Faculty 15 - Mechanical Engineering

Concept Development and Automation for a Benchmark Oriented Weak Point Analysis of Wind Turbines

submitted by

Kai Pape
Contact: k.pape@posteo.de
Matriculation Number: 32209332

A Thesis submitted in partial fulfillment of the requirements for the degree of
Bachelor of Science (B.Sc.)
to the University of Kassel, Faculty 15 - Mechanical Engineering

First Assessor:	Prof. Dr.-Ing. Kurt Rohrig
Second Assessor:	Heiko Dunkelberg, M.Sc.
Academic Advisor:	Philip Görg, M. Sc.

Kassel, June 6, 2019

Eidesstattliche Erklärung/ Statutory Declaration

Hiermit versichere ich, dass ich die vorliegende Arbeit selbstständig angefertigt und keine anderen als die angegebenen Hilfsmittel benutzt habe. Alle Stellen, die dem Wortlaut oder dem Sinn nach anderen Werken entnommen sind, habe ich in jedem einzelnen Fall unter genauer Angabe der Quelle (einschließlich des Internets sowie anderer digitaler Informationsquellen) als Entlehnung kenntlich gemacht. Dies gilt auch für eingefügte Zeichnungen, bildliche Darstellungen, Skizzen und Ähnliches. Keinen Teil dieser Arbeit habe ich bei einer anderen Stelle zur Erlangung einer Studien- und/oder Prüfungsleistung eingereicht. Ich nehme zur Kenntnis, dass die nachgewiesene Unterlassung der Herkunftsangabe als versuchte Täuschung bzw. als Plagiat gewertet und mit entsprechenden Maßnahmen geahndet wird.

Kassel, den 6. Juni 2019

Kai Pape

Abstract

The Windenergy-Information-Data-Pool (WInD-Pool) is a knowledge database that enables a benchmark oriented performance analysis of wind turbines on the basis of the key performance indicators commonly used in the wind industry. Currently, it is possible to carry out this analysis manually within the WInD-Pool Operator-Portal, that was developed as part of the project. However, this process is associated with a great expenditure of time. The objective of this work was to develop a concept for an automated weak point analysis in order to support a targeted evaluation of the stakeholder's portfolios.

As a basis for this concept the pre-calculated key performance indicators of the WInD-Pool are used and implemented into a benchmark system. The benchmark system enables evaluations based on different references (e.g. WInD-Pool total, operator, wind farm, etc.). In order to meet the stakeholder's requirements regarding the definition of critical performance within the evaluations, both the number and composition of the aggregation levels as well as the threshold value defined as critical can be adapted. During the analysis, the wind turbine-specific key performance indicators are validated and examined for criticality by comparing it against the defined critical threshold within each chosen aggregation level. Out of this, the wind turbine-specific results are accumulated individual within a weighting function that calculates a criticality measurement. This measurement is used to generate a relevance sorted wind turbine-list that provides an overview of the wind turbines and their criticality.

The results of this work include a report template that exemplarily presents the results of the analysis concept. The time saving resulting from the automation are estimated at 60 % compared to the manual analysis.

Contents

List of Figures

List of Tables

List of Abbreviations

AEP Annual Energy Production

$\boldsymbol{A_w}$ production-based availability

$\boldsymbol{A_t}$ time-based availability

$\boldsymbol{A_p}$ production ratio

BMWi Federal Ministry for Economic Affairs and Energy

BM Benchmark

GSP Global Service Protocol

IEC 61400 International Electrotechnical Commission

Fraunhofer IEE Fraunhofer Institute for Energy Economics and Energy System Technology

IZP Ingenieurgesellschaft für Zuverlässigkeit und Prozessmodellierung

KPI Key Performance Indicator

MTBF Mean Time Between Failures

MTTF Mean Time To Failures

MTTR Mean Time To Repair

O&M Operation and Maintenance

RAMS/LCC Reliability, Availability, Maintainability, Safety and Life Cycle Costs

RDS-PP® Reference Designation System for Power Plants®

RMSE Root-Mean-Square-Error

SCADA Supervisory Control and Data Acquisition

WF Wind Farm

WInD-Pool Windenergy-Information-Data-Pool

WT Wind Turbine

ZEUS State-Event-Cause-System

1 Introduction

1.1 Subject and Motivation

In recent years, wind energy has developed into a mainstay of the energy system in Germany, as can be seen from gross electricity generation in 2017 which reached 107.5 TWh [1, p.7]. Due to the extensive expansion over the last few years, the share of wind energy in total gross electricity generation has risen to 16% with an accumulated installed capacity of over 50 GW onshore and about 5.4 GW offshore in 2018 [1, p.7]. This trend towards increased output both within installed capacity and Wind Turbine (WT) technology will continue in the coming years, even though the former will be slightly reduced between 2020 and 2025 due to the phase-out of the feed-in tariff for WTs with an operating life of more than 20 years [2, p.7]. The expected expansion path is determined by the expansion quota in the new edition of the Renewable Energy Sources Act of 2017 and, furthermore, the feed-in remuneration for renewable generation technologies will be determined by means of a tender procedure. These tenders aim for the reduction of remuneration of renewable energies and thus increase the pressure on the industry to optimise power plant performances [3, p.2]. Since 2017, a cost regression for the feed-in tariff is can be observed which depends on the development of the WT expansion in the next years and will increase further [4]. This shows, among other things, the huge competition within the wind energy industry.

