EXPERT GROUP REPORT ON
RECOMMENDED PRACTICES

17. WIND FARM DATA COLLECTION AND RELIABILITY ASSESSMENT FOR O&M OPTIMIZATION

FIRST EDITION, 2017

Submitted to the Executive Committee
of the International Energy Agency Implementing Agreement
for
Co-operation in the Research, Development, and Deployment
of Wind Energy Systems

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re•li´•a•bil´•i•ty (ri, līə 'bilətē) *n.*

a person or thing with trustworthy qualities.

Task 33 · Reliability Data

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Foreword

The International Energy Agency Implementing Agreement for Co-operation in the Research, Development and Deployment of Wind Energy Systems (IEA Wind) is a vehicle for member countries to exchange information on the planning and execution of national, large-scale wind system projects and to undertake co-operative research and development projects called Tasks or Annexes.

As a final result of research carried out in the IEA Wind Tasks, Recommended Practices, Best Practices, or Expert Group Reports may be issued. These documents have been developed and reviewed by experts in the specialized area they address. They have been reviewed and approved by participants in the research Task, and they have been reviewed and approved by the IEA Wind Executive Committee as guidelines useful in the development and deployment of wind energy systems. Use of these documents is completely voluntary. However, these documents are often adopted in part or in total by other standards-making bodies.

A Recommended Practices document includes actions and procedures recommended by the experts involved in the research project. A Best Practices document includes suggested actions and procedures based on good industry practices collected during the research project. An Experts Group Report includes the latest background information on the topic as well as a survey of practices, where possible.

Previously issued IEA Wind TCP Recommended Practices, Best Practices, and Expert Group Reports can be found at www.ieawind.org on the Task 11 webpages.

Preface

Reliability is a critical issue for the growing wind energy industry. Safety, availability, maintenance, logistics and costs are all impacted by reliability. Furthermore, reliability is dealt with during all phases of lifetime, from design, testing, construction and operation to decommissioning.

As the global operational wind turbine fleet ages, pressure to reduce both the subsidies associated with wind energy and the Levelized Cost of Energy (LCoE) of wind energy continues. This confluence of events drives the need to improve the reliability of wind assets if profit margins are to be maintained while reducing costs.

To improve the reliability of wind assets, a detailed statistical analysis of the reliability characteristics of systems, components and subassemblies is required. This must be complemented by qualitative assessments of operational and maintenance information sources. Guidelines on how to undertake these tasks will support existing initiatives dealing with reliability issues, ease the merging of disparate databases and would allow for benchmarking and deeper analyses.

Through a series of workshops, web and teleconferences, the IEA Wind TCP Task 33 workgroup explored the challenges, opportunities and value associated with the collection and analysis of reliability data and associated standards, guidelines and taxonomies. These efforts had representation from industry, from Original Equipment Manufacturers (OEMs) to service providers, from research institutions and owners / operators. This study consolidates the results by examining the scope of reliability data in terms of what reliability data is and how it should be gathered from a range of sources and tools.

The recommended practices contained within this study links the reliability ambitions of wind farm owners and operators with a range of use cases, examples, standards and taxonomies to assist in the identification, collection and analysis of reliability data.

This study directs users with a wide range of operational circumstances and reliability ambitions towards existing, appropriate guidelines, standards and taxonomies associated with the collection of valuable data sets from wind turbine control systems and maintenance reports.

Berthold Hahn
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Approved by the Executive Committee of IEA Wind TCP 18 May 2017.

Executive Summary

Overview

As the global operational wind turbine fleet ages, pressure to reduce both the subsidies associated with wind energy and the Levelized Cost of Energy (LCoE) of wind energy continues. This confluence of events drives the need to improve the reliability of wind assets if profit margins are to be maintained while reducing costs.

To improve the reliability of wind assets, a detailed statistical analysis of the reliability characteristics of systems, components and subassemblies is required. This must be complemented by qualitative assessments of operational and maintenance information sources. Guidelines on how to undertake these tasks will support existing initiatives dealing with reliability issues, ease the merging of disparate databases and would allow for benchmarking and deeper analyses.

The IEA Wind TCP Task 33 workgroup has representation from industry and research, from Original Equipment Manufacturers (OEMs) to service providers, from research institutions to owners / operators. Through a series of workshops, web and teleconferences, the workgroup explored the challenges, opportunities and value associated with the collection and analysis of reliability data and associated standards, guidelines and taxonomies.

This study consolidates the results by examining the scope of reliability data in terms of what reliability data is and how it should be gathered from a range of sources and tools.

The recommended practices contained within this study link the reliability ambitions of wind farm owners / operators with a range of use cases, examples, standards and taxonomies to assist in the identification, collection and analysis of reliability data.

Key stakeholders

The key stakeholders with an interest in wind asset reliability and maintenance data include: investors / owners / operators, service providers, OEMs, suppliers, financiers, and insurers.

Of the above groups of stakeholders, the primary audiences for this study are Operators and Service Providers; while the recommended practices contained within this study are primarily directed at these groups, all identified stakeholder groups benefit from the adoption of recommended practices.

Approach

Often the initial questions associated with reliability data are: what data should be collected and what standard should be applied.

Reliability data is multi-dimensional. Geography, age, strategic and tactical operational demands and other factors influence the data requirements and the standards that can, or should, be applied.

To optimize the application of the best practices contained in this report, it is important to first understand individual circumstances and reliability objectives. Then, via identifying suitable analyses and evaluations, the document tries to lead to necessary data and appropriate standards and guidelines.

This study directs users with a wide range of operational circumstances and reliability ambitions towards existing, appropriate guidelines, standards and taxonomies associated with the collection of valuable data sets from wind turbine control systems and maintenance reports.

The IEA Wind TCP Task 33 remit did not cover the development of new standards or taxonomies; however, where there are gaps in the existing set, recommendations have been made.

Key findings

- While there is broad industry recognition that reliability and reliability data are becoming increasingly critical to both profit margins and LCoE, the lack of standards associated with reliability data for owners / operators is adversely impacting industry progress in addressing reliability issues.

- Historically, reliability data is rarely considered by the owners / operators at the early stages of wind asset development and warranty-based operation.

- The reliability ambitions of wind asset owners / operators range from those comfortable with a complete reliance on third parties, such as OEMs to manage asset reliability, to those seeking control of maintenance strategies and actively managing asset reliability.

- While the ability for owners / operators to compare, or benchmark, reliability metrics associated with their assets against those of their peers exists, uptake has been restricted, in part, by the availability and consistency of reliability data.

Recommendations

For owners / operators:

1. Consider reliability data to be of high value from the early stages of wind asset development and a key operational factor throughout the life of the wind asset. Ensure access to reliability data and required data are factored into negotiations with developers / OEMs / suppliers / service providers.

2. Identify use cases linked to your organizational reliability ambitions and use these to define data collection requirements.

3. Map all wind asset components and maintenance activities to one of the taxonomies / designation systems identified in this study. This will allow for improvements in both the consistency and integrity of reliability data throughout an organization and at the interfaces with the supply chain.

4. Align operating states with those specified in IEC 61400-26 1/2, the standard for a time- and production-based availability assessment for wind turbines.

5. All staff engaged directly, or indirectly, in the production, collation and analysis of reliability metrics should be educated on the strategic significance of reliability data and empowered to improve related business processes and practices.

6. Whenever practical, seek to automate the data collection / collation process as a means of reducing the risk of human error and improving data quality.

7. Wind farm owners / operators should engage in the external, industry-wide sharing of reliability and performance data. This will align data collection methodologies, drive organizational improvements and achieve statistically significant populations of data for reliability analyses.

Development of standards for the wider industry:

8. Develop a comprehensive wind specific standard based on ISO 14224, FGW ZEUS, and other existing guidelines/standard. This would provide a core standard for the language and scope of reliability and maintenance data for the wind industry (based on accepted reliability data best practice in oil and gas industry), while minimizing the time and cost associated with the development of the standard.

9. As a longer-term recommendation, there is a need to develop standard definitions for damage classification and severity for structural integrity issues.

The implementation of the above recommendations will improve the quality (accuracy, consistency and integrity) of reliability data and consequently the value derived from it for all stakeholders across wind asset investment, development, operation and insurance.

The development and adoption of reliability data collection standards and reporting across the industry will take time and the commitment of all stakeholders. The value, as realized in oil and gas industry, lies in safer and more effective and efficient maintenance policies, strategies and practices. Failure to do this will restrict the pace at which opportunities to improve operations and maintenance costs can be identified and consequently implemented.

Abbreviations

ADT	Aging, undefined point of time
AI	Artificial intelligence
CCT	Continuous on-condition task
CDF	Cumulative probability function
CMMS	Computerized maintenance management system
CMS	Condition monitoring system
CR	Component reliability
ED	Data group equipment data
EN	European norm
ETA.	Event tree analysis
FD	Data group failure / fault data
FDS	Fault detection system
FEM	Finite element method
FFA	Functional failure analysis
FGW	Federation of German Windpower and other Renewable Energies
FME(C)A	Failure mode and effect (and criticality) analysis
FOM	Force of mortality
FSI	Functional significant item
FTA	Fault tree analysis
GADS	Generating Availability Data System
HPP	Homogenous Poisson process
IEA	International Energy Agency
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
KPI	Key performance indicator
LCC	Life cycle cost
LCoE	Levelized cost of energy
MCSI	Maintenance cost significant item
MD	Data group maintenance and inspection data
MLE	Maximum likelihood estimation
MSI	Maintenance significant item
MTBF	Mean time between failures
MTTF	Mean time to failure
MTTR	Mean time to repair
NERC	North American Electric Reliability Corporation
NHPP	Non-homogenous Poisson process
O&M	Operation and maintenance
OD	Data group operating data / measurement values
OEM	Original equipment manufacturer
OFF	Observable fast failure progression
OGF	Observable gradual failure progression
PDF	Probability density function
PM	Preventive maintenance
RAMS	Reliability, availability, maintainability, safety

RBD	Reliability block diagram
RCM	Reliability centered maintenance
RDS-PP®	Reference designation system for power plants
RF	Random failures
ROCOF	Rate of occurrence of failure
RTF	Run to failure
SCADA	Supervisory Control And Data Automation
SCT	Scheduled on-condition task
SEM	Standard error of the mean
SFT	Scheduled function test
SOH	Scheduled overhaul
SRP	Scheduled replacement
TS	Technical specification
TUD	Nordic nuclear reliability database
VGB	European technical association for power and heat generation

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1. Introduction

Reliability is a critical issue for the growing wind energy industry. Safety, availability, maintenance, logistics and costs are all impacted by reliability. Furthermore, reliability is dealt with during all phases of lifetime, from design, testing, construction and operation to decommissioning.

In 2011, the IEA Wind TCP Executive Committee authorized the working group of IEA Wind Task 33 with a focus on data collection and reliability assessment for O&M optimization of wind turbines. Task 33 commenced in 2012 with the objective to prepare recommendations for the wind industry about suitable data collection and analyses. This report consolidates the findings and recommendations, both in terms of recommendations for wind farm owners / operators and for the wider industry.

IEA Wind TCP Task 33 has focused on data collection from Supervisory Control And Data Automation (SCADA) systems, maintenance activities and reliability issues during maintenance and operation. Testing and design optimization, specialized inspections like vibration measurements and frequency analyses as well as the concatenation of reliability data with real cost were out of scope. Further, it is noted that this recommendation only partly can be applied to verify the requirements in IEC 61400-1:2005 to ensure acceptable safety of the structural components of the wind turbine.

During their work the team has recognized a need for the further standardization of items such as common status and alarm codes or specifications of what physical values to gauge when investigating certain propagating defects of structural components. While the development of new standards is out of scope, identified needs have been captured in the report recommendations.

1.1 Aim of IEA Wind TCP Task 33

All stakeholders in the wind industry use O&M experience to support future decisions and activities. Operators aim at improving maintenance efforts. Owners seek to ensure their future investments. OEM and component suppliers aim at improving their products. Financiers aim to reduce their investment risks and insurers aim to understand and quantify reliability risks. The whole wind industry could benefit from O&M experience, but individual experience is often not prepared systematically and thus no universally valid information is available.

IEA Wind TCP Task 33 has strived to find answers to the questions:

- Which information or support do operators and other stakeholders need?
- What analyses can provide the requested information?
- Which data must get recorded to feed these analyses?

1.2 Target audience and industry involvement

The intended audience for these recommended practices are those working with reliability data and analysis for existing plants. However, other groups will also benefit, including those setting up the data collection and analysis for a new plant, developers exploring the possibility of a new plant, and researchers modeling theoretical plants or turbines.

Industry engagement in IEA Wind TCP Task 33 has been a critical factor from the outset. Several industry representatives were continuously members of the team. In September 2015, an industry workshop with 40 representatives from industry and research discussed opportunities and barriers for collecting and analyzing reliability data from the O&M of wind turbines.

Additionally, several intensive interviews with experts from the industry were held in summer 2016. In general, these experts sanctioned the recommendations provided in the Executive Summary. The existing recommended practices thus contain important contributions from research and industry as well.

1.3 Purpose and structure of this report

This document will lead users to appropriate solutions for their individual challenges.

The initial approach is to thoroughly describe the individual roles and tasks and then, step by step, identify suitable analyses, convenient guidelines and taxonomies along with the appropriate data sets to collect. Some examples will illustrate typical situations.

Chapter 2 ‘Recommendations at a Glance’ presents this approach and the main results. The following chapters provide the background and details supporting the recommendations. General opportunities and preconditions for successfully running reliability databases are given in Chapter 2.10.

Reliability databases are often considered to be an appropriate means for making use of reliability data. General information about opportunities and limitations are given in Chapter 3.

Influencing the performance and reliability of assets during operation and maintenance depends to greatly on the applied maintenance strategies. These strategies are briefly described in Chapter 4, while Chapter 5 explains O&M modeling that can help reduce effort, find the best moment of renewal etc.

A deeper insight into reliability analyses, capabilities and pros and cons of different qualitative and quantitative methods are given in Chapter 6.

Chapter 7 describes the contents of the standards and guidelines relevant for understanding the recommendations and presents benefits from using each.

It also presents the structure of data groups and entries, describes taxonomies provided by existing standards and guidelines and gives an overview about the appropriateness for reliability data collection.

The appendices provide detailed descriptions on the examples of how to find appropriate analyses, data sets and taxonomies in specific scenarios, also briefly described in Chapter 2.9.

1.4 Related standards and guidelines

This document strives to lead potential users of reliability data determining and suggesting guidelines that are most appropriate for them individually. There is a list of standards and guidelines related to the contents of this document; two of these standards provide the foundations of the recommended best practices.

Firstly, this document generally follows IEC 60050 and EN 13306 when using terms and definitions regarding inspection, maintenance, and repair. Secondly, the ISO 14224 from the oil and gas industry is well-structured for identifying data groups and taxonomies. Thus, this document takes ISO 14224 as a model for structuring data groups and sub-groups.

In total, this document refers to the following standards and guidelines and other documents:

EN 13306	Standard: Maintenance - Maintenance terminology, 2010
IEC 60050	International Electrotechnical Vocabulary, http://www.electropedia.org/
IEC 60300-3-1	Standard: Dependability management – Application guide Analyses techniques, 2003
IEC 60300-3-2	Standard: Dependability management – Application guide Data Collection, 2004

IEC 61400-1	Standard: Wind turbines – Design requirements
IEC 61400-25-x	Series of standards: Communications for monitoring and control of wind power plants
IEC 61400-26-x	Series of standards: Time-based and production-based availability for wind turbine generating systems
ISO 2394	Standard: General principles on reliability for structures, 2015
ISO/DIS 14224	Draft standard: Petroleum, petrochemical and natural gas industries -- Collection and exchange of reliability and maintenance data for equipment, 2015
ISO/TS 81346-10	Technical specification: Industrial systems, installations and equipment and industrial products – Structuring principles and reference designation -- Part 10: Power plants, 2015
NERC-GADS	Guideline: North American Electric Reliability Corporation – Generating Availability Data system: Wind Generation Data Entry, 2009
ReliaWind	Project report: Reliability-focused research on optimizing Wind Energy system design, operation and maintenance: Tools, proof of concepts, guidelines and methodologies for a new generation, Deliverable D 6.7 – Recommendations from the ReliaWind Consortium for the Standardization for the Wind Industry of Wind Turbine Reliability Taxonomy, Terminology and Data Collection, 2011
VGB RDS-PP®	Guideline: VGB, Reference Designation System for Power Plants, Application Guideline Part 32: Wind Power Plants, 2014
FGW ZEUS	Guideline: FGW, Technical Guidelines for Power generating Units, Part 7: Maintenance of power plants for renewable energy, Category D2: State-Event-Cause Code for power generating units (ZEUS), 2013

2. Recommendations at a glance

2.1 Challenge

Operational experience with wind turbines can be utilized to learn about the reliability characteristics of plants, systems, and assemblies through statistical analyses and qualitative assessments of operational and maintenance data.

However, optimizing the application of operational experience requires a systematic solution for data collection. Setting up a well working system for collecting all relevant data, from continuously readings of numerous sensors to normalized work order records, implies a considerable initial effort. Furthermore, for many owners / operators the portfolio will be too small to generate a sufficiently broad database for sound results. Currently, wind turbine control systems generate different data sets and they code alarm logs and other messages differently. Operators develop proprietary mappings or manually convert and transfer data to their individual management systems. A further complication for owners / operators of smaller portfolios is building enough width into their databases to provide meaningful results.

Gaining enough similar data sets in the same format for a long enough period of time is thus a great challenge. The first step in addressing this challenge is defining guidelines on which data sets to collect, how to designate items, and how to describe failure modes.

2.2 Approach

As illustrated in Figure 1, the approach of these recommended practices is to start with identifying relevant roles and possible objectives in the wind industry. Next, tasks and analyses which support those purposes are described and the input data to drive these analyses are determined. Finally, standards and guidelines which provide categories and taxonomies or propose data sets are presented. Additionally, some use cases explain how to individually derive the appropriate data sets to collect, how to feed and work with qualitative and quantitative analyzing methods and how to extract relevant results. Following some of these examples, the users will find roles and a suitable approach for their concrete task.

