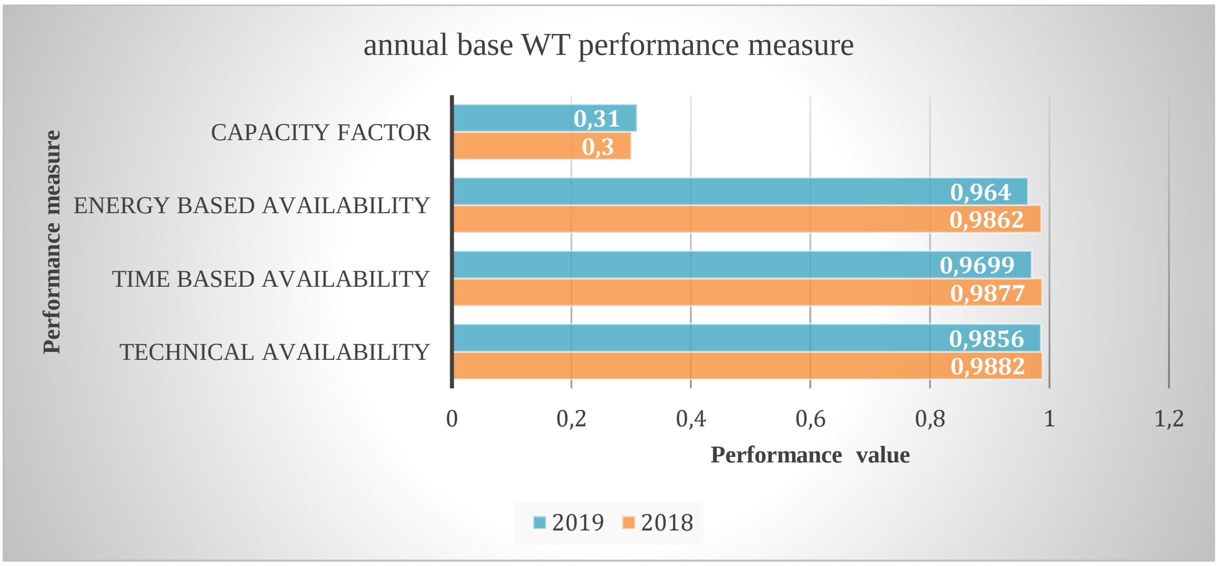

Figure 36: Annual based operational performance analyzed for a single WT.

7.2. Reliability and Down Time Results.

In this section the overall results of the SCADA data analysis for a single wind turbine will be demonstrated. The analyzed results of frequency, downtime and MTBF presented by chart for each fault registered within two-year period (2018 & 2019). Additionally, the faults that are shown on partners data have gathered in the form of turbine subsystem and the same performance measurements illustrated in chart form. As it stated in section 6.1. there was not found proper description to understand fault type and location, so grouping to subsystem has been done by using the names (not sure if the faults belong to the specified subsystem). Turbine fault gathering in subsystem form for this paper is shown on appendix 1. The analysis is mainly achieved using excel form.

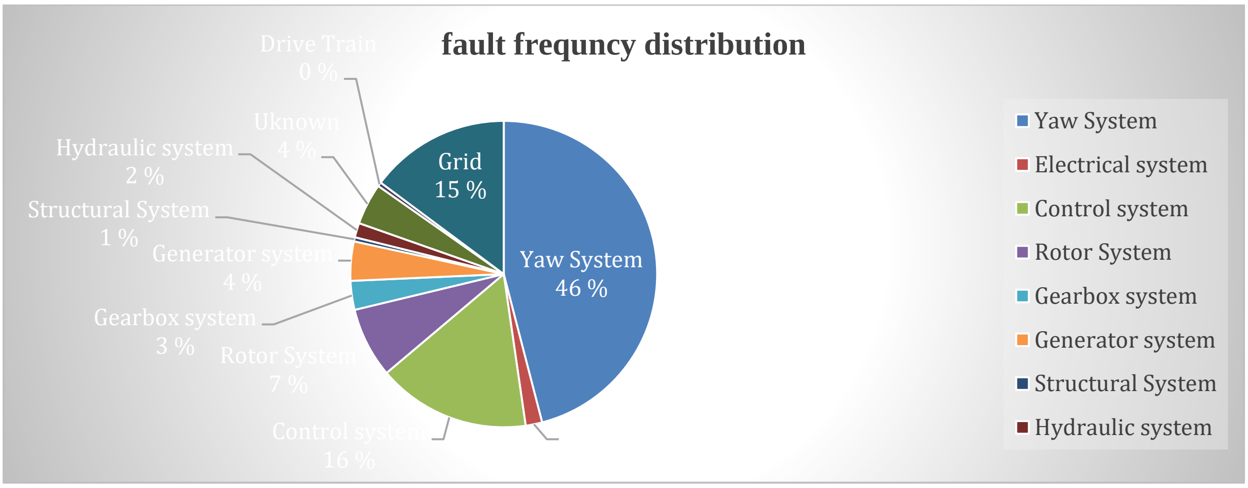

Figure 37: Normalized failure frequency distributions for WT subsystems.