Consequentially, the focus on the economic efficiency of WTs is growing, which is to be achieved by increasing performance efficiency or by reducing process losses and costs. At the same time, the industry is moving in the direction of digitalisation and Industry 4.0, which leads to an interface with possibilities for this increase in efficiency [5]. The growing accuracy of data acquisition enables identifications of weak points in the WT performance and the possibilities to enhance maintenance planning. The motivation for this work lies in the perspective of identifying weak

points to increase the WT performance efficiency.
The Fraunhofer Institute for Energy Economics and Energy System Technology (Fraunhofer IEE) created a common knowledge base within their Windenergy-Information-Data-Pool (WInD-Pool) in which this type of assessment is possible. The WInD-Pool collects data from different operators and contains currently around 3200 WTs with an accumulated capacity of 4.2 GW offshore and 2.1 GW onshore. Furthermore, the data is evaluated according to industry standards as well as to adapted definitions of wind industry's Key Performance Indicators (KPIs) [6]. The WInD-Pool Operator-Portal, a benchmarking and reporting platform created as part of the WInD-Pool initiative, presents these evaluations and allows examinations focusing on the identification of weak points within the WT portfolio. To support the process of the manual analysis, an operating guideline was developed. To carry out the weak point analysis, the level of aggregation and period under consideration can be adapted individually for the KPIs and are shown in comparison to the appropriate Benchmark (BM). Since there is a wide range of assessment possibilities, the process of identifying weak points throughout an evaluation of the WInD-Pool Operator-Portal is time-consuming. To carry out this extensive process for an operator's portfolio within a reasonable time exposure an automated evaluation of the KPIs is required. In this bachelor thesis, a concept for such an automation will be created, that serves as a possible extension for the WInD-Pool Operator Portal.

1.2 Problem Definition and Objective

The WInD-Pool Operator-Portal provides several assessment possibilities for stakeholders or operators to analyse the performance of their WT portfolio. These assessments can vary by different dimensions, by changing the period under consideration or by the level of aggregation to achieve multiple results regarding the performance. To support the weak point analysis there is an operating guideline available which can be used for a more thorough analysis. The extensive analysis and time expenditure are problematic because they can hardly be applied for a WT portfolio on a regular basis which resulted in the request for an automation that was made by different operators. Therefore, this work is intended as a concept for a possible expansion of the WInD-Pool Operator-Portal.
This bachelor thesis pursues the goal of the concept development of an automated weak point identification through a performance assessment for WTs within the

WInD-Pool-Project. In order to make this possible, an assessment methodology will be developed according to the WInD-Pool Operator-Portal's KPIs which will be considered and evaluated. The KPIs in this methodology are predefined and calculated within the WInD-Pool-project and adapted within the assessment with regard to the highest possible informative value [7]. For the purpose to create a robust evaluation, benchmarks for the KPIs and levels of aggregation, e.g. onshore or offshore, based on the collected WInD-Pool-data are defined. The assessment is going to be carried out on a monthly basis in which the individual WT KPIs' are evaluated with regard to the benchmarks. Furthermore, there are variables that can be adjusted to match the individual expectations of the stakeholder regarding the weak point identification. As for these variables, a global threshold regarding the benchmark criticality can be determined as well as a selection of the levels of aggregation to be evaluated. Out of this, a weighting function is going to be defined and validated which ranks the critical assets in terms of the considered evaluated benchmarks and the assessed KPI. The results obtained should serve as support for increasing efficiency through targeted improvement of weak points.

1.3 Procedure and Methodology

This chapter concentrates on the procedure that is applied during the process and also on the methodology used. The following flow chart illustrates the used methodology more clearly. Figure 1.1 gives an overview of the structure of this thesis. The process is split into three main categories, *Objective*, *Planning and Realisation* and *Conclusion*, which are further described further below.
Foremost, the *Objective* described above had to be clarified in order to focus on the following steps.
The category *Planning and Realisation* was divided into four steps starting with the structure development followed by the visualisation of the process, the implementation in Python, in which the weighting function is defined, and the validation of the script.