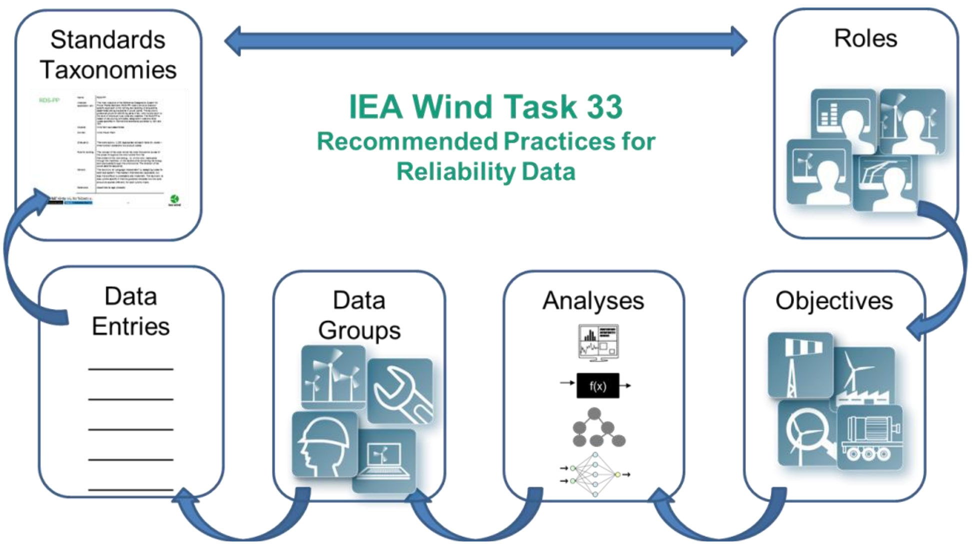


Figure 1: To determine an individual solution, derive appropriate data sets to collect by identifying the applied roles and analyses

This approach was presented to and discussed with representatives from the wind industry and the feedback was incorporated.

2.3 Roles and objectives

To find an appropriate way of collecting and analyzing reliability and maintenance data, it is important to clarify the task at hand and basis of need.

Operators will desire maximizing revenues and as they evaluate their assets, they will analyze availability and energy yield. Service providers will aim at minimizing their efforts and therefore look for grouping tasks. Each case requires different analyses and assessments and thus different data sets.

Obviously, it is useful to distinguish roles and to assign them to objectives and analyses. Table 1 presents key roles in the wind industry and the objectives which serve the tasks of these roles. It is important to note that roles might be shared between companies or companies may take over several roles.

Table 1: Most relevant stakeholders or roles in the wind industry and their objectives for dealing with reliability and maintenance data

Roles	Objective
Owner	Support for investment decisions
Operator	Reporting performance indicators
	Determining availability and weaknesses
	Identifying maintenance strategies
Service Provider	Maintenance optimization
	Optimizing spare parts inventory
OEM/supplier	Design optimization
Financier/insurer	Risk assessment

As operators and service providers have a more direct relationship to the reliability of wind turbines and maintenance tasks, the recommended practices emphasize these two roles.

2.4 Complexity levels

Organizations and individuals have varying views and requirements associated with the reliability of their assets. Depending on the size of their portfolio, on assigned responsibilities or on purchase and maintenance contracts they will be able and willing to collect more or less detailed data and information. Regional legislative or regulatory demands can also influence reliability requirements.

Optimizing O&M procedures by building on analysis of historical failure data, related faults and failures, maintenance effort and associated costs is a complex and sophisticated task. This is particularly true when relating costs to the different efforts of maintaining and repairing, spare parts and logistics.

Design optimization, monitoring and analyzing failure propagation or product degradation are a further set of complex tasks. In this case failure and maintenance data often must be collected from different sources and systematically archived.

Monitoring and reporting the asset's performance with key performance indicators (KPIs) is a further process to take into account when considering the levels of individual reliability ambitions. While less complex than the preceding tasks, the evaluation of automatically provided measurement data will be sufficient for most KPIs.

Table 2: Different levels of complexity may lead to individually appropriate data collections and standards

Level	Possible application	Possible analyses	Needed data groups	Requirement for organizational foundation of reliability
(A) Relatively easy to achieve	Performance, availability	Statistical calculations (e.g. average values, simple plots such as histograms)	Equipment data, Operational data and measurement values	Assessment of assets is recognized as important
(B) Moderate	Plus: failure mode analysis	Fault-tree-analysis, Pareto-analysis, basic physical models (e.g. miner's rule)	Plus: failure/fault data	Reliability is recognized as important, some processes around reliability exist
(C) More laborious	Plus: design optimization, maintenance optimization, degradation monitoring	Degradation models, advanced physical models (e.g. modeling fluid structure interaction), maintenance and logistics optimization, data mining, vibration analysis, optimized renewal, optimized stock-keeping	Plus: maintenance and inspection data (costs)	A clear and formal reliability process is defined and regularly reviewed with stakeholders

Table 2 presents three levels of ambition from (A) Relatively easy to achieve, to (C) More laborious, which enable increasingly complex applications. With each of the two steps one more data group must be captured. The most ambitious level requires a high effort for achieving complete data sets of good quality and some noteworthy manual collection and verification.

2.5 Analysis methods

Different types of analysis methods have different requirements regarding the degree of detail of the data sets and length of data history. The objective of the reliability data collection and the analysis methods to be used to achieve these objectives should therefore be defined in the beginning of a data collection initiative. Operators' experiences show that it is challenging to provide missing data and tidy up historical data that was not dealt with systematically from the beginning.

Different qualitative and quantitative methods serve the objectives of better understanding the reliability behavior of wind turbines and their components (see Chapter 6). The model that is used for data analysis should be chosen according to the intended field of application and the decision that must be made (see Chapter 5). A general model that suits all applications and is suitable for all types of decisions does not exist.

Currently, applying sophisticated reliability analyses still seems quite ambitious because the needs for high-quality data (in terms of accuracy, completeness and degree of detail) are difficult to serve with the currently available data and will be difficult to achieve in the short and medium term.

Collaborative data collection initiatives where many partners contribute data will yield significant benefits, especially when statistical methods and models are used, since the associated increase of the sample size will improve the quality (accuracy) of estimates.

The existing standards and initiatives aiming to estimate (constant) failure rates could be improved through models as suggested in Table 3. For differences between ROCOF (rate of occurrence of failure) and FOM (force of mortality), see 3.4.3.

Table 3: Suggestions for improved reliability analyses

Type of model	Comments/examples
Stochastic failure rate models for non-constant failure rates (ROCOF)	e.g. non-homogeneous Poisson process (NHPP)
Lifetime distributions with non-constant failure/hazard rates (FOM)	e.g. Weibull distribution. For components that are non-repairable
Degradation models	Requires that degradation can be observed/measured and quantified; Well-suited for planning of condition-based maintenance
Physical models	For applications where we have a good understanding of the physical mechanisms leading to failure and where suitable models describing these mechanisms are available
Models for (continuous) condition monitoring data	Models capable for use with a large amount of time series data; Well-suited for fault detection and predictive maintenance

2.6 Wind farm component hierarchy

In the following section, several taxonomies will be presented that divide components of a wind power plant into hierarchical levels.

Unfortunately, taxonomies not only follow different rules for structuring, but also use different terms for similar levels. Table 4 shows the assignment of components of a wind power plant structure into hierarchical levels. This assignation is used in this document. The hierarchical structure is important when for example aggregating failure rates from items on a lower level to the failure rate of the respective item on the next higher level.

When choosing an appropriate taxonomy for designating components of the turbine, it is important to find out whether the individual task requires aggregating figures from one level to the next and thus requires a hierarchical structure or not. The structure in Table 4 broadly follows the hierarchy and the levels of detail of the industry standard ISO 14224.

Table 4: Levels of a wind power plant structure

No	Hierarchical levels	Exemplary items
1	Plant	Wind power plant
2	System	Wind turbine
3	Sub-system	Drive train
4	Assembly	Shaft assembly
5	Maintainable item	Bearing
6	Part	Roller

2.7 Data groups and sub-groups

The aim of reliability analyses is to identify frequent failures of certain items and find out whether they occur at similar ages of the affected turbines or if they occur randomly. To mitigate uncertainties of the results, statistical analyses aim at selecting wind turbines with similar technical concepts operated under similar conditions to derive reliability figures.

It is therefore important to collect data on the turbine type and operational conditions at the site as well as information on the affected components, failure modes and causes and dates of occurrence. These data types have quite different characteristics and can get divided into four data groups. Table 5 provides these data groups and gives some indications which data or sub-groups and objects they consist of.

Table 5: Groups of reliability and maintenance data and objects

Data groups	Sub-groups / objects
Equipment data (ED)	Identification
	Time data
	Technical information
Operating data / measurement values (OD)	Time stamp
	Measurement values (SCADA, etc.)
	Operational states
Failure / fault data (FD)	Identification
	Time data
	Failure description
	Failure effect
	Failure detection
	Fault properties
Maintenance & inspection data (MD)	Identification
	Time data
	Task / measure / activity
	Resources
	Maintenance results

A fifth data group would regard cost information. To optimize the financial benefit of running wind turbines, it is essential to connect reliability and maintenance data with cost information. However, for most companies cost information is classified as competitively sensitive and as confidential; as such, this report does not cover cost data. Nevertheless, the objects ‘resources’, ‘failure impact’, ‘measurement values’, and ‘operational states’ provide information which will lead to financial assessments when connected with individual cost information.

2.8 Taxonomies

Several guidelines and standards from different industries deal with data and values and suggest varying degrees of granularity. For reliability analyses and O&M optimization none of these guidelines provides a complete scheme for all applications.

Table 6 presents an overview of the relevant standards and guidelines available today and considered in the document.

Table 6: Data groups and related taxonomies

Data groups / taxonomies	Equipment data	Operating data / measurement values	Failure / fault data	Maintenance & inspection data
RDS-PP®	o			
GADS	o	-		-
ReliaWind	o			
ISO 14224	(o)		(+)	(+)
ZEUS		o	+	+
IEC 61400-25		+		
IEC 61400-26		o		

+ wind-specific entries with a high level of detail
o wind-specific entries with a medium level of detail
- wind-specific entries on a more general level
(+) entries with a high level of detail, not wind-specific
(o) entries with a medium level of detail, not wind-specific
(-) entries on a more general level, not wind-specific

The document addresses standards and guidelines providing lists of terms for categorizing aspects of components, failures, maintenance tasks etc. as ‘taxonomies’. Unfortunately, the taxonomy properties do not directly fit to the demands of a reliability data collection. Chapter 7.2 presents some general information on the data groups and taxonomies.

2.9 Use cases

Below are four examples of how to find appropriate analyses, data sets and taxonomies in specific scenarios. Three of the examples are written from the view point of a wind farm operator focusing on maintenance with an increasing level of ambition, one example takes the perspective of a component supplier seeking to improve product design.

Example ‘Availability assessment’’

Calculating and reporting production-based availability and lost energy production allows an operator to quantify the impact of reliability and maintenance on the performance and to benchmark several wind farms.

In order to know whether the wind farm generated all of the expected production and whether it achieved the guaranteed availability, it is necessary to calculate the potential production, the real production at each turbine throughout the month, and to classify all operational states.

To that end, the operator must create a complete turbine status log in order to distinguish between periods of availability and unavailability. Additionally, accurate maintenance data and measurement data are necessary.

Example ‘Design comparison’

The second example concerns describing failure behavior through reliability functions like lifetime distributions.

This information is not only important for operators and their maintenance planning but also for manufacturers and suppliers. To improve design, it is necessary to determine weak points and be aware of different failure modes including their frequency and the failure propagation. The requirements regarding data acquisition are therefore higher and especially maintenance and failure data are needed.

Example ‘Grouping of maintenance tasks’

In the third example a wind farm operator wants to optimize maintenance by using optimization models to group preventive maintenance activities into maintenance packages.

The aim of the grouping is to reduce overall maintenance costs by sharing setup costs (e.g. travel costs) between maintenance tasks that are grouped.

The calculation of optimal inspection intervals with or without grouping requires a lifetime distribution for the time to failure for each relevant type of component. Failure modes, failure mechanisms, or failure causes must also be distinguished. Furthermore, the comparison of the total costs with or without grouping requires cost estimates for the different maintenance tasks.

Example ‘Monitoring Degradation Processes’

The last example continues the theme of increasing reliability ambition. An operator wishes to identify the degradation processes of structural components and strives to minimize their effects.

He needs to identify the most endangered components by making use of historical inspection and repair records. Additionally, he has to decide on appropriate inspection methods, adapt schedules and record the results, including a detailed description of detected defects for distinguishing different types of failures and assessing their severity.

In the Executive Summary, the examples above get explained in detail. Step by step, the user of this document may follow the process from identifying the objective and analyses to deriving the necessary input data and finding the appropriate taxonomies.

2.10 Conclusions

There is a strong demand for making better use of operational field data to improve O&M as well as for other applications from design optimization to risk management, but there is no common understanding which data to collect. The industry therefore requires an international agreement or guideline on which data to collect and how to treat it. A wide range of analytical approaches, methods, models and tools help the different stakeholders to serve the objectives shown in Table 1.

Approaches and analysis methods comprise both qualitative approaches like Failure Mode and Effect Analysis (FMEA), simple/basic methods like calculating average values and more advanced models, such as software tools for O&M simulation requiring a large number of input parameters. One example is the calculation of average costs and failure rates— typical input parameters in models and software tools for O&M optimization. Depending on which approaches and analysis methods the stakeholders intend to use, different types of data must be collected to be able to apply these approaches and analysis methods and to estimate necessary input parameters.

The collection of data can be a competitive advantage and could have benefits beyond operations and maintenance. It may provide feedback for those in manufacturing, project development, design, finance, construction, research and other aspects involved in asset management throughout the project’s life cycle.

The decision to collect data depends on who specifically needs it and what will be done with it and on the overheads and costs arising from the collection and analysis of the data. This should be an informed decision that reflects both the contractual and regulatory requirements of the different stakeholders.

Often owners / operators collect all data provided. Many of these collections, however, will not be comprehensive and detailed enough for intensive reliability analyses. To achieve a sound database for reliability analyses, data must be collected systematically from different data sources at an adequate volume and depth.

Automated data collection from SCADA systems is relatively straightforward, but retrieving data from inspection/maintenance reports is a challenge. Collecting data from inspections, maintenance and repair with a high data quality remains difficult, as technicians need to gather this data at least partly manually, which will take them some effort. To achieve complete and valuable data sets, it is recommended to support technicians with mobile electronic devices and informing the staff about their individual and the overall benefit.

A complete data set consist of four data groups, equipment data, operational/measurement data, failure/fault data, and maintenance/inspection data. This data will be retrieved from mainly three sources: wind turbine documentation, maintenance and inspection reports, and SCADA systems. For all data groups, there are suggestions for suitable data sets, but precise requirements depend on the purpose of the data collection.

Currently, there is no comprehensive standard covering all aspects and all data groups. IEA Wind TCP Task 33 provides suggestions on data sets to collect and name corresponding taxonomies. Users must identify combinations of several standards, guidelines, or taxonomies that best meet their needs.

The identified standards and guidelines all have pros and cons. IEC standards 61400-25 (for identifying and naming metering/gauging channels) and 61400-26 (for definitions of operational states) are widely accepted industry standards.

More difficult will be the choice of the appropriate component designation system. RDS-PP® and NERC-GADS are widely in use and provide comprehensive taxonomies, while RDS-PP® provides more opportunities for later analyses and NERC-GADS is easier to use. Moreover, for North American operators reporting to NERC, the use of GADS terminology is mandatory. However, it is possible to collect and structure data using RDS-PP® and map data according to NERC-GADS terminology for reporting.

Unfortunately, there is no easy solution for obtaining failure/fault and maintenance/inspection data. On one hand, operators currently do not always get complete information from service providers; on the other hand, there is no single overarching standard or accepted industry practice for how to collect, organize and store wind farm O&M data. While ISO 14224 is well-structured and already quite substantial, it is still not complete and moreover not wind-specific. The ZEUS guideline was developed to gather reliability and maintenance data, but ZEUS does not entirely cover all aspects. For the remaining gaps, IEA Wind TCP Task 33 has again suggested minimum data entries. This is a key finding of IEA Wind TCP Task 33 along with a recommendation for the development of a wind-centric guideline based on ISO 14224 and ZEUS.

3. Reliability databases

3.1 Experience from existing surveys about wind turbine reliability

To date there has been a substantial effort from both industry and research institutions to develop databases, methods, and statistical analyses of wind turbine failures and reliability. The common challenges for these efforts include:

1. Operators experiencing difficulties in data collection, resulting in poor data quality.
2. A lack of standard methods for O&M reports with a systematic description of affected components and failure modes.
3. Insufficient cooperation of operators, manufacturers, component suppliers, designers, service providers, and research organizations.
4. Ensuring existing plants represent modern turbines.

As a result of different aims, approaches, and methods of data acquisition, the possible analyses, findings and conclusions of the databases are also quite different.

Wind turbine operators may be more interested in knowing about wind turbine availability, downtimes due to unscheduled maintenance, and the most crucial components. Most initiatives gather the appropriate data to answer these questions, but more detailed data is needed to improve maintenance processes, such as waiting times, times to repair, number of exertions of service staff, qualification of personnel, disposability of vehicles, etc.

Additional detailed data must be known to optimize maintenance effort versus availability and life cycle cost. This requires gathering information about damages, causes and means of discovery, etc. Cost information regarding each exertion, broken down into all affected parts, is also needed.

Figure 2 tries to illustrate the dependency of valuable analyses on the level of detail of the gathered reliability data. Due to the complexity of this relation, the two-dimensional depiction is more a qualitative depiction to show the capabilities in general.