From the results in Figure 37 the following observations can be made:

The wind turbine subsystem that contributes to have higher failure frequency are:

- Yaw system (46.6%)
- control system (16.0%)
- Grid (high wind) (15.0%)

Yaw system has shown as a critical subsystem in relative to other subsystems, from 211 event occurrences 157 of them are yaw misalignment (max yaw error and extreme yaw error). Control system includes all automatic and manual operational suspension using control system. Control system has generated in total 74 fault events and 48 of them are sourced from manual and RCS pause in control system. In my findings from maintenance reports and alarm data, pause is related to maintenance and inspection tasks. Grid is assigned mainly represents turbine operational cut-off due to high wind speed (over 25m/s). From the existing wind turbine reliability researches as presented in chapter 4, it is difficult to compare the results as the taxonomy approach in this paper is not similar to these existing researches. In addition to that, the data gathered for this paper is for a single turbine for shorter period in relative to the existing researches.

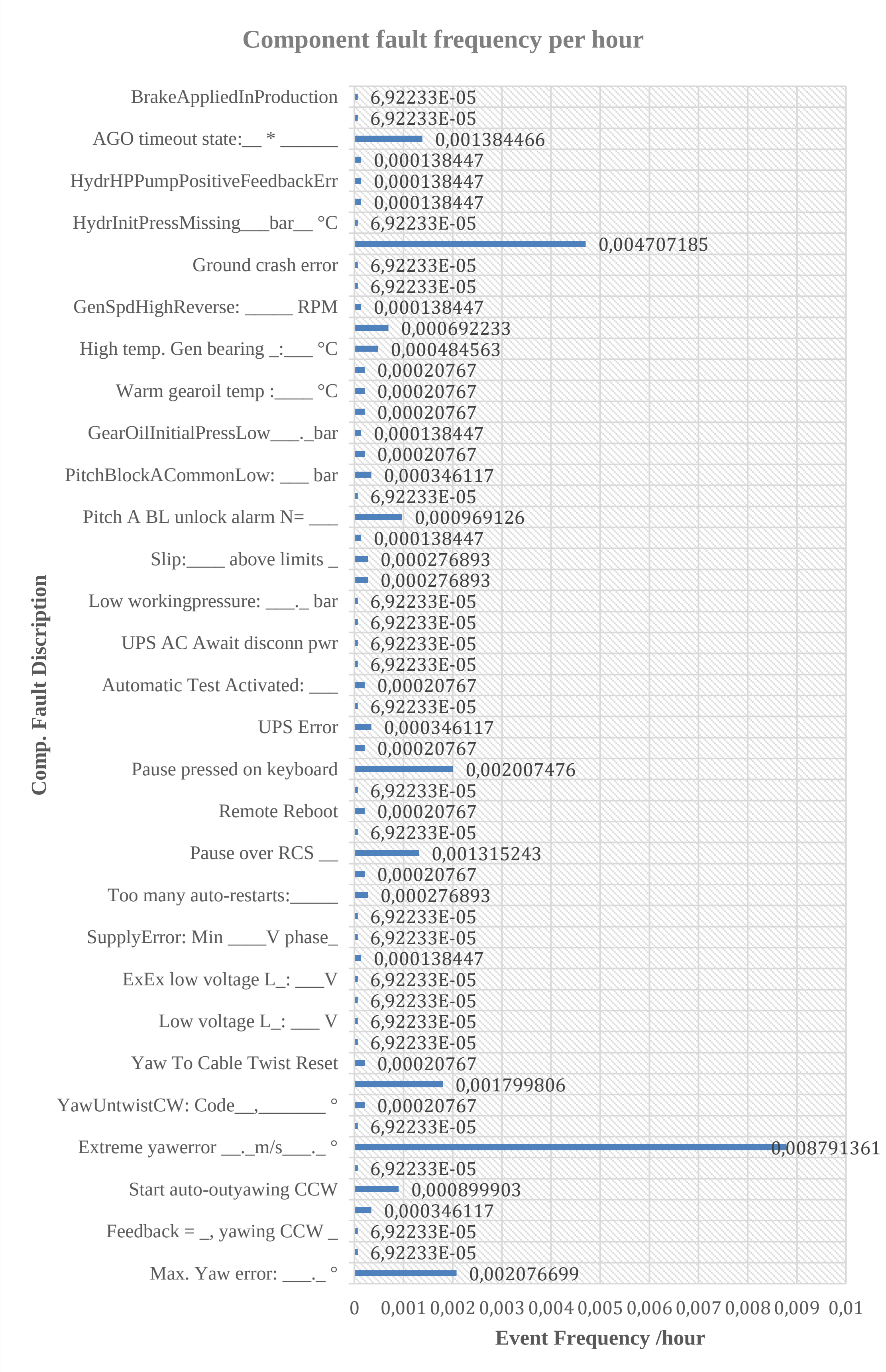

Figure 38: Fault event frequency evaluated based on partners two-year fault alarm data.

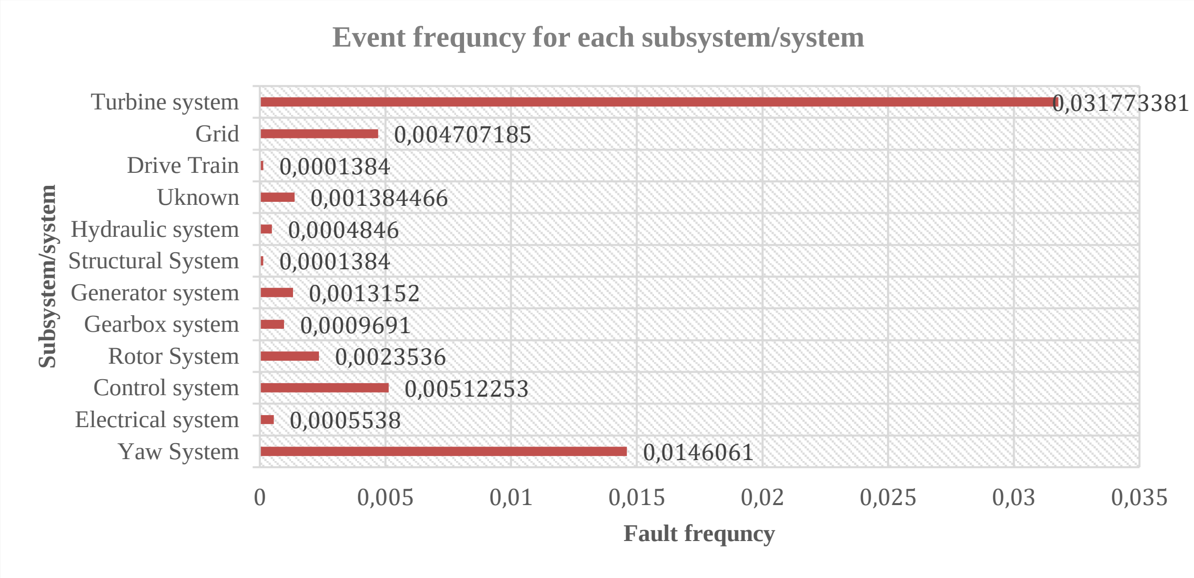

Figure 39: Fault frequency evaluated for each subsystem and turbine system.