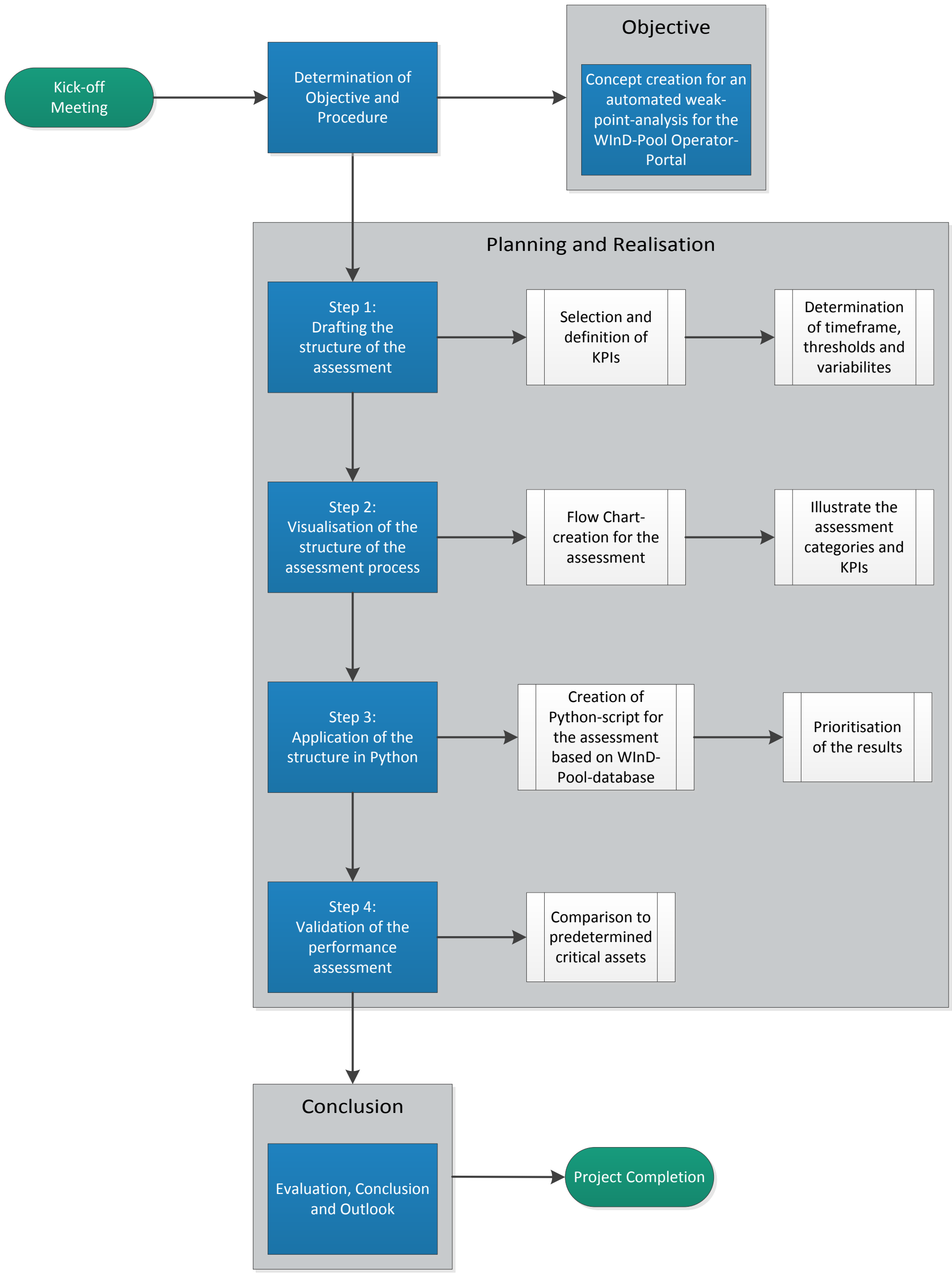


Figure 1.1: Flow chart - procedure bachelor thesis

In the following, these four stages are going to be explained further.
Initially, the development of the general structure of the weak point analysis for the WInD-Pool Operator-Portal that can be found in section 3.2, cf. figure 3.3. Within this phase, the individual parts of the evaluation were worked out. The

structure is divided into three main categories, *Operational Performance*, *Downtime* and *Environmental Conditions*. They contain the information about the evaluations of the individual KPIs. The definition of the KPIs contained in the concept of the weak point identification is based on those of the WInD-Pool Operator-Portal and used as a basis for the analysis.

During the first step, the framework of the analysis was determined in terms of the used KPIs, the repetition of the assessment and the variability regarding the level of aggregation and criticality of the benchmarks. Resulting, the repetition is determined on a monthly basis and a global threshold for all KPIs is implemented, which can be varied by the operator as well as for the used benchmarks. The second step involves the visualisation of the process as the basic structure for the implementation within the Python programming language. The used data basis is presented for the assessed WTs and benchmarks of the individual KPIs to clarify the used input and framework of the analysis. Furthermore, the possible output of the assessment is assigned to different states, which then are going to be included in the weighting function. The Python script is derived from this in the third step in which the evaluation is then applied to the entire portfolio of the WInD-Pool. Therefore, the benchmarks need to be created as well as the general structure of the assessment, including the assessment and weighting function. As a last step in the category *Planning and Realisation*, the automatic evaluation is validated by comparison with previously selected references. Previously known abnormalities of certain WTs of the WInD-Pool portfolio are used for these references.

Within the *Conclusion*, the results of the work are presented, which briefly evaluate the selected work process with regard to its function as well as an outlook on possible improvements or adjustments.

2 Theoretical Background

This chapter presents the background information required for the development of the thesis. It is divided into an overview of possible caused for yield losses, an introduction to the WInD-Pool, fundamentals on benchmarks and further on, about the statistical methodologies used.

2.1 Causes of Yield Losses

This chapter gives an overview of the basic causes of yield losses respectively influences on the WT performance. The various aspects that influence the WT's operational performance and the downtime related influences are explained in the following.

Operational Performance related Yield Losses

This chapter deals with the energy losses that occur during the operation and describes the influences of the WT control system, the environmental conditions and the regulatory measures. The system control is used to increase the energy yield of a WT and at the same time ensure a safe operation with regard to the environmental conditions. Energy losses through the regulation are caused, among other factors, by the pitch control and wind tracking within the partial load range. Within this range, the precise control is challenging and therefore a compromise is aimed for between a component-friendly operation and minimal yield losses [8, p. 469f] [9, p.423f.].

Furthermore, the environmental conditions are relevant, as they provide information about the site, the climatic conditions as well as external influences. Firstly, the site conditions of the WT in general as well as within its WF are influenced by various factors. These can be internal or external shading effects caused by the topology or WT-distribution [10, p.17]. Moreover, the rotor blades are affected by wear and dirt, caused by insects, dust, sand and ice deposits. These losses are caused by a deviation of the rotor aerodynamics, due to changes of the surface structure of the rotor blades [11, p.15]. Regulatory measures also have an impact. These are used, among other things, to minimise the environmental influence of the WT or to keep the wear of the components as low as possible. Examples of this are the feed-in management due to high grid loads [12, p.79] or the noise-reduced operation, which is based on the regulations of the "Technische Anleitung zum Schutz gegen Lärm" and aims at the prevention of noise immissions [8, p.659].