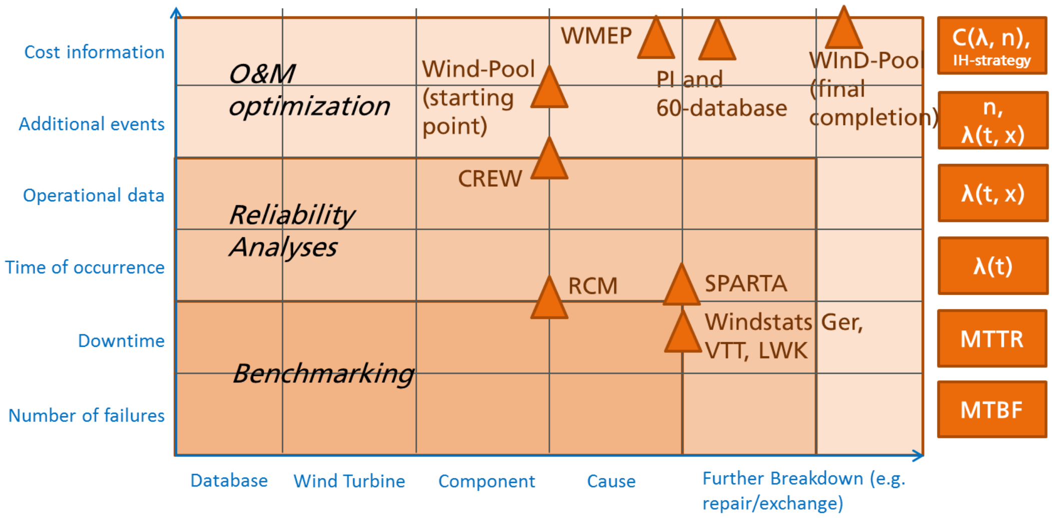


Figure 2: Capability of the databases for more or less complex analyses

Additional information on the y-axis is needed to extract additional KPIs and allow more detailed reliability analyses resulting in further characteristic values.

The overall number of failures for calculating the Mean Time Between Failures (MTBF) or the average failure rate is relatively easy to determine. Two steps further, the failure rate as a function of time ($\lambda(t)$)

can only be investigated when the time of occurrence is known for every single failure. If in addition some operational data is gathered, then it is possible to describe the reliability behavior ($\Lambda(t,x)$) related to the produced energy or to the cumulated loads. To optimize O&M procedures, it is necessary to take additional events, such as regular service activities or shutdowns due to the grid, into account and to combine these events with production losses or needed effort.

Differentiated analyses require a breakdown of faults and activities to sub-systems or maintainable items and a relation of failure rates to causes and maintenance activities. For statements about the reliability behavior, it is crucial to at least regard the affected components.

Nevertheless, additional parameters that enable a differentiation of the extracted KPIs are also needed for the appropriate conclusions. Two examples can be seen in the cause and description of the performed measure. For the description of the reliability behavior, it is important to split internally caused failures from those that cannot be influenced by maintenance activities (e.g. lightning strike). A differentiation between failures that need repairs and those that lead to a component exchange is also needed.

In general, three fields of application can be seen. The first block aims at benchmarking the overall reliability, for which basic information is sufficient. The more advanced option is to describe the reliability behavior in more detail and the most ambitious task is to use the information for O&M optimization.

Based on this approach, the figure shows the capabilities of the identified databases. It depicts at which level the information is gathered and which level of result is hereby achievable. However, the more qualitative depiction only provides a general impression of the differences between the databases. More information need to be considered for a detailed comparison.

A major shortcoming can be seen in the most ambitious part of gathering cost information. Within all the identified databases, only two contain cost information. Since the large WMEP database contains only general cost information, only general results are generated.[1] The Chinese databases PI and 60-database are relatively young and do not contain enough data yet. A real optimization of life cycle cost is thus not possible so far.

3.2 Reliability data use and users

3.2.1 Uses of reliability data

3.2.1.1 Purpose of a reliability database

The purpose of a reliability database is typically to create a continuous picture of the power plant's performance over its expected lifetime. The database should thus support a calculation of performance indicators and feed it into a reliability analysis.

Useful information includes environmental conditions during operation, electrical parameters of the grid, energy and power production, maintenance and inspection data about outages, spare parts or labor and other data needed for performance analytics.

One example of the definition of a reliability database comes from a Nuclear Reliability Database (Nordic Nuclear – TUD). This concise definition covers the key characteristics of any reliability database (Pettersson et al, 2010):

[1] WMEP: The "Scientific Measurement and Evaluation Programme" (WMEP), 1989 to 2006. 193.000 monthly reports of operation and 64.000 maintenance & repair reports from 1,500 WTs in Germany. PI, 60-database: Base for Chinese programmes CGN Wind Farm Operation Reliability Research and FTA wind turbines reliability and O&M.

"It should be able to provide basic reliability data from the statistical distribution of failures and fault times in the form of e.g. failure rates, errors per need, MTBF, MTTR and failure distribution functions. It should not be unnecessarily restricted, but as flexible as possible. Graphic presentation of failure data and estimates of reliability parameters should be presented for any population."

3.2.1.2 Potential purposes of reliability database

The main stakeholders of such a database are power providers, power plant operators and owners, production aggregators or balancing organizations, independent service providers, financiers/banks, insurers, regulators, retail utilities/customers, as well as electrical network operators.

Purchasing optimization and investment decisions

The purchase procedure is a potential application. Information from a Component Reliability (CR), (see Chapter 3.2.2.3) database is very valuable to support decisions on what technique to prefer.

Although major investments normally do not use low-level information on components, improved reporting on performance, reliability, availability and costs can help to identify wind turbine types suitable for harsh operational or site conditions.

In the later phase of operation, investors have to decide on the renewal of their assets. They may replace turbines when the first severe damages occur, because without evaluated historical data they cannot assess the probability of further severe damages. A CR database can support the decision when the data are completely collected and well-structured.

Operation and performance improvement

Systematic and automated monitoring as well as the optimization of operations are valid purposes, although in most cases only SCADA and measurement data will build the basis for reporting. However, over time it will become clearer which operational conditions influence lifetime or degradation and to what extent.

In case of flexible feed in tariffs it will be extremely helpful to know about the expected availability in advance, as well as the costs under upcoming ambient conditions. In these circumstances, a CR database will be the appropriate measure.

Maintenance optimization

Maintenance is a critical factor in the return on investment. Effective and efficient maintenance is often regarded as a priority in the years to come as wind farms age.

RCM (Reliability Centered Maintenance) is a systematic method for determining a good maintenance strategy, i.e. to determine which maintenance actions to carry out and how often. In order to achieve this, high-quality information from O&M as well as detailed cost information are needed and a CR database would be a major source of such information.

Design optimization

Levelized cost of energy (LCoE) may be reduced when O&M experience is taken into account in equipment design. For example, the design of frequently failing equipment can be adapted to different operational conditions.

Some component suppliers rarely get feedback on how their products work and how they are affected by failures. Systematically collected data will help in finding the critical points and improving the design.

Risk assessment

Serial damages will be one of the severe risks for an insurance company. Only a systematically fed CR database can prove or disprove speculation. The risk of less severe but frequent damages must also be calculated and it is often not possible to derive appropriate figures from other techniques. An insurance company could therefore greatly benefit from such a database.

Banks consider overestimations of wind conditions when assessing their financing risk. Additionally, an overestimated availability can lead to significantly lower reimbursements.

3.2.1.3 Limitations of reliability databases

For failure modes in structural components such as towers and blades and some mechanical components, sufficient data on time to failure from a statistically homogeneous population is not available for statistical analysis (e. g. fatigue failures in circumferential welding seams in wind turbine towers) and further the reliability level is high (annual probability of failure of the order of 10^{-4}). For these failure modes structural reliability methods may be applied using limit state equations for the failure modes and stochastic variables modelling the uncertain parameters. However, data bases with information about the basic stochastic variables can be used as basis for reliability analyses.

3.2.2 Different types of databases

3.2.2.1 Computerized Maintenance Management System (CMMS)

A CMMS is a software tool designed to support the maintenance department in all types of maintenance work. It is normally accessible at the dispatch center of the maintenance organization. The CMMS contains information such as:

- Work order: e.g., component to be maintained, work description, etc.,
- Report: e.g., repair has been performed, component restarted
- Material: e.g., two new parts
- Human resources: e.g., two qualified persons, four hours each

A modern CMMS normally consists of modules for preventive, planned and corrective maintenance as well as for supplies and purchases. The storage and purchasing of parts are essential for the system because all purchasing is based on the wish to have safe access to suitable spare parts at the right time.

3.2.2.2 Availability database

Normally an availability database also contains information on more than one unit. The aim of such a database is to show the availability of several units and sometimes also the main reasons for the unavailability of several units. For purposes of the wind plant, the SCADA system(s) can be used for a database history of the individual turbines. This time log function is useful for recording operational, non-operational, and faulted states.

3.2.2.3 Component Reliability (CR) database

A CR database contains information not only on a plant level but also goes into detail for items such as assemblies, maintainable items and in some cases parts (compare Table 4). It also archives information, if known, on time of failure, waiting times, actual time to repair, failure causes, failure mechanism, etc. This information is often based on incident or maintenance reports.

The output of a CR database can include failure rates of certain components, typical repair times, failure causes for different failure mechanisms, probability functions for surviving or failing and more.

A CMMS may contain elements very similar to a CR database, but it is more a tool for identifying upcoming tasks, contracting service personnel, and monitoring performance, while a CR database is specialized for analyzing and characterizing faults and failures.

3.3 Capability of the database – criteria for usefulness

The effective implementation of the outlined methods and tools relies on two key requirements – a significant level of consistency throughout the wind turbine industry in terms of technical definitions, methodologies and taxonomies and the suitable collection of, and access to, data.

3.3.1 Common guidelines and taxonomies

It is critical that all stakeholders in the wind industry use consistent language for reliability. The results from an overview of existing surveys (Chapter 3.1) illustrate the large variety regarding the type of collected data and level of detail. Presently, even on a high aggregation level, it is nearly impossible to derive any general reliability figure, because the surveys are not compatible.

In cases of purchasing wind power plants, the new owner either has to convert all historical data into his own structures and formats and then rerun the analyses, or write it off and start again.

This is the main reason for recommending that the wind industry collaboratively prepare guidelines and taxonomies for collecting reliability data and deriving comparable results. Other industries and even parts of the power generation sector have made good progress in collaborating on standards (e.g. the thermal power assets). This leads to meaningful comparisons across portfolios and the ability to benchmark across organizations.

3.3.2 Benefit and precondition of data sharing

The portfolio of a single owner / operator will often be too small to provide enough failure data for sound statistical analyses. A collaboration of several owners / operators can be a solution. This of course requires some legal regulations, such as nondisclosure agreements and more.

Once a large database consisting of operational and maintenance data is available, more details can be distinguished when grouping data sets. Analyses can distinguish higher amounts of wind turbine types and equipment, different on-site conditions, several years of commissioning, etc.

Additionally, wind industry stakeholders, beyond owner / operators, can realize some benefits from a large, jointly set-up database.

Service providers can improve their inventory management. Component suppliers may learn more about their products, since they often have no or little access to the operational conditions which lead to increased failure rates.

Investors can gain a deeper understanding of actual costs and improve their life cycle costs calculations. Banks and insurance companies may receive sound data for their risk calculation.

A key factor in the development of shared databases is that owner / operators will regard a large portion of operational data and measurement values as confidential. They need to be assured that no other owner / operator or other third party will use or even see their data.

Different national projects have already developed concepts for sharing data and preserving confidentiality at the same time. These may work as bases for other common databases. Some main aspects are:

- A neutral trustee will operate the common database.
- It must be guaranteed that all data providers remain the owners of their data. They may therefore withdraw their membership and ask for deletion of their data.
- Confidentiality of data and analyses is agreed upon in advance.
- Solely the owner / operator has access to confidential results for its wind farms; public access is given only to highly aggregated, anonymous results and depictions.

However, having a solid confidentiality agreement is a precondition for setting up a common database. Since the negotiation will consume some time, it is wise to start on this early.

3.3.3 Requirements for offshore wind O&M

Employing O&M tools for offshore wind farms involves additional requirements due to the challenge of operating in the marine environment and the additional deployed technology. A key requirement is the knowledge of the environmental constraints an organization must operate within. Examples include wind speed limits for lifting operations and wave height limits for crew transfer onto turbines.

There are significant differences in the technology that is employed offshore, including the foundation and subsea structures, the offshore substations, and the electrical network. There are also additional roles and responsibilities related to operating at sea, such as marine coordination and vessel charter. It is vital that these additional sub-systems and responsibilities are incorporated in any O&M method such as reliability modeling and the optimization of maintenance strategies.

3.3.4 Possibility to precisely select data samples for analyses

Another key requirement for users is that it must be easy for a user to select one specific item or to create groups of similar items, based on user-developed definitions. Other criteria available in the database should also be included in the selection, such as operating or environmental conditions, equipment properties, etc. As an example, the group can consist of pumps between 1 kW and 5 kW located in off-shore units and made by one certain supplier. For any desired group, the user can then generate customized and valuable reliability data.

It is also important to be able to select a suitable time frame. As an example, compare the above selection of pumps from the years 2010-2011 to those from 2012-2013.

3.4 Principles for the use of reliability data for O&M modeling and reliability analysis

3.4.1 Raw data vs. processed data

A basic principle for the analysis of reliability data is distinguishing between *raw data* and *processed data* (see Figure 3). Raw data are observations from real (existing) equipment, such as wind turbines. Processed data are related to generic equipment, representing a particular type or group of equipment that is comparable (comparable properties, design, etc.).

Processed data are estimated/generated through the analysis of the raw data. The data analysis process therefore basically results in parameter or statistical estimates for the sample or population that the raw data is collected from. Three examples that illustrate the difference between raw data and processed data are illustrated in the lower part of Figure 3.

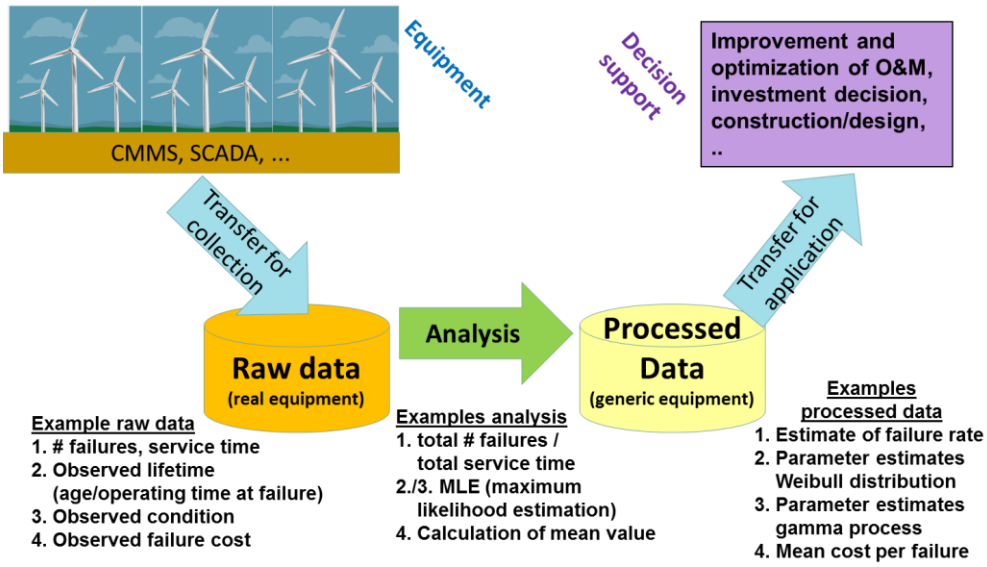


Figure 3: Raw data vs. processed data

3.4.2 Uncertainty

The handling and understanding of uncertainty is an important aspect in data analysis and modeling. It can be examined in the following ways: different categories and sources of uncertainties, different uncertainty quantification problems, and methods for uncertainty handling.

There are different sources and categories of uncertainties that can basically be classified into two main categories:

- Epistemic uncertainty
- Aleatory uncertainty

Epistemic uncertainty is caused by the lack of adequate knowledge, which means that when we collect more data or get a better understanding of the problems, we can reduce or eliminate epistemic uncertainty. Examples of epistemic uncertainty are modeling uncertainty (uncertainty about what the correct model is) and parameter uncertainty (uncertainty about what the correct values of the model parameters are). For example, the better our understanding of the actual problems, the better we can choose the models, which finally will lead to improved analysis results and predictions. Good reliability data will contribute to building a good understanding of the problems we have with wind turbines. Furthermore, the better the data quality (i.e. both large amounts of data and correct data/no errors in data), the better the quality of the estimates of MTTF, downtime and other reliability measures and the better the quality of the input parameters for the models for O&M optimization and reliability analyses.

Aleatory uncertainty (also called statistical uncertainty) is caused by variability or randomness and is often assumed to be "irreducible." The outcome of tossing a die, or long-term weather forecasts (months and years ahead), might be considered as aleatory uncertainty. Aleatory uncertainty should be represented by a suitable stochastic model.

The focus in uncertainty reduction should therefore be on reducing epistemic uncertainty by collecting more and better information and data, e.g. getting better parameter estimates or making better decisions on which model to use. Note that the existence of both uncertainty categories has been discussed for years without reaching a final consensus (Mosleh, 1994; Winkler, 1996; Vose, 2000; Aven, 2003). Apostolakis (1990) and Chhibber et al. (1992) propose handling different types of uncertainties with a general Bayesian modeling framework. The framework represents a classical example for distinguishing different types of uncertainties and for propagating these uncertainties through the model, from the model input to the model output (forward propagation).

3.4.3 Force of mortality (FOM) and rate of occurrence of failures (ROCOF)

The use of the term "failure rate" might be confusing, since it may refer to *force of mortality* (FOM) and to *rate of occurrence of failures* (ROCOF).