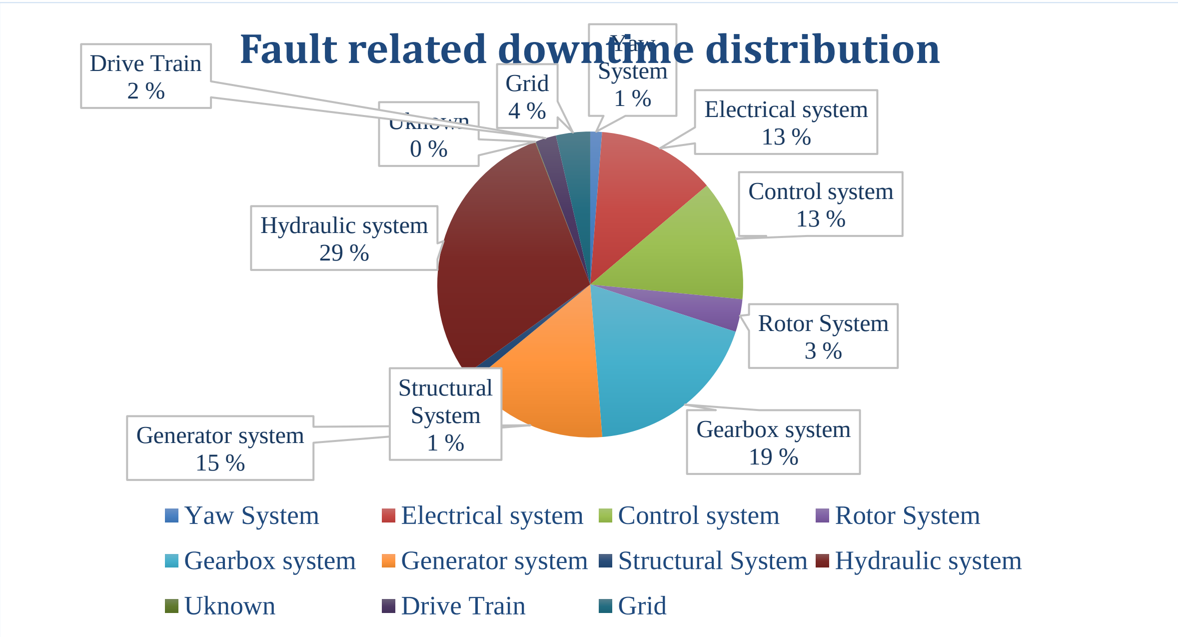

Figure 40: Fault related downtime distributions for turbine subsystems.

From the results shown Figure 40 the following observations can be made:

The wind turbine subsystem that contributes to longest downtimes are;

- Hydraulic system (29%)
- Gearbox system (19%)
- Generator system (15.0%)

It obvious that fault events that demands major repair contributes to extended downtime compared to the other fault categories.

The Hydraulic system failures have a significant contribution to the total downtime (29%) compared to its failure frequencies to the total number of failures (2%). In contrary yaw system has lower contribution (1%) of total downtime in compare to its failure frequencies (46%). The same trend as hydraulic observed to Gearbox and generator systems. Generally, subsystems that contributes to the total number of failures doesn't show necessarily their contribution to the total downtime. Often, fault alarms that comes from Hydraulic, Gearbox and generator systems needs physical inspection, oil and lubrication service tasks. In addition to that moving parts like bearings often demands major repair tasks.

Referring to the existing research on wind turbine reliability it was observed that the generator and gearbox had a higher contribution to the total downtime compared to the percentage of failures occurred. So, even if we may not have similar fault grouping technique, it would be more rational to compare the result with WMEP project figures.

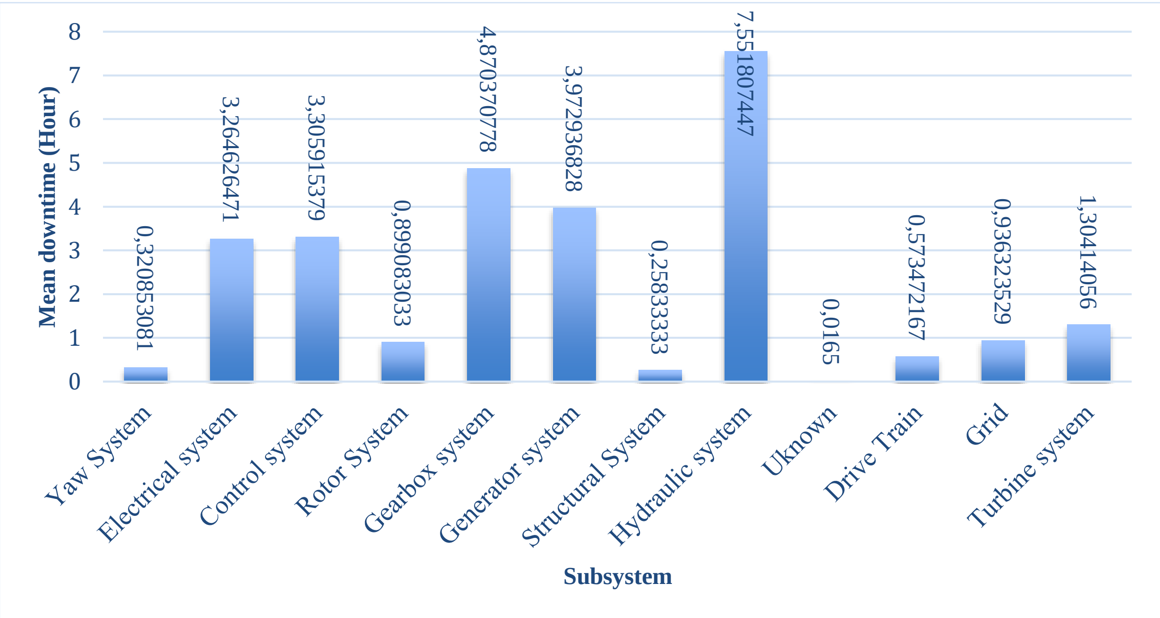

Figure 41: Production downtime related to faults on subsystems and on the system.