Downtime related Yield Losses

The second part of this chapter deals with yield losses due to downtimes. These are mainly due to regulatory constraints and maintenance activities, however, they can have a significant impact on the energy yield.
The regulatory restrictions mostly refer to the influence of WT on the environment. The protection of species is one part of this. In order to avoid bird strike, but above all bat strike, the operation must be adapted to the bat activities and, if necessary, partially interrupted. Furthermore, the shadow cast of the WT has an influence on the environment. The increasing size of the rotor blades leads to the formation of greater dynamic shades during the operating period [8, p.665ff.]. Finally, yield losses due to shutdowns caused by technical malfunctions and maintenance activities are described. The technical malfunctions consist mainly of two areas. On the one hand, the frequent short standstills and further on, the rare long standstills. The former occur due to component failure of often small electrical components and the accumulated downtime is significant due to the high error frequency. Long downtimes due to failure of large components, e.g. the rotor blades or the drive train components, lead to correspondingly long downtimes, though the frequency is much lower [13, p.331ff.]. Regular maintenance and condition checks as well as inspection also have an impact. These tasks are aimed at a fault-free operating behaviour and can be scheduled effectively through the regular repetition [14, p.21-25]. Accordingly, their impact on the loss of yield is relatively low, as foresighted planning allows actions to be postponed to favourable times. In contrast to this is the repair due to malfunctions. This can only be planned to a limited extent by models, since the component lifespan varies and failures and malfunctions occur often rather randomly [15, p.447].

2.2 The WInD-Pool

The WInD-Pool is an initiative, funded by the Federal Ministry for Economic Affairs and Energy (BMWi), between the Fraunhofer IEE, the Ingenieurgesellschaft für Zuverlässigkeit und Prozessmodellierung (IZP) and various project partners throughout the wind energy industry. It aims at the development of a common knowledge data base within the wind energy sector that enables statistical robust evaluations for the WTs Operation and Maintenance (O&M) processes [16]. This includes weak point and root cause analyses that can be used to identify potentials for optimisation which provide further support in the decision making process. The mainstays of the WInD-Pool are the creation of a reliability characteristics library and, further on, performance benchmarks. The first element mentioned above purposes the improvement of the reliability-oriented maintenance through examinations of technical systems and its components regarding e.g. their failure rates and fatality possibilities, etc. Through the use of Reliability, Availability, Maintainability, Safety and Life Cycle Costs (RAMS/LCC) techniques applied to the database, a comparability of maintenance strategies is enabled, that, as well as the characteristics library, aim at an increase in reliability and availability of WTs [17]. Contrary to this, the performance benchmark focuses on the assessment of the operation of the WT. Through the benchmarking concept, operational and environmental KPIs, e.g. mean wind speed, are compared to the entirety of the WInD-Pool data. They purpose the classification of assets within the participants' portfolios as well as the improvement of operational strategies [17, 18]. To built the database, the participants provide their WTs root, operational and maintenance data. To create comparability between the stakeholders, the data is going to be standardised and validated and, afterwards, assigned to determined levels of aggregation. Within this bachelor thesis, the focus lies on the performance benchmarks that are further explained in the following.

The performance benchmarks were created with regard to the KPIs that allow more precise evaluations. They are generated through an aggregation of the operational data that is accumulated into the specific KPI definition. For the creation of an automated weak point analysis for critical WTs, the predetermined KPIs of the WInD-Pool are used as a basis for the assessment. The performance benchmarks are presented within the WInD-Pool Operator-Portal which gives the participating stakeholders, operators, etc. an insight on the performance of their WT portfolio. The elaborated concept is built as a possible add-on for the Operator-Portal to support this process.

2.2.1 Database

The WInD-Pool database is the basis of the project and contains the present and historical O&M data of the assets of individual participants. To obtain values that are as current as possible, a regular data flow is set up and maintained. Currently, it contains about 6,3 GW capacity and circa 21 000 years of operating time from around 3 000 WTs. The data is acquired with regard to various industry standards, e.g. IEC 61400, RDS-PP®[1], ZEUS, GSP, etc., to enable an industry wide and statistical comparability [16]. There are three major groups within the acquisition of the data that are *root* data, *operational* data and *maintenance* data. In the following, the contained information of the categories are listed:

- **Root data:** WT-Id, WF-Id, turbine-type, turbine-type group, technical specifications (tower height, generator type, etc.)
- **Operational data:** SCADA[2]data, power, wind speed, wind direction, temperature, pitch angle, etc.
- **Maintenance data:** SCADA data, ZEUS[3], events (ID, description, position and duration), status code (start, end and duration, operational mode), etc.

As the data contains a broad range of information, it is the base of various analyses that are carried out within the project duration. Therefore, a robustness of the data quality must be guaranteed. To achieve this, following to the acquisition the data is validated with regards to extreme values, plausibility and consistency and thus, is filtered. After this, the data is processed to the individual KPIs and into its application environment.

2.2.2 Benchmarking Platform

Benchmarking platforms offer a very trivial and yet relevant use in the area of data analysis, more precisely operational data. The accumulated data creates a statistical robustness for different analyses that can be used as a reference to valuate assets [19]. This enables weak point as well as root cause analyses that support the decision making process of the operation improvements. It is made possible by the increased

1 Reference Designation System for Power Plants® (RDS-PP®)
2 Supervisory Control and Data Acquisition (SCADA)
3 State-Event-Cause-System (ZEUS), etc.

accessibility to O&M data and the associated possibility for data analysis. This can be seen in the growing number of commercial and non-commercial platforms that have been built in the renewable energy sector within recent years. These include the performance benchmarking platforms of DVN-GL [20], *WEBS* of Wind Energy Benchmarking Services Limited [21], Catapults' platform *SPARTA* [22], *True Power Plattform* of WinJi in cooperation with DKB [23] as well as Greenbytes WF management platform Breeze, that also features the performance assessment [24]. For the WInD-Pool-project, the WT performance benchmarks are presented within the WInD-Pool Operator-Portal. It is used as a reporting platform for the stakeholders that allows an overview of the generated evaluations as well as interactive analyses of the individual portfolio. The figures below give an overview of the structure and variables that are implemented in the portal.