The FOM is a relative rate of hazard for a single item, which normally is not repairable. FOM is "a function of the life distribution of a single item and an indication of the 'proneness to failure' of the item after time t has elapsed" (Rausand & Høyland, 2004). In lifetime modeling, we are interested in the shape of the FOM, if the FOM is constant over the lifetime or increasing after a while. The latter means that preventive maintenance actions like repair and replacement are relevant maintenance strategies. Multiplied with a small time interval Δt, the FOM is an estimate of the probability of failure within this time interval.

ROCOF is the absolute rate of change of an expected number of failures of a repairable system or a system composed of several items. ROCOF is "the occurrence rate of failures for a stochastic process" (Rausand & Høyland, 2004). Multiplied with a short time interval Δt, the ROCOF is an estimate of the expected number of failures within this time interval. For a more detailed discussion and description of

FOM and ROCOF, see Ascher & Feingold (1984, p. 19 & p. 153) and Rausand & Høyland (2004, p. 19 & p. 237).

When estimating the failure rate, a typical approach is to count the number of failure events from several items (e.g. several wind turbines) over a given time period, and then calculate the failure rate as: (total number of failures) / (total observation time or time in operation for all items). The resulting failure rate is the average ROCOF over the observation period. To be able to estimate the FOM, the age ***t*** at time of failure of the individual items must be recorded and an analysis of the failure distribution over the lifetime must be carried out, e.g. by fitting a Weibull distribution to the failure data.

3.4.4 Restrictions due to unavailability of data and limited data access

Unavailability of data, limitations in the amount of data as well as restrictions in access to data are major problems for wind turbine reliability analyses. Methods such as expert judgment, a combination of different types of information and a prediction of turbine reliability based on experience from different (old) designs may thus be of interest.

However, incomplete data sets must be brought in accord and thus the start and end dates of the observation and data collection must be noticed.

4. Maintenance strategies and optimization

This chapter provides a general framework for describing the activities, actors and outputs related to the operation of a wind farm. The framework identifies all the actors that produce, control or consume wind farm data.

4.1 Introduction to maintenance strategies

4.1.1 Corrective maintenance vs. preventive maintenance

Maintenance strategies can be divided into two categories, see Figure 4:

- Corrective maintenance
- Preventive maintenance

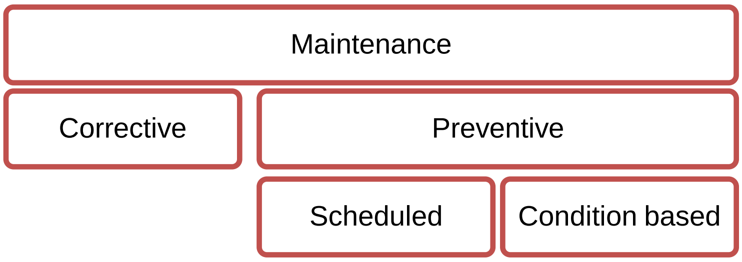


Figure 4: Maintenance types

In corrective maintenance, the repair or maintenance activities are performed whenever there is a failure of a component. Corrective maintenance is often of an emergency nature, requiring immediate performance. Therefore, it is usually more costly than preventive maintenance. For offshore wind turbines, this is mainly due to restrictions in access imposed by limited weather windows.

Generally, there are two methods for preventive maintenance, scheduled and condition-based, see Figure 4. For scheduled preventive maintenance, maintenance actions are already scheduled in the planning phase and the method can be used if the lifetime of the component is known with a high degree of confidence.

Scheduled maintenance is typically time-based. In case of higher uncertainty in the deterioration models, and thus in the lifetime, condition-based maintenance can be used. Here the maintenance decisions are based on information about the actual condition or health of the component, which can be obtained, for example, by using condition monitoring or structural health monitoring.

Figure 4 is based on the definitions given in the international standards EN 13306:2010 and IEC 60050-192:2015 and the maintenance terms and relations between them are defined in the same standards. Note that the classification of different maintenance types has always been under ongoing discussion and various other classifications have been presented elsewhere. However, the presentations in this section will be restricted to the definitions provided in the two international standards.

Depending on which models are used for the planning and scheduling of preventive maintenance, maintenance strategies are classified into further sub-groups and strategies, such as rule-based maintenance, reliability-based maintenance, risk-based maintenance and predictive maintenance, not all of which are defined in the mentioned international standards. However, some of these strategies are briefly discussed below.

If a corrective maintenance strategy is used, then information about failure rates and costs is needed to estimate the expected maintenance costs. If a preventive, scheduled maintenance strategy is used, this also requires information about the expected lifetime and costs of preventive maintenance actions. Furthermore, if a preventive, condition-based maintenance strategy is used, information about the deterioration of the component and the costs of obtaining information from e.g. condition monitoring is needed as well.

4.1.2 Rule-based vs. risk-based maintenance

The main idea behind maintenance optimization is to balance the cost of executing maintenance with the benefit achieved by the maintenance. Due to the random nature of the problem at hand, maintenance optimization methods are denoted as risk-based methods. Historically the maintenance effort has not been decided by means of formal optimization methods but has been based on the experience or judgment of engineers. Often such informal approaches to determine the maintenance have been implemented as a rule-based regime, where the interval of tasks and maintenance intervention limits have been stated as either company-internal rules, or even rules stated in national laws and regulations.

If a rule-based regime for maintenance is followed, the rules tend to be "ideal rules" which assume that sufficient resources for maintenance are available. This is generally a big challenge, since in reality, maintenance resources are limited, making the rules unsuitable for prioritizing available resources.

The strength of risk-based methods is that they also allow considerations of extra risk by exceeding maintenance limits or maintenance intervals, thus giving stronger decision support in cases where it is impossible to follow the "optimal" strategy, because here it is possible to prioritize among maintenance tasks.

A risk-based theoretical basis for the planning of operation and maintenance can be formulated with the principles for engineering decision-making described in ISO 2394:2015; see description below. It is noted that various simplifications to this theoretical framework are often made in practical applications.

Maintenance can be defined as "the combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore to, a state in which it can perform a required function" (IEC 60050). Optimizing maintenance efforts means balancing the cost and benefit. There are many aspects of maintenance optimization which need to be considered, including, but not exhaustively:

- Deciding the amount of preventive maintenance (i.e. choosing maintenance intervals)
- Deciding whether to do first-line maintenance (on the site) or depot maintenance
- Choosing the right number of spare parts in stock
- Preparedness with respect to corrective maintenance
- Time of renewal
- Grouping of maintenance activities

4.1.3 The bathtub curve and the failure/hazard rate

Most methods and approaches for maintenance analysis involve the concept of *hazard rate*. Very often the hazard rate shows bathtub-like behavior as illustrated in Figure 5. The hazard rate defines the probability that an item will fail in a small time interval from time t to $t + \Delta t$ given that the item has survived up to time t.

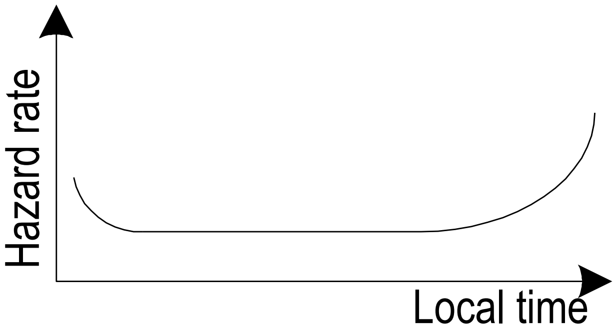


Figure 5: Bathtub or hazard rate function

In Figure 5 the term "local time" refers to the fact that time is relative to the last failure (or maintenance point), rather than to the global system time. The bathtub curve indicates that the number of failures will be reduced if the component is replaced or maintained before the time runs into the right part of the curve. There is also another bathtub curve related to the *global* system time as shown in Figure 6, where the local bathtub curves are also illustrated.

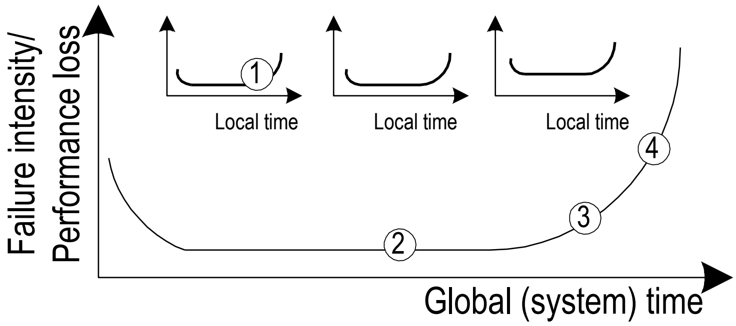


Figure 6: Global system time

As an example, consider a signaling system with lights, logic, relays etc. The local time (time horizon 1 to 5 years) applies to components such as the light bulbs, the relays etc., whereas the global time (time horizon 30-60 years) applies when the entire signaling system is considered. Note further that on the *y*-axis the dimension is *failure intensity*, or performance loss. This reflects that the important issue now is the number of failures per unit time, or generally loss of performance, independent of what has happened up to time *t*.

Additionally, Figure 6 presents four points in time where the following maintenance situations apply:

1. Component maintenance, related to the explicit failure modes of a component. FMEA and RCM analysis is relevant.

   A typical question is: "When should light bulbs in the signalling system be replaced on a preventive basis?"

2. Life extension maintenance. The idea here is to carry out maintenance that prolongs the lifetime of the system.

   A typical example is: "Addition of mass in the blades to compensate rotor imbalance."

3. Maintenance carried out in order to improve performance, but not renewal. A typical example is: "Adding ballast to pumping sections to improve track quality and reduce the need for track adjustment".

A typical example is: "Adding erosion and abrasion prevention coating on the leading edge of rotor blades."

4. Complete renewal of major components or systems.

4.1.4 Renewal and life cycle cost

When the system deteriorates to a certain level, traditional preventive maintenance activities may not bring the system back into a satisfactory state and renewal of the entire system or part of the system is required. The cost of renewal is often very high and formalized methods are needed to determine when to perform renewal. Methods for optimum renewal strategies presented here are based on life cycle costs (LCC) modeling. The following dimensions are included in the LCC model: *i*) safety costs, *ii*) punctuality costs, *iii*) maintenance & operational costs, *iv*) cost due to increased residual life length, and *v*) project costs. The LCC models apply to ②, ③, and ④ in Figure 6.

4.1.5 Condition monitoring contribution to reliability

The implementation of an adequate condition monitoring system (CMS) and fault detection system (FDS) will significantly improve the ability of a device to perform the required functions under the given conditions for a given time. In the case of a wind turbine, this equates to the extraction of the maximum energy available from wind.

A CMS tool evaluates the continuous component health of the wind turbine using a collection of techniques, such as vibration analysis, acoustics, oil analysis, strain measurements and thermography (Garcia et al, 2012). Data are sampled at regular time intervals with sensors and measurement systems.

Using data processing and analyses, a CMS can determine the states of the key wind turbine components. By processing the data history, faults can be detected (diagnosis) or predicted (prognostic) and the appropriate maintenance strategy can be chosen.

CMS descriptions and models can be found in (Garcia et al, 2012; Hameed et al, 2010, Sheng et al, 2011; Jardine et al, 2006). This description can be combined with concepts provided in (Ahmad & Kamarruding, 2012; Dhillon, 2002), which address maintenance techniques and methods.

The CM process is performed in three main steps (Figure 7): data acquisition using sensors, signal processing using various data processing techniques, and feature extraction via the retrieval of parameters that will aid in establishing the current status of the monitored equipment. Using both (i) current information sources and (ii) information on the system's past status obtained from stored data, the system's present state is obtained via online monitoring such that a fault can be detected or predicted.

After a fault is diagnosed, corrective maintenance is carried out. If a fault is predicted, preventive maintenance is carried out before the fault can occur.

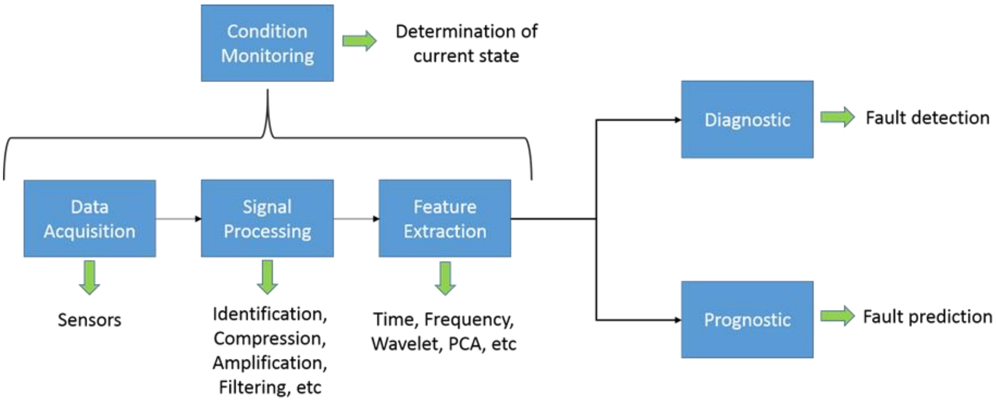


Figure 7: CM process from measurements to diagnostics and prognostic

4.1.6 Reliability modeling

Formalized maintenance optimization models rely on system reliability models. These are models that express the system (reliability) performance as a function of component performance. The component performance is expressed in terms of component reliability models. Some basic models are:

- Reliability block diagram (RBD) and structure functions
- Fault tree analysis (FTA)
- Event tree analysis (ETA)
- Markov analysis
- Failure Mode Effect (and Criticality) Analysis (FMEA/FMECA)

4.1.7 Parametric reliability models on component level

The reliability modeling techniques above usually take a very simple approach when it comes to component models. Usually component lifetimes, and repair times are assumed to be distributed exponentially. Reliability parameters in the models are often limited to constant failure rates, λ, and constant repair rates μ. For system modeling this might be appropriate, but in that case it is important to recognize that λ is then the effective failure rate given a maintenance strategy (e.g. a given maintenance interval) and that the repair rate is conditioned on a given spare part strategy.

4.2 Reliability centered maintenance

4.2.1 Preventive maintenance and RCM

Preventive maintenance (PM) is defined as "the maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item" (EN 13306). There exist several approaches to determine a preventive maintenance program. A concept that is becoming more and more popular is the concept of RCM. RCM is a "systematic method for determining the respective maintenance actions and associated frequencies, based on the probability and consequences of failure" (IEC 60050).

An RCM analysis is usually conducted as a purely qualitative analysis with a focus on identifying appropriate maintenance tasks. However, the RCM methodology does not usually give support for quantitative assessment in terms of e.g. interval optimization.

The strength of RCM is its systematic approach to considering all system functions and to setting up appropriate maintenance tasks for these functions.

RCM is a structured and traceable approach to determining a type of preventive maintenance. This is achieved through an explicit consideration of failure modes and failure causes. A major challenge in an RCM analysis is to limit the scope of the analysis so that it is possible to carry out the analysis within the time and budget constraints. Most implementations of RCM put the main focus on the identification of maintenance tasks. RCM cannot be claimed to be an approach for maintenance optimization, but it may form the basis for maintenance optimization. The core of an RCM analysis is the qualitative structuring of systems, functions and components and this structuring concludes with the FMECA analysis and the maintenance task assignment. Typical steps of an RCM analysis are shown in **Error! Reference source not found.**.

4.2.2 RAMS data

The collection and analysis of reliability data is an important element of maintenance management and continuous improvement. There are several aspects of utilizing experience data and in the following, we will focus on:

- Learning from experience. That is, when a problem occurs, the failure and maintenance databases can be searched for events which are similar to the current problem. If the database

- is properly updated, one might find information about solutions that proved to be efficient in the past.
- Identification of common problems. By producing “Top ten” lists (visualized by Pareto diagrams) the database can be used to identify common problems - for example, which component contributes most to the total downtime (cost drivers), what are the dominate failure causes, etc. “Top ten” lists are used as a basis for deciding where to spend resources for improvements.
- Estimation of reliability parameters. Important parameters to use in the reliability-availability-maintainability-safety (RAMS) analyses are the Mean Time To Failure (MTTF), aging parameters, P-F intervals and repair times.

With respect to maintenance optimization, RAMS data will mainly be used as the basis for parameter estimation. The standard approach to parameter estimation is the application of the maximum likelihood principle (MLE). In many situations, only a limited amount of data is available and the use of Bayesian methods is recommended where the systematic use of expert statements in combination with statistical data is used to assess the reliability parameters of interest.