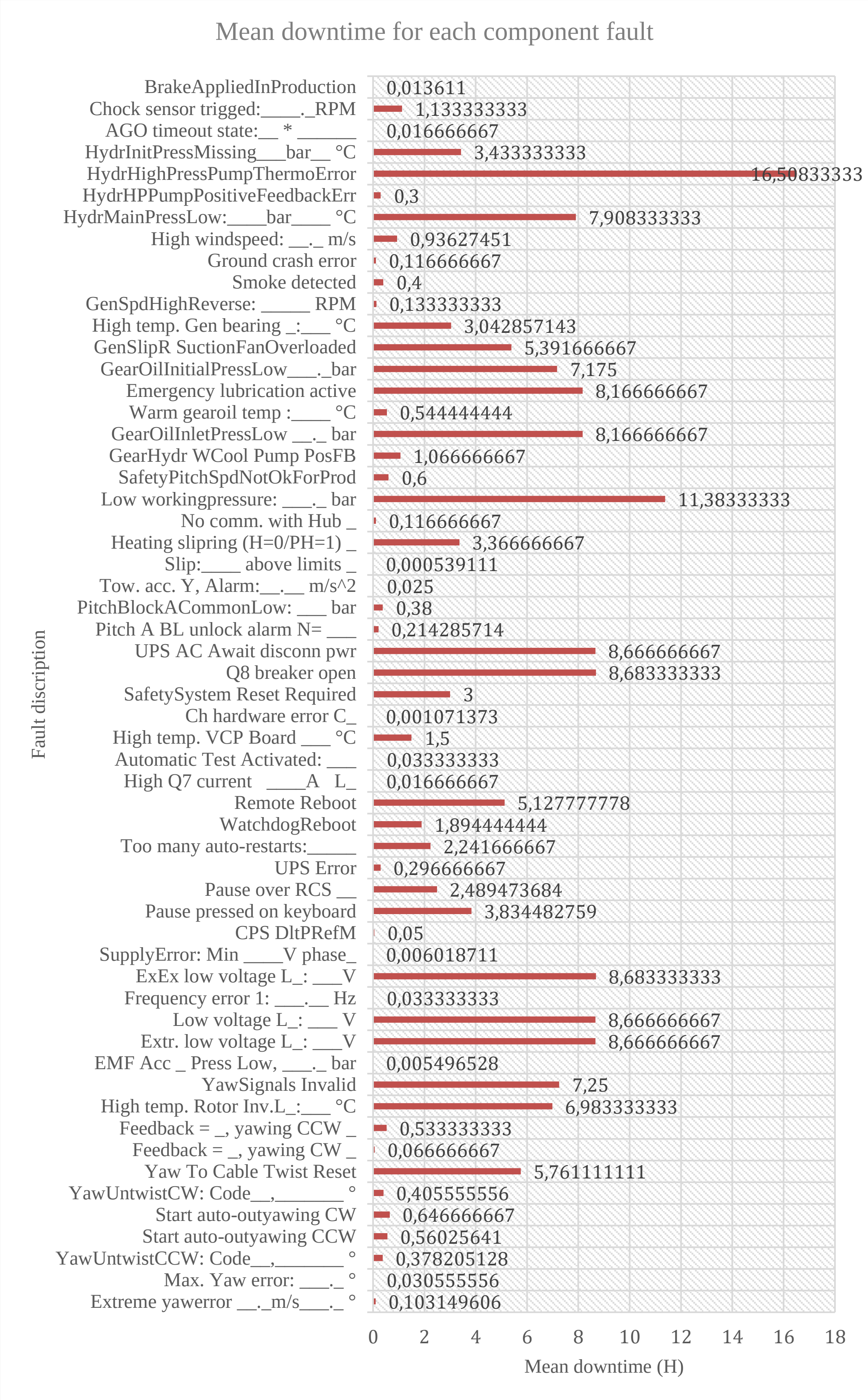

Figure 42: Production downtime for each fault observed within two years.

Referring to Figure 42. the following observations can be made:

The turbine subsystem that has to shortest time between two successive failures are:

- Yaw system (68,46 hours)
- Control system (195,21 hours)
- Grid (212,44 hours)

Mean time Between failures (MTBF) is inversely related to failure frequency. The items with higher failure frequencies are obvious to show lower time between two consecutive failures. In two years, operational period, it was registered 211, 74 and 68 fault occurrences from Yaw system, control system and grid respectively. These values are generated from an equation with constant rate which doesn't include a number of factors that could alter the values with time and operational status.

The best values might be generated from the best data fitted statistical distribution formulas using reliability software's like Weibull, Reliasoft etc. Due the time limit and workload, the analysis method couldn't be exercised in this paper.