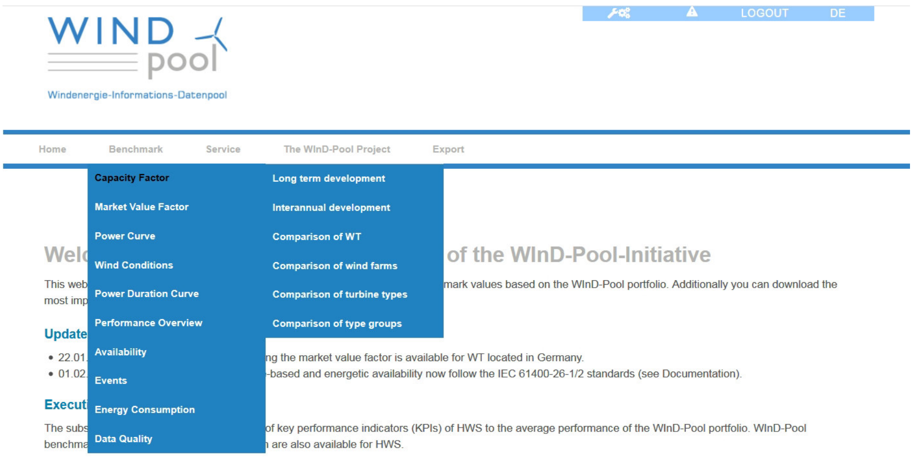


Figure 2.1: WInD-Pool Operator-Portal: assessment possibilities

Figure 2.1 shows the initial page, *Home*, of the operator-portal. It provides an overview of the accumulated, assessed KPIs of the stakeholders portfolio with an comparison to the WInD-Pool. The characteristics listed within the dropout menu are the KPIs for which the calculated evaluations can be found within the submenu. Within figure 2.2, such an evaluation, the *Capacity Factor - Comparison of wind turbines*, is illustrated.

Figure 2.2: WInD-Pool Operator-Portal: capacity factor [25]

While the center presents the specific KPI, the drop-down list boxes can be used to adjust the evaluation. The drop-down menu was implemented to change the considered WTs, Wind Farms (WFs) as well as the period or level of aggregation. This allows the analysis of the WTs within the stakeholder portfolio that can be varied by the given choices with regard to different aspects.

In general, benchmarks are used as a reference to classify the quality or quantity of a system into a context, which is further explained within the section 2.3. Applied to the WInD-Pool this means, the WTs operational phase can be classified into a variable context, regarding the period under consideration and reference, that is used to identify weak points in various areas.

2.2.3 Key Performance Indicators

This bachelor thesis builds a concept for a benchmark orientated weak point analysis that is applied on the basis of the previously calculated KPIs of the WInD-Pool. Hence, the following section provides a general definition as well as of the applied KPIs.

Key Performance Indicator Definition

The term *key performance indicator* is used for a measurement of the operation that quantifies or qualifies a specific condition, e.g. the punctuality concerning the operations used by British Airlines [26]. Since KPIs are a tool for process improvements, they are defined for a variety of application areas, i.e. "individual equipment, subprocesses, and whole plants" [27, p.18] [28, p.2]. Thus, the concerned measurement of KPIs can include different areas of power plants. While they are part of the industry standard for conventional power plants, e.g. nuclear power plants [29], they have only become relevant in the field of renewable energies respectively the wind energy sector within the last few years [30, 31]. This leads to a number of KPIs that are defined for the WT performance as well as regarding the reliability, e.g. time-based availability and production-based availability, MTTF[4], MTBF[5] or MTTR[6], etc. [30, p.563-567].

Properties of KPIs Before the implementation of KPIs, the necessary properties of the measurement needs to be defined. Within the wind industry it is defined as follows [32, pp.25f]:

- **Relevance:** The KPI must contain information that is relevant to the user and that has the potential to be modified.
- **Specific:** The KPI must be defined explicitly and comprehensibly with regard to their measure and measurement methodology.
- **Measurable:** The KPI must be measurable either quantitatively or qualitatively.
- **Comparability:** The KPI must ensure comparability within different aggregation levels, for example between sites or turbine types.
- **Traceable in different timescales:** The reference period to which the KPI refers can be determined by the operator itself.
- **Standardised:** In order to avoid any uncertainties, a standardisation should be carried out, e.g. as for the time-based availability, to guaranty the comparability and robustness of the KPI.

4 Mean Time To Failures (MTTF)
5 Mean Time Between Failures (MTBF)
6 Mean Time To Repair (MTTR)

KPIs in the Wind Industry

The KPIs relevant due to their definition regarding the operational phase of WTs are presented within this section.

Power Curve:

The power curve is a measurement for the power of a WT regarding the relevant wind speed range [33] and, thus, can be used to predict the potential power outcome of a WT. Therefore, a realistic reference of the asset's performance is enabled. The power curve has various application areas. It is used by the project developer in the planning phase of the plant to allow an assessment of the Annual Energy Production (AEP). Furthermore, it can be used as an insurance of the power generation for the acquirer. Within the operational phase, it enables the assessments of the performance level, which can be used either for performance improvements or for planning at other locations [34].