4.2.3 Maintenance task assignment

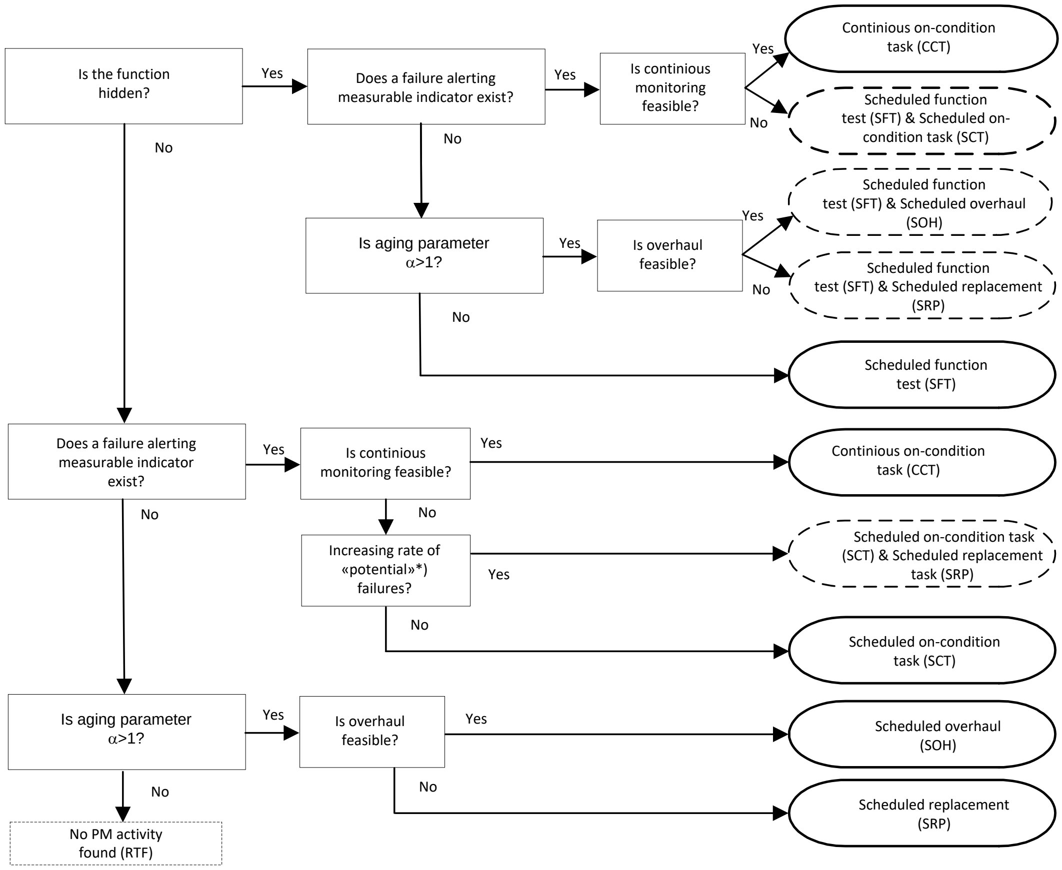
This phase is the most novel compared to other maintenance planning techniques. A decision logic is used to guide the analyst through a question-and-answer process. The inputs to the RCM decision logic are the dominant failure modes from the FMECA. Each dominant failure mode requires a decision on whether a preventive maintenance task is suitable or whether to let the MSI deliberately run to failure and afterwards carry out a corrective maintenance task. There are generally three reasons for doing a preventive maintenance task to:

- Prevent a failure
- Detect the onset of a failure
- Discover a hidden failure

Only the dominant failure modes are subjected to preventive maintenance. To obtain appropriate maintenance tasks, the failure causes or failure mechanisms should be considered. The idea behind performing a maintenance task is to prevent a failure mechanism to cause a failure. Hence, the failure mechanisms behind each of the dominant failure modes should be entered into the RCM decision logic to decide which individual or combinations of the following basic maintenance tasks is (are) applicable:

- Continuous on-condition task (CCT)
- Scheduled on-condition task (SCT)
- Scheduled overhaul (SOH)
- Scheduled replacement (SRP)
- Scheduled function test (SFT)
- Run to failure (RTF)

The RCM decision logic is used to structure the process of identifying relevant maintenance tasks. The logic is shown in Figure 8, where tasks with a dashed line represent combined tasks.



* A "potential" failure corresponds to a failure progression (condition) between the points P and F in the P-F-interval (see 'OFF' in table 7). A potential failure can for example be an initial repairable crack prior to a critical size (functional failure).

Figure 8: Maintenance task assignment through use of the RCM decision logic

5. O&M Modeling

5.1 Operation and maintenance

Wind farm operations and maintenance (O&M) is a multifaceted discipline comprising many tasks. A good introduction to the wind farm O&M is provided in (The Crown Estate, 2010) and (Scottish Enterprise, 2013).

The key wind farm O&M tasks that are addressed by a wind farm operator are shown in Figure 9. The three main categories of O&M tasks that all wind farms must consider are turbine maintenance, balance of plant maintenance and commercial operations. Offshore wind farms have the additional challenge of managing vessels and marine logistics. This chapter will outline the methods and tools that are utilized within the wind farm reliability community in support of these O&M tasks. A wind farm O&M team will aim to carry out these tasks in a way that optimizes the trade-off between increasing wind farm availability while reducing costs.

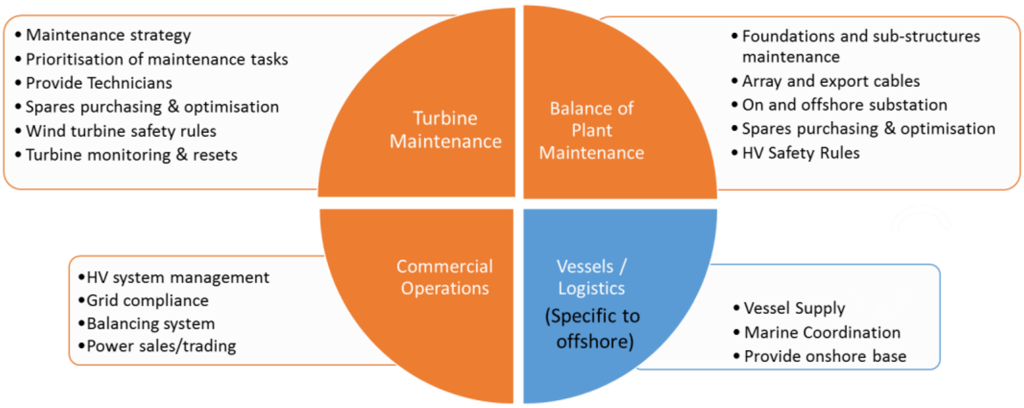


Figure 9: Wind farm operations and maintenance tasks

The key decisions that a wind farm operator must make can be categorized into the following areas:

Maintenance strategy: Given information on the state of a wind farm, what is the most critical failure and in what order should existing issues be addressed? Can scheduled maintenance can be carried out concurrently with required turbine visits? Can the stock-keeping of spare parts be optimized? Can the logistics of both maintenance crew and spare parts be optimized?

Personnel management: Are the health and safety of all people involved in maintenance activities ensured? Is the necessary staff in terms of head count and qualifications to carry out the maintenance strategy in place? Are the personnel qualified to manage suppliers and service providers?

Data management: How will data necessary for the delivery of an efficient maintenance strategy be collected and communicated? Which equipment data is needed, what is the format and frequency of the data collection during operation and what system for archiving data and results should be implemented?

Performance and reliability reporting: What definitions, taxonomies and methodologies will be used to report on performance, availability and reliability? What information is required for reports such as the business model, generation forecast, O&M strategy, upgrades, lifetime extension, and asset liquidation?

Commercial: What production is forecasted and can this be sold to the grid? Have forecasts been realized and do they comply with the contracts? What ancillary services are required?

The method of delivery of these tasks will depend on the ambition level of the operator. The most ambitious operators will endeavor to carry out O&M tasks in-house to generate knowledge and experience while the less ambitious operators will sub-contract the tasks out to a service provider. This is a critical concept that impacts many aspects of this report.

5.2 Interval optimization

For each task, or combination of tasks, it is required to determine the interval(s) of the task(s). This comprises the following steps:

1. Establishing appropriate model(s) for the failure characteristics involved, e.g. related to characteristics in Table 7.
2. Establishing the system models required to establish the objective function to optimize. This typically involves reliability models like fault tree, reliability block diagram, etc.
3. Minimizing the cost with respect to the maintenance interval. This involves the use of numerical methods.

5.2.1 The four basic situations related to preventive maintenance

There are basically four situations that are treated in the optimization process. These situations are described in the following sections.

5.2.1.1 Observable gradual failure progression (OGF)

These are situations that allow the observation of the failure progression prior to the final failure. The situation is illustrated in the row (OGF) in Table 7. To prevent unnecessary failures, the affected component will get replaced or overhauled at a predefined degradation level.

The probability of a failure will decline with a higher frequency of inspections and lower maintenance limits. However, many inspections and a low maintenance limit will imply a very high maintenance cost.

The failure progression model indicated in the OGF row in Table 7 is applicable both for online (continuous) monitoring and offline monitoring (CCT& SCT).

5.2.1.2 Observable "sudden" failure progression (PF model)

The situation is similar to the situation in the previous section, but now it is assumed that the system could operate for a very long time without any sign of a potential failure – however, at some point in time a potential failure would be evident as illustrated by the OFF row in Table 7. Here we have indicated a "P" for potential failure, i.e., the time where a coming failure is observable. The time interval from the failure is first observable and until a failure occurs is very often denoted as the *PF interval*. Below we will refer to this situation as the PF situation because the PF interval will be central in the understanding of effective maintenance strategies.

5.2.1.3 Non-observable failure progression (aging)

Another issue is wear inside a closed bearing (Figure 10) where a dashed line presents the failure progression due to the fact that it is not observable.

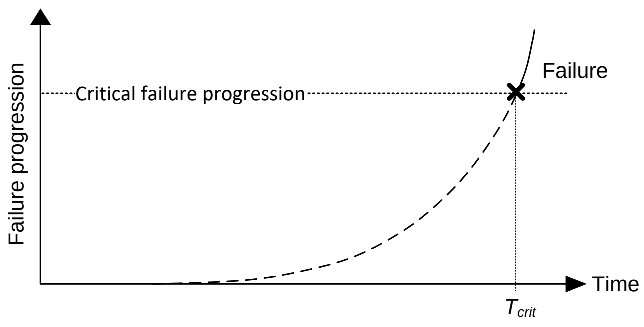


Figure 10: Non-observable failure progression

Since there is an aging phenomenon behind this failure situation, the distribution of the time to failure will have an increasing failure rate function. An appropriate maintenance action in this situation would be to replace the component periodically. However, since observing failure progression is not possible, the time elapsed since the previous maintenance is the only indicator of a coming failure. This model corresponds to the ADT and AUT situations in Table 7.

5.2.1.4 Shock

The situation is similar to the PF interval situation above, but now the PF interval is extremely short and there is no possible inspection method that can reveal a potential failure in due time. In this situation, the time to failure will be approximately exponentially distributed.

5.3 Grouping of maintenance activities

Grouping of maintenance activities is often based on an idea to execute related tasks with similar intervals at the same time to save so-called setup cost. The setup cost is the cost that may be "shared" between several activities if conducted simultaneously. In many situations, no formal methods are used to form the groups. However, since the optimum interval depends on the cost of the preventive maintenance, the interval will be influenced by how much setup cost could be saved. One of the most comprehensive presentations of grouping is the PhD thesis by Wildeman (1996).

5.3.1 Static grouping

Grouping is often categorized into static and dynamic grouping. In static grouping the activities going into one group are fixed and will not change during the considered time horizon. This makes this method easy to implement because it fits into most computerized maintenance management systems (CMMS). A major challenge with static grouping is that it is not easy to change the plan and the groups if the situation changes, e.g., some of the estimated failure rates are updated based on new statistical evidence or the load on some components changes.

5.3.2 Dynamic grouping

In dynamic grouping the groups are not fixed. The idea is to establish the groups "on the fly" which will enable updates of the strategy when new information becomes available, e.g. new failure rate estimates. The plan can also be rescheduled if opportunities arise, e.g. upon a failure there will be an opportunity for advancing the next planned preventive maintenance. Dynamic grouping allows taking into account that the usage of a component is not fixed. Dynamic grouping is more intractable from a modeling point of view, and from an implementation point of view. But if these problems are overcome, the cost per unit time is usually lower than for static grouping.

5.4 Spare part optimization

Spare part optimization is challenging from a modeling point of view because the models must be based on queue theory, which usually becomes so complex that Monte Carlo simulation methods are required. In some situations very simple analytical results may get derived. In these cases, the starting point for analyzing the impact of spare parts is to link spare part strategies to the downtimes, i.e., MTTR. A very simple model now comprises the following steps:

1. Assess the value of MTTR for the two situations, either whether a spare is available or not.
2. Identify the relation between the MTTR and the expected cost of an expected critical event.
3. For each level of the considered spare parts, calculate the probability that a spare part is available upon a component failure.
4. Find the yearly capital cost associated for each level of considered spare parts and calculate the cost per unit.
5. Optimize the maintenance interval for each value of the spare part levels and compare the minimum values in order to find the spare part level that minimizes the overall cost.

The approach is rather simple compared to those given in the literature where queue theory is applied to model so-called backorders explicitly. Also, note that a complicating factor will be how to treat the possibility of different stocks, for example one central stock, one stock at maintenance depot A, and another stock at maintenance depot B.

However, for spare part optimization very accurate and complete data from O&M are needed and must get concatenated with solid cost information.

5.5 Optimization of renewal

The objective is to establish a sound basis for the optimization of renewal. Since the time between renewals of a system is often in the order of decades, it is required to perform some kind of discounting of future costs. Different “headings” are used for such an analysis, e.g. LCC analysis, cost/benefit analysis and NPV (Net Present Value) analysis. The idea is to choose renewal activities in time and space such that costs are minimized in the long run. Systems are deteriorating as a function of time and operational load. This is why the right part of the bathtub curve in Figure 6 is increasing.

This deterioration can be transformed into cost functions, and when costs become very large it might be beneficial to perform maintenance on or renew the infrastructure. The notation $c(t)$ is used for the costs as a function of time. In $c(t)$ we include in principal costs those related to i) production/punctuality loss, ii) accident costs, and iii) extra maintenance and operation cost due to degradation. Through a renewal (or execution of a major maintenance project), we typically reset the function $c(t)$, either to zero or at least a level significantly below the current value. The operating costs will thus be reduced in the future if we are willing to invest in a maintenance or renewal project.

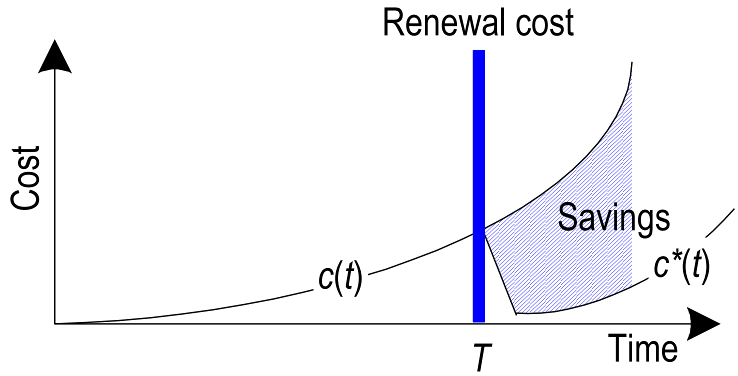


Figure 11: Cost savings with optimized renewal

Figure 11 shows the savings in operational costs, c(t) - c*(t), if the maintenance or renewal is performed at time T. In addition to the savings in operational costs, savings are often also achieved due to an increased “residual life time”.

6. Reliability analyses

6.1 Qualitative assessments

6.1.1 Functional failure analysis (FFA)

An analysis of potential failures helps designers focus on and understand the impact of potential process or product risks.

FFA is a systematic approach to identify and describe the potential failure modes of a system. The objectives of the three main steps of the FFA are:

1. To identify and describe the systems' required functions
2. To describe input interfaces required for the system to operate
3. To identify the ways in which the system might fail to function.

Often, a FFA is a first step prior to Fault tree analyses or Failure mode effect (and criticality) analyses.

6.1.2 Critical item selection

The objective of the critical item selection is to identify items that are potentially critical with respect to functional failures identified in the FFA. These analysis items are denoted as functional significant items (FSI). Note that some of the less critical functional failures have been disregarded at this stage of the analysis. Furthermore, the two failure modes "total loss of function" and "partial loss of function" will often be affected by the same items (FSIs).

For simple systems, the FSIs may be identified without any formal analysis. In many cases, it is obvious which analysis items have influence on the system functions.

Complex systems with an ample degree of redundancy require a formal approach to identify the functional significant items.

The main reason for performing this task is to screen out items that are more or less irrelevant for the main system functions, i.e. in order not to waste resources by analyzing irrelevant items.

In addition to the FSIs, it is also important to identify items with high failure rate, high repair costs, low maintainability, long lead time for spare parts, or items requiring external maintenance personnel. These analysis items are denoted as maintenance cost significant items (MCSI).

The sum of the functional significant items (FSI) and the maintenance cost significant items (MCSI) are denoted as maintenance significant items (MSI).

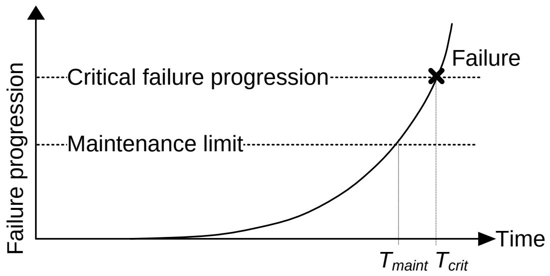
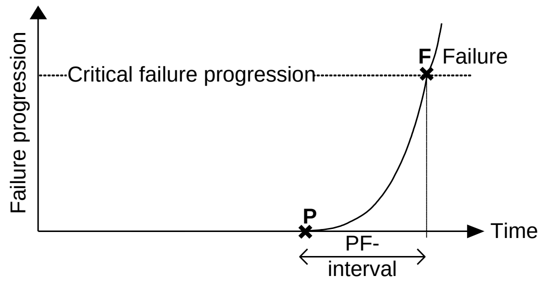
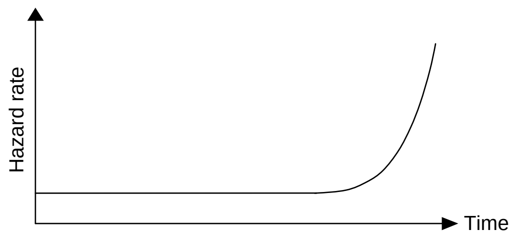
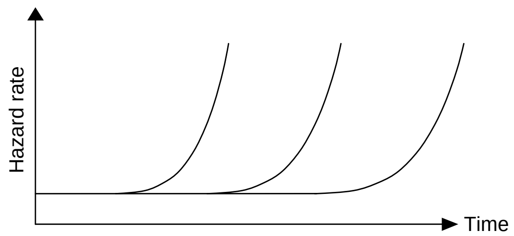
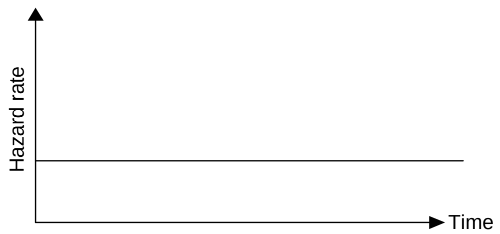
In a FMECA, each of the MSIs will be analyzed to identify their possible impact upon failure on the four consequence classes: (S) safety of personnel, (E) environmental impact, (A) production availability, and (C) economic losses.