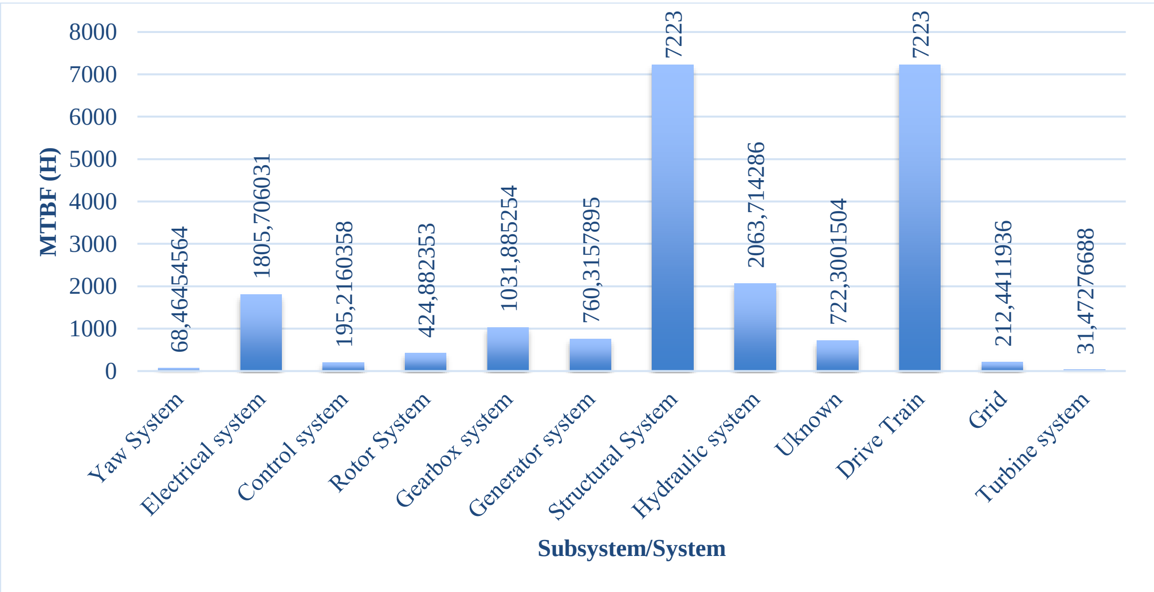

Figure 43: Subsystem/System MTBF evaluated from two-year alarm log data.