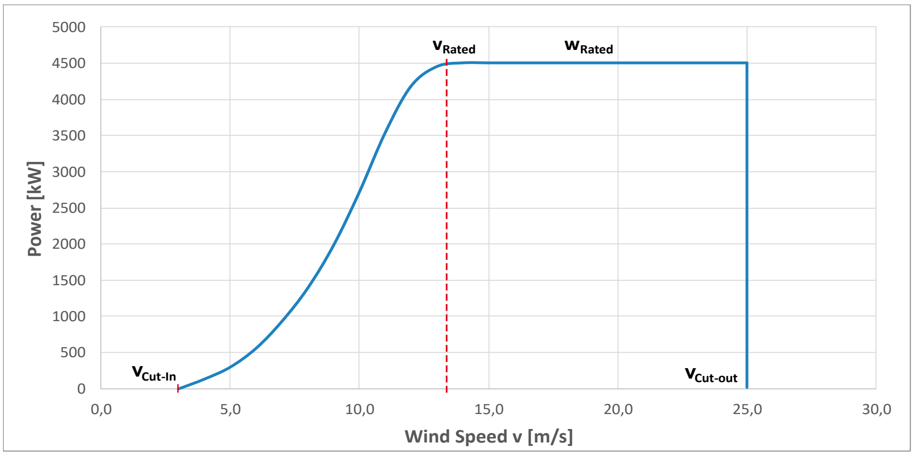


Figure 2.3: Wind turbine power curve

Figure 2.3 illustrates a typical power curve of a 4.5 MW WT [33]. The main parameters of the power curve are cut-in wind speed (v_{Ci}), rated wind speed (v_r) along with rated power (w_r) achieved by the WT and cut-off speed (v_{CO}) [35] [33, pp. 618 - 621]. It is calculated individually for every asset that deviate, depending on the definition applied, in their curve progression. The following definition is based on the IEC 61400-12-1 [36] and 61400-12-2 [34]. To generate the power curve, the power data and its' assigned wind speed values are clustered into wind bins. Within these bins the mean is used to get the average power production and average wind speed per bin. At last, to replenish missing or implausible values, a linear interpolation is applied. There are several methods to achieve the best possible fit of the curve progression. Within section 3.2 - Power Curve, the method applied in the WInD-Pool evaluation is further explained. Since the wind speed does not provide a comprehensive information of the wind power density, the influence of the varying ambient temperatures, atmospheric pressure and humidity as well as turbulence need to be included within the power curve generation.

Time-based Availability:
The time-based availability (A_t) is one of the most used KPI within the wind energy sector, since it provides information about the period under consideration in which an asset is technically available for electricity generation [33, pp. 644-647]. For the WInD-Pool, it is defined and calculated with regard to the international standard IEC 61400-26-1 section B.2.3 (System operational availability), in which an information about the implemented operational states is provided. The time-based availability compares the available time with the total time per period under consideration. The standardised equation within the IEC 61400 is the following:

$$Availability = \frac{Available\ Time}{Available\ Time + Unavailable\ Time} \tag{2.1}$$

Available Time is calculated by aggregating all periods during which the specific WT-state is considered as available (e.g. operating, waiting for wind, etc.). It does not contain information about the energy production and losses [37]. There are several standardised availability definitions that vary either in terms of the considered system or the included states of the WT operation (e.g Wind-in-Limits or scheduled maintenance) [38, p.7]. The definition applied depends on the interests of the involved parties and varies between the manufacturer and the operator [38, p.9]. The manufacturer's definition focuses on the period under consideration in which the WT is operating within its technical specifications [37, Annex B.3]. Contrary to this, the operator related definition, that only includes the period within the WT is actually performing [37, Annex B.2]. Therefore, the comparison of the time-based availabilities is considerably complicated.

Production-based Availability:
The production-based availability (A_w) is generally defined in the IEC 61400-26-2, while the WInD-Pool definition refers to section B.1 [34]. Contrary to the time-based availability, it focuses on the energetic losses during the periods defined as unavailable [38]. It creates a comparison between the actual power production and the theoretically possible power outcome, calculated with regard to a reference power

curve 2.2.3. This implies that the KPI includes the wind speed distribution. It can have a significant influence on the power generation depending on the time of the occurrence of a standstill.

$$Production\text{-}based\ availability = 1 - \frac{Lost\ Production}{Actual\ Production + Lost\ Production} \tag{2.2}$$

As it states the energetic losses of the performance, it can also be seen as the actual efficiency of the WT and enables an evaluation of the plant efficiency [30]. As well as for the time-based availability, there are different and interest group-specific definitions for the production-based availability that have similar specifications. The manufacturer's definition establishes the theoretical reference based on the WTs' power generation within its technical design specifications and, therefore, excludes e.g. planned maintenance [39, Annex B.3.1]. The operator's view determines the reference as a duration in which the WT is available to perform with full efficiency and includes most causes of energy losses [39, Annex B.2.1].

Production Ratio

In addition to the production-based availability, the production ratio (A_p) is defined as a measurement of the operational performance of the WT within the IEC 61400-26-2 section C.3 (Production Ratio) [34]. It serves as a comparison between the real and the theoretically possible power generation IEC 61400-26-2 section C.3 (Production Ratio).

$$Production\ ratio = \frac{Actual\ Power\ Generation}{Theoretical\ Power\ Generation} \tag{2.3}$$

Only the operating states of the electrical power generation are considered and therefore, downtimes are neglected. Similar to the production-based availability, the calculation of the theoretical reference can vary depending on the methodology used for the power curve calculation. In general, the generation ratio states that the reference power curve is based on the assumption that the WT is fully efficient over the period. This enables a prediction of possible deviations of the performance behaviour due to e.g. degradation or problems in the control system [39, Annex C.3].