6.1.3 Failure Mode, Effect and Criticality Analysis (FMECA)

The objective of this step is to identify the dominant failure modes of the MSI identified during the FFA. In addition to ranking the components with respect to their criticality, basic information will also be revealed during the FMECA that is later used when maintenance intervals are to be optimized. During the FMECA exercise, reliability data is required.

Structuring the FMECA in terms of predefined failure causes, failure types/characteristics, etc., will often speed up the process and will also make the assignment of maintenance tasks more intuitive. Table 7 shows typical failure characteristics to be assigned during the FMECA.

Table 7: Failure characteristics

Code	Description	Failure characteristic
OGF	Observable, gradual failure progression. It is possible to detect the failure prior to the event.	
OFF	Observable fast failure progression. The Point P is the first point in time where it is possible to reveal an emerging failure. When the failure progression exceeds a limiting value, a failure (F) occurs. This model is often referred to as the PF model.	
ADT	Aging, defined point of time for an increasing hazard rate, $z(t)$. In the Weibull model, we assume an aging parameter (α) in the order 3 to 4.	
AUT	Aging, undefined point of time for increasing hazard rate. In the Weibull model, we assume an aging parameter (α) in the order 2.	
RF	The hazard rate is time independent (random failures, aging parameter 1). This is typical for components where a failure is caused by external shocks, e.g., for some electrical components.	

6.1.4 Screening of MSI failure modes

Based on the criticality assignment in the FMECA, each failure mode of each maintenance significant item is grouped into three levels of criticality:

- Low criticality
- Medium criticality
- High criticality

Failure modes of high and medium criticality are subject to a formal assignment of maintenance tasks described in Chapter 4.2.3. Tasks of low criticality are either deliberately assigned a run to failure strategy, or assigned maintenance tasks as described by the manufacturer.

6.2 Statistical analysis and quantitative assessments

6.2.1 Model classes

Different basic types/classes of mathematical models are available for reliability analysis. Models may be classified as in Welte and Wang (2014):

- Stochastic models
- Physical models
- Data-driven models and machine learning
- Combined models

A short description of the model classes can be found in Table 8, where the descriptions are partly based on Loucks and van Beek (2005):

Table 8: Brief description of different model classes

Model class	Description
Stochastic models (SM)	Models are based on probability theory and statistical methods "Purely" stochastic models do not represent a physical process or mechanism Models make a relation between model inputs and outputs using any mathematical equation or expression that provides a good fit given the data
Physical models (PM)	Also called process-based models or mechanistic models Models are based on a physical mechanism (failure mechanism) or process (failure process) that finally leads to a failure of an item
Data-driven models and machine learning (DM)	Also called data-based models Models are based on methods to identify abstract information and/or relationships from large sets of data Data-driven methods are particularly suitable for data from continuous monitoring

The combination of different models allows for creating new and more advanced models. Examples of typical models for the classes stochastic models, physical models and data-driven models are also briefly discussed here.

The descriptions in the following chapters are restricted to an overview level. More detailed descriptions of the models and mathematical equations are not given here.

Other ways to classify the models are as follows:

- Model transparency: white (clear and easy-to-understand relations between model input and output), grey, black (unclear relation between input and output)
- Quantity to be modeled: e.g. failure models (modeling of time to failure, time between failures or the number of failures), degradation models (modeling a variable/ measure/indicator indicating degradation
- Uncertainty representation: none (deterministic), stochastic, fuzzy
- Model generality: general (universal) models or (problem-) specific models

6.2.2 Stochastic models

A large number of different stochastic methods and models are suitable to apply to reliability data. Both non-parametric and parametric methods are briefly described here.
In this chapter, we distinguish between models for repairable and non-repairable systems. Since it is customary to use the term "system" in this context, "repairable system" and "non-repairable system" are

also used here, even though a system can represent any item or entity that can be considered individually.

6.2.2.1 Non-parametric methods

Descriptive statistics
Descriptive statistics provide an overview and a summary of a data sample. Typical quantities commonly used in descriptive statistics are:

- Mean
- Variance and standard deviation
- Minimum and maximum value
- Median and percentiles
- Frequencies
- Standard error of the mean (SEM)

Typical applications are cases where a sample for a stochastic (i.e. random) quantity is available. The advantage of this method is that it is simple. The results are very informative and many computer programs have built-in functions for descriptive statistics.

The use of descriptive statistics requires a sample of the stochastic quantity that is modeled. The size of the data sample will influence the uncertainty related to the estimated quantities.

6.2.2.2 Models for non-repairable systems

Probability distributions
Probability distributions are used to describe the statistical distribution of a stochastic (random) quantity. They can be fitted to data/observations from a stochastic quantity and estimates of the distribution parameters can be established. The focus here is on continuous probability distributions. Often used distributions are exponential distribution, Weibull distribution, normal distribution, lognormal distribution and gamma distribution. The exponential distribution is the simplest distribution; however, it is based on the assumption of a constant failure rate function (FOM).

Typical applications are cases where a data sample for a stochastic quantity is available, e.g. data of the lifetime, the downtime, the repair time or the repair costs of a specific type of component. The size and quality of the data sample will influence the uncertainty related to parameter estimates. Large, high-quality datasets will produce higher-confidence results. Methods for parameter estimation for data sets with both complete and censored observations exist. Taking into account censored observations, e.g. the age of components that have not failed yet, is important when only observations from a restricted period of the lifetime ("observation window") are available.

The estimated probability distributions can be used to calculate statistical quantities like mean or standard deviation, or they are used for further analyses such as O&M optimization.

The advantage of this method is that it is accepted and well-known. Statistical computer programs have built-in functions for the estimation of parameters (e.g. with the maximum likelihood method) and for the calculation of distribution functions (probability density function (PDF), cumulative probability function (CDF), inverse of CDF, etc.)).

Proportional hazard models
A popular model which links the hazard rate with factors that influence this rate (so-called covariates or explanatory variables) is the Proportional Hazards Model (PHM) (Vlok & Coetzee, 2000; Banjevic et al., 2001). The PHM is based on the concept that the hazard rate is modeled proportional to a baseline hazard function, which e.g. can be defined as a Weibull hazard function (Banjevic et al., 2001). An advantage of the proportional hazard modeling method is that it can predict the changes in the hazard

rate based on the changes in the covariate values. Examples of covariates for wind turbine applications are different climatic zones, the annual mean wind speed, the turbine diameter and the rated power.

6.2.2.3 Models for repairable systems

When we talk about failure rates in this section, we are referring to the *rate of occurrence of failures* (ROCOF) or *the recurrence rate*. Assuming a constant ROCOF / recurrence rate means assuming that failures represent events from a homogenous Poisson process with (constant) intensity λ.

Homogenous Poisson process

This is the most often applied reliability model for repairable systems. A maximum likelihood point estimator for the constant rate λ is given by Vatn (1997):

$$\hat{\lambda} = \frac{\text{total number of failures}}{\text{total service time}}$$

The rate can be split, for example, by considering failures for different failure modes individually. As it can be seen from the equation above, the minimum requirement for applying the HPP is counting the total number of failures and the total service time. Additional data, such as failure modes for each failure, must be collected if the rate is split.

Non-homogenous Poisson process

A non-homogenous Poisson process (NHPP) is a Poisson process model with non-constant ROCOF (Meeker and Escobar, 1998). This means that failures may be more likely to occur at certain times than others. The NHPP is often used to model trends in the times between failure events (intercurrence times) (Rausand & Høyland, 2004). Parametric NHPP models that are often used to describe the ROCOF are the power law model, the linear model and the log-linear model; see Rausand & Høyland (2004) for further details.

An advantage of NHPP is that it is not restricted to constant intercurrence times. However, the model is restricted to the assumption of minimal repair, which means that the item is as bad after failure as before the failure. This assumption may not be realistic for many cases.

6.2.2.4 Stochastic degradation models

Degradation models can be applied when degradation can be expressed and measured by a quantity which describes the change in the technical condition or strength over time (or another measure of usage). Failure is assumed to occur when degradation crosses a failure threshold. Examples of stochastic degradation models are Markov chains and Markov processes, the gamma process or the Wiener process.

6.2.3 Physical models

Physical models represent a physical mechanism (failure mechanism) or process (failure process) that causes degradation and finally leads to the failure of an item.

The input parameters in physical models typically have a clear meaning and represent real (and often measurable) quantities or natural, physical or material constants.

Such models provide a better understanding of the mechanisms and processes leading to failure; see also Loucks and van Beek (2005). However, good knowledge of the physical mechanism/process is required to be able to model the relation between the model input and model output with a physical model.

It is a challenge to establish a good physical model. However, once a good model is available, or when it is available from literature/previous research, the model can be applied to all comparable problems where good estimates and measurements of the model input parameters are available. Since real physical processes are usually quite complicated and are affected by many mechanisms and effects, physical models usually include only the main mechanisms and effects and do not account for effects of minor importance.

6.2.4 Data-driven models and machine learning

Machine learning is a branch of statistical techniques where data is used to train the parameters of a model, to best describe the relationship between a set of input and output parameters.

This section does not concern frequency based, probability models (i.e. failure distributions which are covered earlier) but modelling techniques appropriate for prediction of specific failures. These techniques range from classical statistics models such as ARIMA, to more flexible methods such as those relying on kernels (e.g. Gaussian Processes or Artificial Neural Networks - ANNs) or classification (e.g. Random Forests).

ANNs have often been used for detection of faults based on condition monitoring data. The advantage of ANNs is that they can be used to establish a relation between model input and output without prior specification of the functional form of that relationship. The downside of this approach is that the model generated is a “black box”, where the detail of how it operates is difficult to extract. It also needs careful “training” to ensure the model is not over-fitted to the data provided.

Examples of data-driven models and machine learning applied to wind turbines can be found in Kusiak and Verma (2012), Kusiak and Li (2011), Mesquita Brandão et al. (2012), Kim et al. (2011) and Garcia et al. (2012).

6.2.5 Combined models and other types of models

An example of combined models is the Finite Element Method (FEM) where the combination of a simple, computational model by repetition of small steps results in a more advanced model. Another example is the combination of Bayesian inference with deterministic physical models, resulting in models with both improved predictive power and uncertainty estimation. Models applied in structural reliability may also be considered combined models.

Structural reliability

The reliability of structural components and systems is generally estimated by using methods from structural reliability as described in this section. For wind turbines, structural reliability can be applied for components such as blades, tower, foundation and cast components, incl. e.g. the main shaft, see IEC 61400-1 (2005) and for the general principles of reliability of structures ISO 2394 (2015).

The main steps in the reliability assessment are:

1. Identification of failure modes in the considered structural elements and modeling the failure modes by systems of limit states (reliability elements)
2. Formulation of limit state equations for the considered limit states
3. Identification of uncertain parameters and stochastic modeling
4. Estimation of the probability of failure of limit states, e.g. Using the so-called reliability index
5. System modeling of failure modes by limit states
6. Risk assessment where the probability of failure modes is combined with the consequences. (system reliability and risk assessment are not considered in this section).

Reliability of structural systems can be defined as the probability that the structure under consideration has a proper performance throughout its lifetime.
Structural reliability methods are used to estimate the probability of failure. The information used to formulate the models which the reliability analyses are based on is generally not complete. The estimated reliability should therefore be considered as a nominal measure of the reliability and not as an absolute number. However, if the reliability is estimated for a number of structures using the same level of information and the same mathematical models, then useful comparisons can be made about the reliability level of these structures. Further design of new structures can be performed by means of probabilistic methods, if the applied models and information are similar to those of existing structures

that are known to have a satisfactory performance. The reliability estimated as a measure of the safety of a structure can be used in a decision-making process (e.g. in design or during operation).

To be able to estimate the reliability using probabilistic concepts, it is necessary to introduce stochastic variables and/or stochastic processes/fields and to introduce the failure and non-failure behavior of the structure under consideration.

Typical failure modes to be considered in a reliability analysis of a structural system are yielding, buckling (local and global), fatigue and excessive deformations. The failure modes (limit states) are generally divided into:

Ultimate limit states
Ultimate limit states correspond to the maximum load-carrying capacity which can be related to e.g. the formation of a mechanism in the structure, excessive plasticity, rupture due to fatigue and instability (buckling).

Conditional limit states
Conditional limit states correspond to the load-carrying capacity if a local part of the structure has failed. A local failure can be caused by an accidental action or by fire. The conditional limit states can be related to e.g. the formation of a mechanism in the structure, exceedance of the material strength or instability (buckling).

Serviceability limit states
Serviceability limit states are related to normal use of the structure, e.g. excessive deflections, local damage and excessive vibrations.

6.2.6 Summary

The following table presents some advantages (+) and disadvantages (-) for the different main types of models presented and discussed in this chapter.

Table 9: Overview of advantages and disadvantages of different models

Physical models	Stochastic models	Data-driven models and machine learning
+ White-box model + Clear meaning of model parameters - Problem-specific model - Challenging if good model is not available	+ General model + Takes uncertainty into account + Requires a group consisting of comparable items - Parameter estimation requires observations related to lifetime/reliability - Often black-box model	+ General model + Large data sets + Short-term predictions + Identification of faults + Fault detection and diagnosis - Often black-box model - Parameter estimation requires data related to lifetime/reliability - Few examples on lifetime prediction and reliability estimation

6.3 Model choice and data requirements

This chapter offers some general suggestions. More specific recommendations and specifications could be established in collaboration with component experts from manufacturers, turbine operators, service providers and research.

6.3.1 Choice of model

Since different models have different properties, the choice of a model depends on the intended application. The following paragraphs will cover different aspects that will influence the choice of a reliability model.

6.3.1.1 Prediction horizon

The prediction horizon of a model is the time interval for which the model provides a good prediction. "Good" in this context does not necessarily mean that the model and its prediction are "exact" (i.e. with low uncertainty), but that the model has the required exactness and uncertainty that fit the intended application.

The prediction horizon of the models presented in Chapter 6.2 ranges from short term to long term. The prediction horizon for different models is illustrated in Table 10 where the green-shaded fields indicate areas where the models listed in the table have their main applications.

Table 10: Prediction horizon of different models

Model	**short term ← prediction horizon→ long term**			
	<<MTTF*	< MTTF	MTTF	≥ 2 MTTF
Stochastic models				
Failure rate models				
Lifetime distributions				
Stochastic degradation models				
Physical models				
Machine learning				

*Condition monitoring systems that provide warnings and alarms hours, days or months before a failure.

6.3.1.2 Size of population

The size of population will have a large influence on the choice of the model. When we are interested in making a prediction for an individual item, we are interested in reliability and the remaining useful life for this particular item, rather than the statistical failure rate or the general average behavior of this type of item. We therefore need models that take individual (i.e. item-specific) aspects into account. When making a prediction for a large group of items, however, we are probably interested in averages, such as the number of failures per time interval, rather than the point in time when the individual items fail (
Table 11).

Table 11: Prediction capability depending on size of group

Model	**small ← size of population → large**	
	single unit, item	group, population
Stochastic models		
Failure rate models		
Lifetime distributions		
Stochastic degradation models		
Physical models		
Machine learning		

6.3.1.3 Fields of application

The potential field of model application will influence the model choice. Some suggestions and examples can be found in Table 12.

Table 12: Applications and suitable models

Field of application	Aim	Examples of suitable models
Lifetime prediction	Early warning of faults and end-of-life prediction for individual components.	Models with short and medium time prediction horizon such as data-driven models and AI, utilizing condition monitoring data, stochastic degradation models, physical models representing the failure mechanism(s) of interest.
	Prediction of mean lifetime for an individual item or prediction for a population of items. General statements about the "normal"/average lifetime and the variance of the lifetime.	Failure rates, lifetime distributions and other models for characterization of mean lifetime and lifetime distribution.
	Explaining individual differences in lifetime behavior for items where much operational experience and historical data are available.	Stochastic models with explanatory variables, e.g. hazard rate models with covariates. Failure rates for different groups (e.g. different designs, different operating conditions or external loads such as weather/climate, etc.) allowing for distinguishing differences in lifetime behavior.
O&M modeling and optimization	Strategic O&M modeling (long-term perspective)	Models with long-term prediction capability such as failure rates.
	Operational O&M modeling (short- and medium-term perspective)	Models with short-/medium-term prediction capability such as lifetime distributions, data-driven models and models using condition monitoring data, artificial/ computational intelligence models.
	O&M optimization (mathematical optimization)	Mathematical optimization usually requires reliability models with simple mathematical reliability expressions (e.g. failure rates) that can be integrated in an objective function. The aim is to reduce computational time for solving the optimization problem.
Design improvement	Improvement of component design	Requires a good understanding of the component design, their failure mechanisms and the relation between design, operation, environmental factors, external loads, degradation and lifetime. Physical models are well-suited to gain an understanding of these factors. Failure statistics and stochastic models may be used to identify critical components and poor designs.
	Improvement of wind park farm design	Models with long-term prediction horizon and prediction capability for large populations, such as failure rates, because wind park design takes into account a large number of turbines and other components. Wind park farm design improvement is part of the planning phase and has a long-term perspective.
Purchasing optimization	Optimal investments and purchasing of equipment and technical solutions with low life-cycle costs (LCC)	Models that can help to make general statements about the "normal" useful lifetime of a specific component or turbine model/design given the environmental and operational conditions at the site. Rich operational experience (e.g. in form of statistics) is very useful for making good purchase decisions.

6.3.1.4 Other aspects and criteria for model choice

IEC 60300-3-1:2003 presents several other aspects and criteria for selecting the appropriate analysis method such as system complexity, system novelty, qualitative vs. quantitative analysis, single vs. multiple faults, time or sequence-dependent behavior, usability for dependent events, bottom-up vs. top-down analysis, level of experience required, acceptance and commonality of the analysis method, need for software tool support, availability of software tools, and standardization.