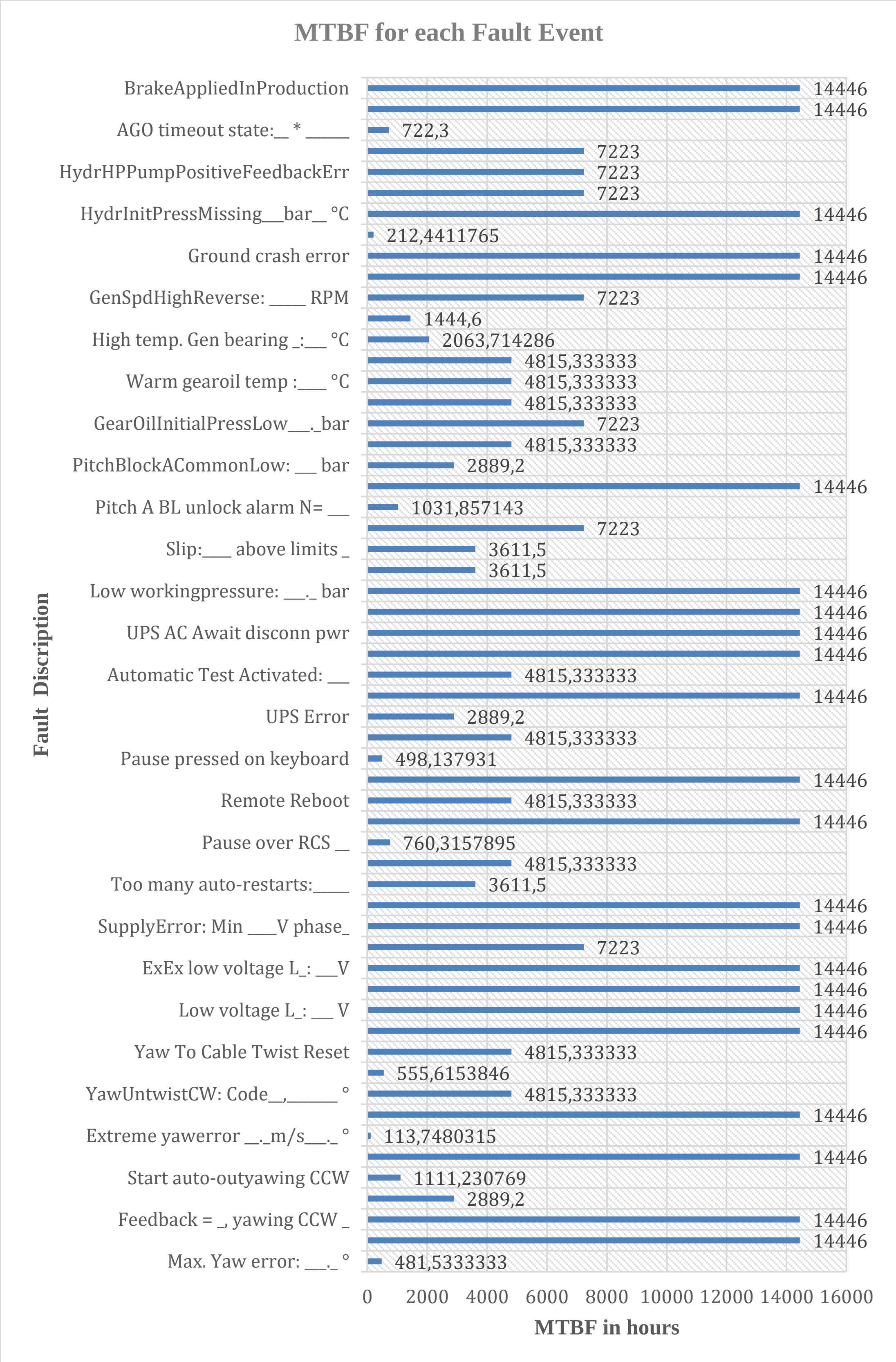

Figure 44: MTBF evaluated for each fault event observed within two years operational period.

8. Closure

This chapter, Summarizes the key finding on this research project. The general conclusions are presented, the limitations on the scope of work are specified out and recommendations for future work on this project are mentioned.

8.1. Conclusions.

This paper presents an analysis of the key performance measurements for a single turbine using operational field data. During this process two years operational field data such that 10-min SCADA data along with relevant Alarm log, energy production data and maintenance reports gathered from local WF owner. The project focused on three different performance parameters (turbine availability, capacity factor and reliability) to evaluate technical and environmental uncertainties on energy production. Following the analysis of turbine operational and production availability in three different methods and the outcome results observed in monthly and annual bases. Capacity factor was also an interesting performance measurement to measure the actual production in relative to the rated value and the values observed as availability in monthly and yearly bases. Finally, the main WT reliability parameters like failure frequency, downtime and mean time between failures based on fault type and subsystem evaluated. All the values are driven from the formulas or equations that are found from different books and research papers used in different Wind farms. All the mathematical analysis and plotting's has managed by using excel software. This project is case study to identify amount of energy or production losses due to a number of operational uncertainties and identify the main root causes that contributes production losses. All the evaluation methods were correlate and the conclusions are formed as follows;

Observing availability values for 2018 operational year, May (production and time-based), are showed lower. This difference on the values of technical and time-based/production-based availability tells us that higher energy production losses due to high wind cut-out downtimes. In addition to that the average wind speed was in the range of power production (4m/s to 25m/s) during turbines fault related downtimes. These figures could give WF owners the bigger picture on technical and environmental factors on their investment.

On the other hand, in July (technical and time-based) and December (technical and time-based) showed lower availability values in related to production-based availability. This indicates that turbine technical failures have small effect on turbine's productivity as failure downtime happen during potentially low energy production period as a result of low wind speed. Operational and maintenance managers could use these figures as a diction making tool for preventive and inspection tasks.

Both in 2018 and 2019 the value of capacity factor showed high from November to March, this indicates winter is potentially good season to produce wind power. WF owners or operators could plan their energy shortage backup or the number of wind turbines for their energy demand using these values.

The values of production-based and time-based availability during January, February March and July showed relatively low, this can be described winter was high wind season that turbine operation cut-out due to excessive wind energy input (≥25m/s). In addition to that July was the month that most preventive maintenance performed, when the local wind condition was in energy production range.

WT reliability is measured using average failure frequency, failure related operational downtime and average time between two successive failures. Observing turbine failure frequencies in subsystem level, the most critical subsystems which are exposed for frequent failure are yaw system (0,0146 failures/hour), control system (0,00512 failures/hour) and Grid effect/high wind (0,00471 failures/hour). However, most of these yaw system fault alarms are just misalignment alarm between nacelle position and wind direction, the alignment process achieved automatically within 1 to 2 min. Control system includes manual shutdown from control room (all inspection maintenance work operational shutdown included). In this paper Grid effect fault includes only high wind speed operational shutdowns.