Wind Speed:

The wind speed measurement is part of the data acquisition and is used to display the environmental conditions of the site. The procedures for the wind speed measurement are standardised through the IEC 61400-12-2 section 7.2 [34]. The wind speed is recorded by multiple anemometers attached on the rear part of the nacelle [40]. Further on, the values are averaged to 10-, 15- or 20-minute values that are later aggregated to a period under consideration, evaluation specific mean. Further on, the values are quantified to a reference wind distribution. The method used in theWInD-Pool Operator-Portal is illustrated in figure 2.4.

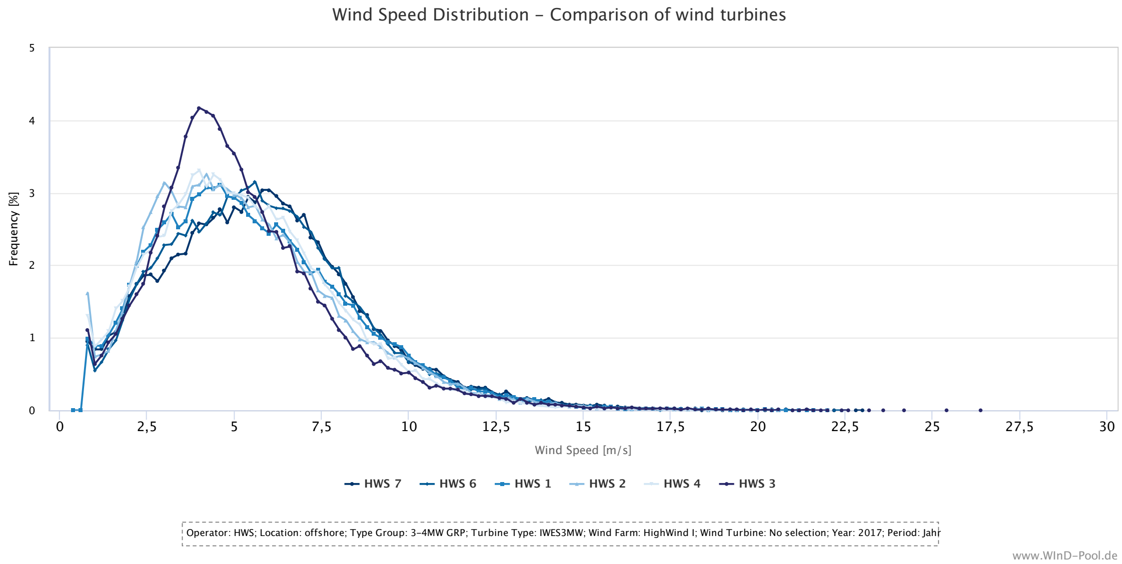


Figure 2.4: Wind speed distribution - comparison of wind turbines

Figure 2.4 illustrates the weibull distributions of example WTs that are quantified into wind bins with a range of $0.2\frac{m}{s}$.

Wind Direction:

The Wind Direction provides information about the measured wind direction distribution that is classified into wind bins for each aggregation level within a determined duration. It is divided into 36 classes with a range of 10° and contains the frequency of the occurrence of the wind speed. Figure 2.5 illustrates the WInD-Pool presentation of the wind direction. It shows the wind direction distribution of an example WF compared to the WInD-Pool benchmark.

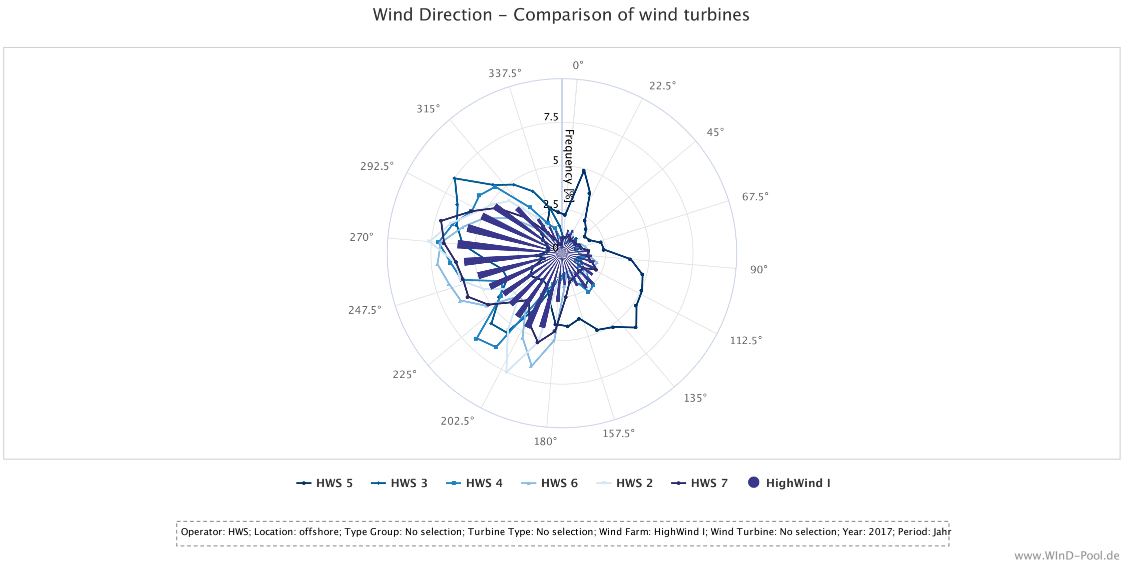


Figure 2.5: Wind direction - comparison of wind turbines

Data Quality: The data quality is a measurement for the robustness of the evaluations. In order to assure a statistical resilience, the SCADA data is validated. The data quality is defined as the ratio of the sum of the validated and, therefore, plausible data to the target data amount of the specific duration.