6.3.2 Input data requirements

The choice of the model will have implications for the data collection, because different models require different types of data. In the following, the discussion is restricted to a selected number of main types of models.

It is important to note that it is difficult to give detailed recommendations and specifications on which data to be collected and how often to collect the data (collection/sampling frequency), because this depends on the intended application. The detailed database specification must thus be done by involving experts on the different wind turbine components, i.e. component experts from manufacturers, operators and research.

Table 13 briefly discusses different aspects of data requirements for different types of models. Data requirements are also discussed in Chapter 7. IEC 60300-3-2:2004 presents data requirements for different analysis and modeling purposes.

Table 13: Type of models and data requirements

Type of model	Data requirements
Stochastic failure models	Failure data (see Chapter 7.1.3) and factors and effects that influence degradation and lifetime and the occurrence/frequency of failures (to be able to make more a detailed analysis, include covariates, etc.) Since the basic principle of stochastic analysis is to draw conclusions for a population from a data sample, the data that represent factors and effects that influence failure must be collected in a way to define and distinguish different (meaningful) populations and samples.
Degradation models	When using degradation models, a suitable degradation variable must be defined. Degradation could be measured directly or it could be measured indirectly by means of indicators. For example, the length of a crack is a direct measure of degradation, whereas oil temperature or vibrations are indicators for degradation (e.g. wear) of a gearbox. Degradation/condition data can also be in form of discrete states, such as "as good as new", "some degradation", "much degradation" and "failed". The latter approach represents a quite general approach which could be applied for most types of wind turbine components; however, the challenge is to provide meaningful and unambiguous definitions of the states. Degradation models allow for the optimization of condition based maintenance. This should not only include data for stochastic degradation models but also physical degradation models.
Physical models	The data collection must include the data required for using physical models that have been identified as potentially useful for assessing the reliability of the wind turbine and components. For example, if fatigue and cracks are a typical problem for a given wind turbine component, the use of a fatigue and/or crack growth model, such as Miner's rule and Paris' law, should be considered.

7. Data collection

The user of reliability and maintenance data has to systematically collect and manage large volumes of information and data–data regarding the power plant itself as well as occurring failures or maintenance measures.

Some information is collected only once, i.e. identifiers or technical data of the system and sub-systems, while measurement values need continuous capturing.

IEA Wind TCP Task 33 has followed the international standard ISO 14224 from the offshore oil and gas industry suggesting the four data groups:

- Equipment data
- Operation & measurement data
- Failure data
- Maintenance data

Table 5 in Chapter 2.7 presents an overview of these data groups and their sub-groups.

The following tables provide examples of what is meant by these data groups and sub-groups. More details shall be found in the named standards, guidelines, and taxonomies. In general, each sub-group contains a list of possible entries, which the IEA Wind TCP Task 33 team assumes to be relevant and minimum. However, it is always up to the user to refer to the appropriate taxonomy and to decide whether to collect all suggested data or select the most relevant for his/her task. After certain standards are selected and the data structure of the CMMS or CR database is settled, expanding the data collection with more entries from the taxonomies in use will not be a major problem. On the contrary, changing taxonomies during the course of the data collection will require more effort.

The taxonomies named in this study were deemed to be the most capable of covering the needs of data collection for reliability assessment. But only few of these taxonomies were developed directly for use in the wind energy industry and may not meet the needs of a specific user's task. The tables and listings on the following pages should therefore only be taken as suggestions. Explanations of these taxonomies follow in Chapter 7.2.

As mentioned previously, IEA Wind TCP Task 33 intends to direct potential users towards existing standards, guidelines and taxonomies that suit their individual task. However, in some cases, especially for equipment data, no complete wind-specific guideline was found. In these cases, Task 33 suggests some data entries by themselves.

7.1 Data groups

7.1.1 Equipment data (ED)

Equipment data describes the configuration of the power plant equipment. It is used to identify parts of the whole asset and to relate it to maintenance tasks and failures. It is necessary to group identical or similar wind turbines with comparable operational and ambient conditions for certain analyses and assessments.

The designation of wind turbine systems, assemblies and parts is more complicated. Several guidelines suggest designation systems, all following different approaches of grouping parts to maintainable items, maintainable items to assemblies, etc.

These designation systems regard different system boundaries, from only covering the wind turbine to the complete plant with infrastructures. Furthermore, the structures differently divide wind power plants down to the level of maintainable parts or remain at higher levels as sub-systems. The most promising designation systems for wind power plants seem to be NERC-GADS and RDS-PP®.

Table 14 gives an overview of equipment data, sub-groups and possible entries. Please note: The required data depends on the hierarchical level of the item. Location means different entries for a wind farm than for an assembly. Complexity levels are defined in Chapter 2.4 and Table 2.

Table 14: Data group equipment data, sub-groups/objects, possible entries and taxonomies addressing equipment data (complexity levels defined in Table 2)

Equipment data (per hierarchical level of the plant)		
Sub-groups/objects	Entries	Complexity level
Identification		
	Identification code	A, B, C
	Coordinates, location	A, B, C
Time data		
	Start of operation	A, B, C
	Start of observation	C
Technical information		
	OEM	A, B, C
	Type	A, B, C
	Serial number	B, C
	Design data relevant for each equipment class and item	B, C
	Maintenance manual	C

When providing a root-cause-analysis, for example, it is important to gather some technical data for the respective item. IEA Wind TCP Task 33 abstained from defining these important technical data for items and faults. The entry 'Design data relevant for each equipment class and item' thus remains on a general level.

When improving the maintenance strategy for certain items, it is important to know the original specifications for the regarded items, such as the type and frequency of activities. Again, the entry 'Maintenance manual' remains with such a general description, because IEA Wind TCP Task 33 was not able to go further into details.

7.1.2 Operating data / measurement values (OD)

For observing the performance of a turbine in terms of power production, availability or lost power, continuous measurements of variables like wind speed, power output, or rotor RPM are essential.
The measurement of ambient conditions can support the assessment of their impact on the health of components as wells as for monitoring the propagation of faults.

Additionally, for availability calculations as well as for assessing critical events, the operational and functional states of the plant and the affected components are important. As there is no common standard for the status codes of wind turbines in use and all turbine types produce different codes, it is still up to the operator to map the most important status codes to the definitions of an existing guideline. The standard IEC 61400-26 and the guideline ZEUS (see Table 15) seem most promising.

Table 15: Data group operational data, sub-groups/objects, possible entries and taxonomies addressing operational data

Operating data/ measurement values		
Objects	Entries	Complexity level
Time data		
	Time stamp	
Measurement values (SCADA / CMS / etc.)		
	Wind speed	A, B, C
	Wind direction	A, B, C
	Active power	A, B, C
	Ambient temperature	A, B, C
	Air pressure	A, B, C
	Measurement values (i. e. CMS data) relevant for each equipment class and item	C
Operating / functional status		
	Operating state (plant)	A, B, C

For conducting failure-cause-analyses, measurement values and operational states from the operation are often necessary. Measurement values are extremely important especially for the assessment of structural components. Again, IEA Wind TCP Task 33 did not go into that much detail but only suggests collecting data with regard to the planned analysis.

7.1.3 Failure / fault data (FD)

Differentiating between failures and faults can be confusing. Following IEC 60050, a failure of an item is an event leading to a fault of that item, where fault is a state. The type of a fault may be associated with the type of the associated failure.

However, definitions and uses of the terms failure and fault differ in literature and standards. When suggesting entries for failure and fault data, such as ‘kind of defect’ or ‘size of defect’ (see Table 16), this document uses the term ‘defect’ when the meaning is more general, and the term ‘fault’ when the level of defect exceeds a critical size implying a maintenance or repair activity to be done. Of course, the calculating method is the same for both, failure rates and fault rates.

Failure descriptions in terms of failure mode, failure mechanism, failure cause, etc. help to distinguish different problems from each other and allow the capture of the proper failure rates. Information about the subsequent impacts of failures/faults on the component or plant provides an opportunity for assessing their severity.

When optimizing O&M, it is important to know which occasion allowed the detection of a failure/fault. All measures (additional equipment or activities) allowing an early detection are optimal, assuming there are adequate and available resources.

The analysis of degradation and fault propagation needs information and measurement values of the defect. Up to now, there has been no comprehensive work that names promising measurements for all components–electrical, mechanical, or structural. It is thus again up to the user to select and install appropriate measurements.

Table 16 presents the data group failure / fault data and gives examples for appropriate entries. ISO 14224 and ZEUS provide the user with suggestions on which information to record for many of these entries, but not all.

Table 16: Data group failure data, sub-groups/objects, possible entries and taxonomies addressing failure data

Failure/fault data		
Objects	Entries	Complexity level
Identification		
	Failure record ID	
Time data		
	Date of occurrence of failure	C
Description		
	Failure mode	B, C
	Failure/fault mechanism	B, C
	Failure cause	B, C
Effect		
	Failure effect on plant	C
	Failure effect on component	C
Detection		
	Detection symptom	B, C
	Detection method	B, C
	Occasion for detection	B, C
Fault properties		
	Kind of defect (deviation from target state)	B, C
	Location of defect (on structural components)	B, C
	Size of defect (on structural components)	B, C

7.1.4 Maintenance & inspection data (MD)

Detailed maintenance data is needed when striving to optimize maintenance effort versus availability or earnings. Date of shut-down, start of repair, and restart are necessary for deriving waiting times, repair times, or down times. This information together with man hours and qualification is needed for estimating different efforts and e.g. deciding on grouping preventive maintenance measures.

Maintenance & inspection data complement failure data when concatenating failures and maintenance effort for assessing the severity of faults and failures. Furthermore, reliability calculations need to distinguish repair from replacement. To optimize maintenance strategies, it is necessary to know whether a measure was taken correctively or preventively.

A lot of information therefore has to be drawn from maintenance reports. Two guidelines, ISO 14224 and ZEUS, propose data sets to collect. However, none of these guidelines suggest all the required entries regarding maintenance resources, tools, or staff qualifications (see Table 17).

Table 17: Data group maintenance data, sub-groups/objects, possible entries and taxonomies addressing maintenance data

Maintenance and inspection data		
Objects	Entries	Complexity level
Identification		
	Maintenance record ID	
Time data		
	Begin of activity	C
	Time of restart	C
	Delays	C
Task / measure / activity		
	Category (preventive, corrective)	C
	Type of activity	C
	Impact on plant	C
Resources		
	Man hours	C
	Qualification	C
	Auxiliary equipment	C
	Spare parts	C
Maintenance results		
	Recommended subsequent action	C
	Inspection results	C

In Table 17, ‘delays’ address periods like waiting for spare parts or availability of certain auxiliary equipment, or vessels to reach the turbine. Since again, it depends much on the individual situation and objective, there is no concrete suggestion yet, which delay to consider. ‘Inspection results’ regard outcomes of the conformity check of an item against its technical specifications. Parts subject to wear and tear need to be checked regularly as to whether they are still within the specifications. As long as an initial wear or defect does not exceed a certain size, it is not regarded as a fault but still counted as a maintenance result. Defects exceeding their acceptable limits are counted and reported as faults.

7.2 Taxonomies

The previous sections covered the issue of mapping to well-understood, common, unambiguous organizing principles. This section presents a number of possible component taxonomies as well as a classification for operations, maintenance and failures.

It is important to have organized system classifications for various aspects of asset management. While there may be some degree of choice in picking one, they offer controlled vocabularies, definitions and other principles in various standards and users can benefit from the content. Adoption in some form should be considered as a best practice.

7.2.1 RDS-PP®

The main objective of the Reference Designation System for Power Plants Standard (RDS-PP®) was to arrive at a sector-specific approach to the naming and labeling of all systems, sub-systems and assemblies in power plants. The German company VGB organized a working panel that was jointly developed by manufacturers and operators and contributed to national and international standardization activities. It has the characteristic features of a proven identification system which are:

- Applicability to all power plant types

- Consistency throughout the entire life cycle
- Identity in sense for all technical disciplines
- Language independence

The RDS-PP® is based on structuring principles, designation rules and letter codes specified in international standards published by IEC and ISO. It complies with the national/international sector-specific standards for power plants DIN 6779-10:2007-04 and ISO/TS 16952-10. The system is powerful in that it gives a functional structure for identifying parts of any wind turbine down to the level of single parts.

Table 18: Properties of the RDS-PP® taxonomy for component designation

Name	RDS-PP®
Intended application	An approach to the naming and labeling of all systems, assemblies and sub-systems in power plants.
Domain	Power plants in general
Scope	Sector-specific guideline for wind power plants, including BOP like infrastructure
Objects	• Equipment data • Mainly designation system of all hierarchical levels down to parts • Geographical information
Granularity	Approx. 2,200 tags spread across 5 hierarchy levels
Rule for dividing	The order follows the function of the components
Generic	The taxonomy is “language independent” by assigning codes for each sub-system. This makes it internationally applicable, but also more difficult to understand and implement. The taxonomy is also turbine-specific in that the guidance indicates how the code should be applied differently for each turbine model.
Reference	https://www.vgb.org/en/rds_pp_part_32.html

7.2.2 NERC-GADS

North American Electric Reliability Corporation (NERC) promotes the reliability and adequacy of bulk power transmission in the electric utility systems of North America. The Generating Availability Data System (GADS) is a database operated by NERC and it includes annual summary reports comprising the statistics for power stations in the United States and Canada. All electricity producers have to report prescribed data to NERC and to apply GADS taxonomies.

Besides terms for equipment data, NERC has included some terms for operational states of a plant and distinguishes between preventive and corrective maintenance tasks.

Table 19: Properties of the GADS taxonomy for component designation

Name	NERC – GADS
Intended application	GADS is a database used to collect, record, and retrieve operating information for improving the performance of electric generating equipment.
Domain	Energy supply systems
Scope	Monitoring of reliability and availability of components in an energy supply system
Objects	• Equipment data Mainly designation system in two hierarchical levels considering components down to the sub-assembly level Geographic information • Operating data Operational states of wind turbines
Granularity	• 63 objects across 13 categories • 30 tags for describing wind power plant downtime
Rule for dividing	The equipment taxonomy follows an object/location model.
Flexibility	The equipment taxonomy is a general taxonomy and can be used to describe any make or model of wind turbine
Reference	http://www.nerc.com/files/GADS_Wind_Turbine_Generation_DRI_080910_FINAL.pdf

GADS also provides component taxonomy as part of its published material. The GADS component taxonomy consists of 96 components and 14 sub-categories.

7.2.3 ISO 14224

This international standard is applicable to equipment types used in the petroleum, natural gas and petrochemical industry, including but not limited to equipment categories (e.g. process equipment and piping, safety equipment, pipeline systems, etc.).

The equipment may be permanently installed at the facilities or used in conjunction with installation, maintenance or modification phases. It is applicable to data collected during the operational life cycle of equipment, including installation, start-up, operation, maintenance and modification. Laboratory testing, manufacturing and fabrication phases are excluded from the scope of this International Standard. It is, however, emphasized that an analysis of relevant historic RM data shall be used in the dimensioning of such testing prior to operation.

When it comes to terms regarding failures and maintenance it differs from IEC 60050 and EN 13306. The recommendation is to use terms and definitions from IEC.

Table 20: Properties of the ISO 14224 standard

Name	ISO 14224
Intended application	Comprehensive taxonomies for reliability assessment
Domain	Offshore oil and gas
Scope	All aspects from equipment issues via failure properties to maintenance activities
Objects	• Equipment data: manufacturer's data, design characteristics • Operation data, e.g. operating mode, operating power, environment • Failure data, e.g. failure date, failure impact, failure mode, failure cause, failure detection method • Maintenance data: type and date of action, maintenance activity, impact of maintenance, resources, maintenance times, down time
Granularity	• 4 hierarchical levels for equipment • Maintenance data have 9 parameters, maintenance resources have 3 parameters, maintenance items have 3 parameters. • Failure data has 11 parameters • Room for additional data
Rule for dividing	The number of subdivision levels for the collection of RM data depends on the complexity of the equipment unit and the use of the data. A single instrument might need no further breakdown, while several levels can be required for a large compressor
Flexibility	Equipment, failure and maintenance data attributes are generic
Reference	http://www.iso.org/iso/catalogue_detail.htm?csnumber=36979

7.2.4 ReliaWind

The ReliaWind project was an EU-funded project within the frame of the European Union's Seventh Framework Programme for RTD (FP7). The project commenced on 15th March 2008 and concluded in March 2011. The project goal was to achieve better efficiency for wind turbines through the deployment of new systems with reduced maintenance requirements and increased availability.

One of the deliverables of the project is "WTG Reliability Model Specifications" (Barbati, 2008). As part of this deliverable, ReliaWind has proposed a wind turbine system tree (Appendix A - WTG80 System tree). This system tree represents comprehensive turbine taxonomy for a common class of turbine.

Table 21: Properties of the ReliaWind taxonomy for component designation

Name	ReliaWind
Intended application	Wind turbine structure as part of a research project
Domain	Wind energy
Scope	Wind turbine
Objects	• Equipment data 5 hierarchical levels • Operational data Operational states of wind turbines
Granularity	A wind turbine system is partitioned into 261 independent elements spread across five hierarchy levels – systems, sub-systems, assemblies, sub-assemblies and components.
Rule for dividing	For the most part location-based but for electrical elements a functional approach was taken, resulting in a hybrid model.
Generic	Generic names are used for constituent parts of a wind turbine so this taxonomy lends itself to applications involving multiple turbine models.
Reference	http://cordis.europa.eu/result/rcn/55560_en.html

7.2.5 IEC 61400-25

The International Electrotechnical Commission (IEC) is a worldwide organization for standardization bringing together IEC National Committees. The object of the IEC is to promote international cooperation on all questions concerning standardization in the electrical, electronic and associated fields.

The IEC publishes International Standards prepared by Technical Committees established as a result of representations from National Committees. The 61400 standards set of design requirements are made to ensure that wind turbines are appropriately engineered against damage from hazards within the planned lifetime. While they address many of the components and systems seen in the taxonomies described above, they concern most aspects of the turbine life from site conditions before construction, to turbine components being tested, assembled and operated. The relevant standard applicable to WTs is IEC 61400 and it contains 16 high level sub-system categories.