The second reliability measurement is the amount of failure related downtime. To that end the three most critical subsystems registered with high failure downtimes related to others, these are Hydraulic system (7,55 hours), Gearbox system (4,87 hours) and Generator system (3,973 hours). This are the assemblies that demands manual inspection and major maintenance task for some of fault alarms. These figures can be essential for decision making tools in operations and maintenance management.

The third and the final reliability measurement is Mean time between failures (MTBF). In this paper the most critical subsystems that shows shortest average time between two successive failures are Yaw system (68,46 hours), Control system (195,21 hours) and Grid (212,44 hours).

These values give an insight for operational and maintenance personals to plan their maintenance and repair task.

8.2. Limitations

Luck of a detailed information on fault alarms could affect the fault categorization and then the exact values of subsystem reliability figures.

Maintenance reports specifies the general amount of time that maintenance personal allocated for maintenance works (transport, report writing, repair work etc.). The reports don't show the exact repair time or system maintenance downtimes.

Due to lack of information, not environmental or grid related uncertainties are included in the evaluation of performance and reliability values.

Due to time limit, couldn't learn important reliability software's to evaluate reliability values as statistical distribution values.

Luck of exact air density data could make it complex to estimate the potential energy production that used to evaluate the correct values of production-based availability.

8.3. Recommendations for Future Research

The evolution and design of large-scale WTs are in continuous and rapid progress, so the performance and reliability data from existing projects may not be applicable for the recent design. So, a continuous reliability data update is crucial.

Considering the limitations mentioned above, improved performance and reliability data can be generated in future project. Expense and profit related economic analysis could be assessed using the operational performance and reliability data.

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Appendix 1.

Subsystem	Fault Code	Fault Description
Rotor System	2908	Pitch A BL unlock alarm N= ___
	4669	PitchBlockACommonLow: ___ bar
	297	Tow. acc. Y, Alarm:__.__ m/s^2
	338	Slip:____ above limits _
	893	Heating slipring (H=0/PH=1) _
	38	No comm. with Hub _
	163	Low workingpressure: ___._ bar
	4183	SafetyPitchSpdNotOkForProd
Gearbox System	5585	GearHydr WCool Pump PosFB
	5644	GearOilInletPressLow __._ bar
	5645	Warm gearoil temp :____ °C
	5663	Emergency lubrication active
	5637	GearOilInitialPressLow___._bar
Generator	5253	GenSlipR SuctionFanOverloaded
	151	High temp. Gen bearing _:___ °C
	5936	GenSpdHighReverse: _____ RPM
Structural	401	Smoke detected
	5810	Ground crash error
Grid	144	High windspeed: __._ m/s
Hydraulic	5452	HydrMainPressLow:____bar____ °C
	5459	HydrHPPumpPositiveFeedbackErr
	5460	HydrHighPressPumpThermoError
	5446	HydrInitPressMissing___bar__ °C
Unknown	876	AGO timeout state:__ * ______
Drive train	156	Chock sensor trigged:____._RPM
	3099	BrakeAppliedInProduction

Subsystem	Fault Code	Fault Description
Yaw system	356	Extreme yawerror __._m/s___._ °
	79	Max. Yaw error: ___._ °
	3273	YawUntwistCCW: Code__,_______ °
	276	Start auto-outyawing CCW
	275	Start auto-outyawing CW
	3272	YawUntwistCW: Code__,_______ °
	3298	Yaw To Cable Twist Reset
	181	Feedback = _, yawing CW _
	182	Feedback = _, yawing CCW _
	320	High temp. Rotor Inv.L_:___ °C
	3209	YawSignals Invalid
Electrical	444	EMF Acc _ Press Low, ___._ bar
	127	Extr. low voltage L_: ___V
	135	Low voltage L_: ___ V
	202	Frequency error 1: ___.__ Hz
	315	ExEx low voltage L_: ___V
	2956	SupplyError: Min ____V phase_
	5818	CPS DltPRefM
Control	900	Pause pressed on keyboard
	309	Pause over RCS __
	2676	UPS Error
	100	Too many auto-restarts:_____
	232	WatchdogReboot
	604	Remote Reboot
	1008	High Q7 current ____A L_
	3634	Automatic Test Activated: ___
	324	High temp. VCP Board ___ °C
	707	Ch hardware error C_
	3472	SafetySystem Reset Required
	5434	Q8 breaker open
	5506	UPS AC Await disconn pwr

Table 24: Fault categories to WT subsystems used to this paper.