Table 22: Properties of the IEC 61400-25 industry standard

Name	IEC 61400-25
Intended application	Standardized communications in wind power plants.
Domain	Wind energy
Scope	Wind turbine
Objects	• Operational data / measurements
Granularity	13 items across two levels
Rule for dividing	The logical nodes correspond to functions in the real physical devices
Flexibility	The equipment taxonomy is generic and does not distinguish between different turbine manufactures or turbine technologies
Reference	https://webstore.iec.ch/publication/22813

7.2.6 IEC 61400-26

The IEC 61400-26 standard (draft) (IEC, 2010) provides a wind turbine state information model which is based on a decision matrix that reflects whether the data is available or not, whether the plant is operational or not and whether it is generating or not and if not, why. It also identifies the possibility of force majeure situations. One of its purposes is to provide a common basis for an organized information exchange about performance indicators between owners, utilities, lenders, operators, manufacturers, consultants, regulatory bodies, certification bodies, insurance companies and other stakeholders in the wind power business. It is used to help define requirements to support a clear understanding of contract terms. The following table describes the condition states.

Table 23: Properties of the IEC 61400-26 industry standard

Name	**IEC 61400-26**
Intended application	Common understanding of operational periods during the lifetime of a wind turbine and suggestions for availability calculations
Domain	Wind energy
Scope:	Wind turbine
Objects	• Operational states
Granularity:	14 mutually exclusive operational states are defined and spread across 5 levels of hierarchy
Rule for dividing	Each operational state has well-defined entry and exit points within the standard
Flexibility	Generic names are used for the operational states that are not tied to specific turbine models
Reference	https://webstore.iec.ch/publication/5445

7.2.7 ZEUS

The editor of ZEUS, the national German association FGW, strives to find factual technical solutions for matters of different concerns, represented by different stakeholders.

ZEUS was developed in response to missing common terminology for failure aspects in the wind industry and provides a standardized description of states, events and causes. It is intended for providing, in combination with a standardized designation system for components, input data for both condition-based and predictive-oriented maintenance. With a variety of codes, it describes the current operational and functional states of a plant and its components, aspects of maintenance activities and results derived from the operational monitoring or from inspection reports.

Table 24: Properties of the FGW guideline ZEUS

Name	ZEUS ("State-Event-Cause code")
Intended application	Comprehensive taxonomies for reliability assessment
Domain	Energy supply
Scope	Energy supply system and components
Objects	• Maintenance data • Failure data • Operational / measurement data
Granularity	Two blocks of terms for a main system, i. e. wind turbine, and defect sub-systems, assemblies and parts. 4 keys within block 1 13 keys within block 2
Rule for dividing	Rules are drawn up for the state-event-cause code (ZEUS) to reduce the range of information to a sensible volume, to structure, to illustrate and to collect detailed information for analysis
Generic	ZEUS describes the current states derived from the operational monitoring or from inspections as well as failures, events and causes. This information is assigned to the relevant originator within a function-oriented structure as per RDS-PP® (Reference Designation System for Power Plants).
Reference	http://wind-fgw.de/tr_engl.html

7.2.8 Taxonomies for equipment data

RDS-PP® has the most comprehensive taxonomy; while this is of value, it also makes the taxonomy look complicated. However, it provides the best potential for all applications and the taxonomy is ready to relate functions to locations and products.

ReliaWind and GADS are both respected, but have not been universally accepted. Their potential for universal acceptance is perhaps less than RDS-PP® and there is no ongoing development; however, considering the fact that GADS will become mandatory for North American wind plants, GADS will likely become the *de jure* standard in the United States.

Both ReliaWind and GADS taxonomies can get mapped to RDS-PP® codes, however the reverse is not true.

Table 25: Equipment taxonomies in comparison

Data groups	Equipment data		
Objects	Identification	Time data	technical information
RDS-PP®	+		+
GADS	o	o	+
ReliaWind	-		
ISO 14224	(+)	+	(+)

+ wind-specific entries with a high level of detail
o wind-specific entries with a medium level of detail
- wind-specific entries on a more general level
(+) entries with a high level of detail, not wind-specific
(o) entries with a medium level of detail, not wind-specific
(-) entries on a more general level, not wind-specific

7.2.9 Taxonomies for operational data and measurements

Although there is a demand from the industry for standardizing operational states and alarm codes, no guideline presents a comprehensive suggestion for operational data and measurements. A combination of suggestions and definitions of several standards is the only option.

Regarding time of occurrence and timestamp, IEA Wind TCP Task 33 suggests using 10-minute values, which will be available in most cases.

Table 26: Standards and guidelines for operating and measurement data in comparison

Data groups	**Operating / Measurement data**		
Objects	Time data	Measurement values	Operational/ functional states
GADS	o		+
ZEUS			+
IEC 61400-25	+	+	
IEC 61400-26			+

+ wind-specific entries with a high level of detail
o wind-specific entries with a medium level of detail
- wind-specific entries on a more general level

7.2.10 Taxonomies for failure data

Again, no standard presents a complete and suitable list of values. Additionally, the definitions deviate from IEC and EN standards. ZEUS is a bit more comprehensive, but also gives only little support for describing faults in size and location for monitoring purposes.

Table 27: Taxonomies for failure data in comparison

Data groups	**Failure data**				
Objects	Identification and time data	Failure description	Failure effect	Failure detection	Fault properties
ISO 14224	+	+	o	o	
ZEUS		+	+	+	-

+ entries with a high level of detail, suitable for wind application
o entries with a medium level of detail, suitable for wind application
- entries on a more general level, suitable for wind application

7.2.11 Taxonomies for maintenance data

For maintenance optimization, some information is needed about the effort for different activities. However, while ZEUS and ISO 14224 provide some help, no comprehensive taxonomy has been available so far.

Table 28: Guidelines for maintenance data in comparison

Data groups	**Maintenance and inspection data**			
Objects	Time data	Task/ measure	Resources	Results
GADS		-		
ISO 14224	+	+	o	-
ZEUS		+	o	-

+ entries with a high level of detail, suitable for wind application
o entries with a medium level of detail, suitable for wind application
- entries on a more general level, suitable for wind application

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9. Appendix

9.1 Example ‘Availability assessment’

Complexity level:	A
Data groups:	Equipment data (ED), operational data (OD)

‘User Story’

Who am I?
I am a wind farm operator and my wind farm is under an OEM warranty.

What do I want to do?
I am trying to accurately calculate the production-based availability for the previous month at my wind farm.

Why?
I want to know whether my wind farm generated the expected production and whether it achieved the guaranteed availability. Additionally, I want to be able to compare the performance of several of my wind farms.

The following steps will lead to a suitable solution:

1. Firstly, the operator has to create a turbine status log that specifies the operative states throughout the month for each turbine in the farm. For a user working with 10-minute SCADA data, each turbine must have a defined operative state for every 10-minute period. A key recommendation from this report is that the user should align the operative states with the taxonomy provided in the IEC 61400-26 information model (see Chapter 7.2.6).

   The IEC 61400-26 series describes various ways to combine operative states to calculate an availability value. The user is recommended to align any contractual availability definition with the methods and language of this standard and, crucially, have clearly defined rules for any carve-outs.

2. To calculate a production-based availability value, the user now needs to calculate the potential production and the real production at each turbine throughout the month. For real power, IEC 61400-25 provides measurement nodes and labels. The standard IEC 61400-26-2 suggests various ways to calculate potential production, which can be done either by using a reference wind speed and power curve or by using adjacent turbine power values.

3. Finally, the user will calculate the production-based availability by dividing the real production by the potential production (having removed any potential production that is considered as a carve-out).

Table 29: Overview of input required for calculating production-based availability

Task	Data groups	Data	Guidance / suitable taxonomy
Identify individual wind turbine	ED	As a minimum, note identifier and geographical co-ordinates of the turbines	
Create a turbine status log that contains the operative states for each turbine in the farm, following IEC 61400-26	OD	Turbine operative states	IEC 61400-26 series specifies a standardized taxonomy for operative states. A user should reconcile between various sources of maintenance data to ensure an accurate representation of the statuses of wind turbines and events on site.
Clearly define the components of the availability calculation. Distinguish between periods of availability and unavailability.	OD	Turbine operative states	The IEC 61400-26 series describes various ways to combine operative states to calculate an availability value. Align contractual availability definitions with this standard and have clear descriptions of carve-outs. Assure all stakeholders have a consistent interpretation of the availability calculation details before it is put into practice
Determine real power production at each turbine across the month	OD	Active power	IEC 61400-25 provides measurement nodes and labels
Calculate potential power production at each turbine Case A) Use a wind speed reference (for example nacelle anemometer, lidar or satellite hindcast among others), infer the ambient conditions (such as air density and pressure) and apply with a reference power curve Case B) Use power metering from neighboring wind turbine	OD ED	Wind speed, air density, power curve Active power Identifying neighboring turbines.	The standard IEC 61400-26-2 suggests various ways to calculate potential production.
Calculate production-based availability	OD	Actual production, potential production	IEC 61400-26-2 suggests suitable equations

9.2 Example 'Design comparison'

<u>Complexity level:</u> B
<u>Data groups:</u> Equipment data (ED),
Failure data (FD)
Optional: Maintenance data (MD)

> ## 'User Story'
>
> **Who am I?**
> I am a wind turbine manufacturer and I am verifying the optimum design of my turbines.
>
> **What do I want to do?**
> I want to evaluate reliability data of two different makes of blades.
>
> **Why?**
> I suspect that one of the two similar makes suffers more often and more severely from structural damages. I thus want to make sure that the failure of the one make is indeed higher than the other. If possible, I want to find the most typical failures and their causes.

A wind turbine manufacturer wants to compare the reliability of two different wind turbine designs. The design differences are given through different types of blades delivered by different blade suppliers. The operator has a service contract with the wind farm owner. The service agreement includes responsibility for the inspection and maintenance of the turbines, which are installed in a large wind farm featuring turbines with both types of blades. Through the service contract, the manufacturer is able to collect failure data. In order to check if one of the designs is more reliable than the other, the manufacturer calculates the failure rate for both designs based on the collected failure data.

Case 1:
Basically, the manufacturer could simply count the number of failures for both types of blades and calculate the failure rate as number of blade failures during the period the data is collected, divided by the length (or operating hours) of the data collection period and the number of turbines (or blades) with the different blade design the data is collected from.

Case 2:
However, assuming now, and in the table below, that a structured reliability database is used for data collection that also contains maintenance and data from all other components, the manufacturer must be able to identify blade failures in the database and must be able to identify if the blade that failed was either of the one or the other type of design. The latter can either be done by having a separate database/list where the type of blade design/blade manufacturer is registered for each turbine, or the information about the blade design/blade manufacturer must be integrated as part of the reliability database.

Case 3:
If the manufacturer is interested in differentiating between different types of blade failures (major/minor, which blade part failed and how: crack, delamination, fracture, lightning damage, ...) much more detailed information should be collected, such as failure consequences/maintenance after failure, repair costs or cost of blade replacement, etc. Ideally, the different types of blade failures should be classified by e.g. failure mode, failure causes, failure consequences, severity, etc. Table 30 summarizes the options and presents a suggestion for which data to collect.

Table 30: Overview of input required for design comparison and recommended taxonomies

Task	Data groups	Data	Guidance / suitable taxonomy
Identification of the type of component (blades and design/manufacturer of blade) and number of components	ED	Item ID Blade design or blade manufacturer	RDS PP or other taxonomies that can provide the suitable level of detail to identify the component of interest (blade)
Identification of individual failure registration and description of failure	FD	Failure mode Failure cause	ZEUS presents data entries for describing the failure as well as the impact on the function of the component and the turbine as a whole.

9.3 Example 'Grouping of maintenance tasks'

Complexity level:	C
Data groups:	Equipment data (ED), Failure data (FD), Maintenance data (MD) (Costs)

'User Story'

Who am I?
I am a wind farm operator and I service my assets on my own.

What do I want to do?
I'm trying to group preventive maintenance activities.

Why?
To reduce the maintenance effort without reducing the availability / reliability of my assets. I want to avoid needless missions and save travel and set-up costs.

A wind farm operator wants to group scheduled preventive maintenance tasks into maintenance packages by using models as described in the Executive Summary. Note that these maintenance grouping models are restricted to a category/type of scheduled preventive maintenance activities that bring the overall condition of the component (or the condition regarding the failure mode/mechanism that is addressed by this maintenance task) to a condition as good as new. Typical maintenance activities in this category are preventive replacements.

Maintenance grouping is based on an analysis approach consisting of the following tasks and steps:

1. Identification of components and maintenance tasks

2. Selection of (types of) components and maintenance tasks to be considered for grouping. Note 1: There could be one or several different maintenance tasks per type of component that could be suitable for grouping with tasks for the same type of component, or with tasks for other types of components, or with tasks carried out at other turbines or other places in the wind farm.

   Note 2: Each maintenance task "addresses" (influences) one or several failure mechanisms and modes. Preventive maintenance (PM) will in some cases not address and "remove" all failures, because some failures might be caused by external causes (e.g. lightning).

3. Calculation of optimal inspection intervals for the individual maintenance tasks, i.e. the optimal maintenance intervals when the preventive maintenance tasks are optimized individually (without grouping).

4. Maintenance grouping, which consists of the following steps:
   a. Selection of a group of maintenance tasks
   b. Calculation of optimal maintenance interval for selected group
   c. Calculation of maintenance costs for the strategy with grouping
   d. Calculation of maintenance costs for a strategy without grouping
   e. Calculation of the cost reduction (increase) compared to the strategy without grouping.

These tasks require a number of inputs as summarized in Table 31.

Table 31: Overview of input required for maintenance grouping models and recommended taxonomies

Task	Data groups	Data	Guidance / suitable taxonomy
Identification of components Maintenance tasks	ED MD	Component ID Maintenance task ID	Reference designation RDS PP, GADS ReliaWind ID for identification of maintenance tasks (as usually used in CMMS)
Selection of (types of) components and maintenance tasks to be considered for grouping Different alternatives (A1, A2) for getting this information: A1: Statistics on PM maintenance activities carried out A2: Work orders defined in the CMMS	ED MD	Item ID Date of PM task Type of task (PM/CM) Condition after having carried out PM task (repair vs. replacement) Item ID Date and/or frequency Type of task (PM/CM) Condition after having carried out PM task (repair vs. replacement)	Same as above ISO 14224, ZEUS Same as above ISO 14224 or ZEUS could already be used when establishing work orders in CMMS to use a consistent taxonomy in work order descriptions
Calculation of optimal inspection intervals and maintenance grouping This requires a lifetime distribution (e.g. Weibull) for the time to failure for each type of component broken down to different failure modes and mechanisms --> need to collect data on failure events	ED FD	Item ID Dates/times (for e.g. commissioning, failure etc. to be able to calculate age/operational time at failure) Failure mode Failure mechanism Failure cause	Same as above ISO 14224 (if date/time cannot be extracted from other sources (e.g. SCADA) On generic level (but no wind turbine specific details included): ISO 14224 Wind turbine specific: ZEUS

Calculation of optimal inspection intervals, and maintenance grouping This requires cost estimates (PM, CM) Alternatives: A1: Rough analysis of recent PM and CM events and their costs A2: Collection of detailed costs for PM tasks (events) and CM tasks after failure events	ED MD FD MD	Item ID Type of maintenance task (PM/CM) PM: Condition after having carried out maintenance task (repair vs. replacement) Setup costs and other shared costs All other costs for PM task (incl. losses) Failure and CM: Failure mode/mechanism/cause Total costs of CM (incl. losses)	same as above ZEUS ZEUS - For calculation of lost production: IEC 61400-26 Part 2 (Energetic Availability) Same as above For calculation of lost production: IEC 61400-26 Part 2 (Energetic Availability)

9.4 Example 'Monitoring Degradation Processes'

Complexity level:	C
Data groups:	Equipment data (ED), Failure data (FD) Maintenance & inspection data (MD)

'User Story'

Who am I?
I am a wind farm operator and teams of the OEM service my turbines.

What do I want to do?
For a few initial faults of structural components, I want to learn about the typical propagation.

Why?
I operate many wind farms, some of them consist of the same type of turbines. I thus want to transfer knowledge from the affected wind farms to others.

An operator looks for identifying degradation processes of structural components and strives to minimize their effects. Part of his scheduled maintenance activities is the regular inspection of the foundation, tower, and rotor blades. A continuous evaluation of the inspection records visualizes initial abnormalities and their progress in time.

1. Firstly, he needs to identify most endangered components by making use of historical inspection and repair records.

2. Secondly, he has to decide on appropriate inspection methods, adapt schedules and record the results. Maybe defects, e.g. cracks in the edges of the blades, will start at weak points and progress in size over time. As long as they remain below a certain order of magnitude, a monitoring of the propagation will be sufficient. Service technicians will therefore take the size repeatedly and note it in inspection reports.

3. A detailed description of detected defects is necessary for distinguishing different types of failures and for assessing their severity. It is therefore also important to note information like failure causes, occasion of the first detection, method of detection, etc.

Table 32: Overview of input required for reducing risk of degradation

Task	Data groups	Data	Guidance / suitable taxonomy
Identify endangered structural components	ED	Item ID	RDS PP, GADS or other taxonomies that can provide labels or codes for identifying structural components
Find or prepare appropriate maintenance and failure data for assessing probability of failures	MD FD	Date of inspection Inspection results, failure causes, failure mechanism	ZEUS helps describe failures systematically and wind specific Find suitable measures for identifying typical faults and for detecting propagation (location and size of damage, etc.)
Monitor health and failure propagation of selected components	MD, FD	ditto	Implement appropriate structures and data entries in your CMMS
Compare results of several turbines and turbine types	MD, FD	ditto	There is no common understanding of how to characterize fault propagation for the different structural components of a wind turbine.