2.3 Benchmarking

This section gives an overview on the topic *benchmarking* and its implementation in the context of this work.
The term benchmark is defined multiple times by various dictionaries, e.g. as a "standard or point of reference against which things may be compared." by the Oxford Pocket Dictionary [41], as "something that serves as a standard by which others may be measured or judged" by the Merriam-Webster Dictionary [42] or as a reference point of a measured peak performance [43]. The similarity of these definitions is the specific reference point from which a measurement is to be performed and evaluated. In general, the purpose of benchmarking is a performance improvement through regular monitoring of the associated processes in order to achieve the best possible result [27, 44]. Originally, benchmarking was used as a business practice for management systems to evaluate workflows through a comparison to a competitor [44]. Out of this, it has developed to a versatile analysis tool that can be embraced either to concrete parameters, which is called quantitative benchmarking,

or to measure or valuate process structures or concepts, which is called qualitative benchmarking [45].
Within the WInD-Pool, a quantitative benchmark is used to measure determined KPIs by averaging the particular KPI from different stakeholders to a reference value. The mean values of the level of aggregation are used as the benchmarks. The specifications for the weak point identification are explained within section 2.2.1.

2.4 Applied Statistics

The following provides a theoretical overview of the applied statistics that have been used within this work.

Root-Mean-Square-Error
The Root-Mean-Square-Error (RMSE), also called Root-Mean-Square-Deviation, is defined as the root of the second momentum, also called variance, of a probability distribution [46]. It is mostly used to examine the consistency of a predicted or estimated distribution to the observed one and, therefore, it can be also applied to measure the deviation between two sample distributions [47].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widetilde{y}_i)^2} \tag{2.4}$$

Resulting of the equation, lower deviations lead to a low RMSE with the limit of zero when the distributions are identical. This also means that higher errors lead to a higher RMSE, which is caused by the proportionality to the square of the error.

Arithmetic Mean
The arithmetic mean can be categorised as a "measure of central tendency" [48, p. 15-18]. The arithmetic mean indicates the "center of a frequency distribution of a quantitative variable" and has as the condition that the weighting of the individual elements is the equal.

$$\widetilde{x} = \frac{\sum\limits_{i=1}^{n} x_i}{n} \tag{2.5}$$

The equation implies that $\widetilde{x}$ is equal to the sum of the values of the variables divided by their number.

Weighted Arithmetic Mean

The weighted arithmetic mean's definition is similar to the aforementioned, but deviates in the condition of equal weights [48]. This means, that observations, as part of an overall system, that deviate in their importance can be assigned to different weights to measure the central tendency [49, p.565-566]. This leads to the following equation:

$$\widetilde{x} = \frac{\sum\limits_{i=1}^{n} x_i w_i}{\sum\limits_{i=1}^{n} w_i} \tag{2.6}$$

The equation summarises the multiplication of the observation with its assigned weights and then divides it by the sum of the weight [50]. The advantage of this method lies in the consideration of importance into a system of variables.

3 Methodology

In the following chapter, the applied methodology for the automated assessment is further explained. Therefore, the framework conditions and structure of the assessment are firstly going to be generally described in 3.1 and are then applied to the KPIs in 3.2.

3.1 Benchmark

This chapter concerns the framework and methodology applied on the benchmarks. It is structured by describing the levels of aggregation at which it is implemented and the definition, creation and thresholds of the benchmark.

Level of Aggregation
Within the WInD-Pool initiative, benchmark based evaluations were developed to generate a variety of comparabilities. Therefore, the WT information is aggregated into predetermined categories, which are on the one hand used for the created evaluations connected to the WInD-Pool Operator-Portal and, furthermore, as a variability considering the extent of the weak point analysis. These levels of aggregation are described in the following section as well as their subcategory, the assessment types.

- **Location**: The highest aggregation level is *location*, which is divided into the categories *onshore* and *offshore*. It includes the complete site-dependent WTs of the WInD-Pool portfolio and, therefore, can be seen as the WInD-Pool-benchmark as presented in the Operator-Portal. Since it includes the largest amount of data, it is the most robust reference within this analysis, but it also has the lowest comparability to the individual asset.
- **Operator**: The level of aggregation *operator* is defined as an operator specific benchmarks. It aggregates the WT data within the operator portfolio,

regardless of the turbine type, turbine type group or location and is used to create an individual reference for each operator.

- **Turbine Type Group**: The level of aggregation *turbine type group* contains the benchmark for each WT within the same turbine type group. This includes turbine types that have a similar technical characteristics and is applied to increase the statistical robustness for less common turbine types. Since the WInD-Pool is based on a confidentiality agreement, at least three operators must include the corresponding turbine type group in their portfolio. Furthermore, to create a solid reference, the minimum number of WTs contained in the benchmark is five WTs and the minimum operating time must exceed 60 months, respectively the number of WTs multiplied with twelve month of operation. These thresholds are determined to prevent comparability and generate robust benchmarks for the evaluation.

- **Turbine Type**: In terms of technical comparability, the generated *turbine type* benchmark provides the relatively best reference that results from the comparison of similar WT types. As well as for the *turbine type group*, the same thresholds for generating this benchmark needs to be fulfilled.

- **Wind Farm**: The level of aggregation *wind farm* is defined in order to create a WF specific benchmark, that records the deviations of the WT performance under similar environmental conditions. Equal to the preceding segments, thresholds are determined for the minimum count of WT included in the benchmark as well as for the minimum number of month in operation.

Figure 3.1 illustrates the correlation of the data amount and individual comparability of the levels of aggregation. As can be seen, the higher the underlying data amount, the lower the individual comparability, and vice versa. This is due to the fact that levels such as location and operator contain various turbine types and can therefore rely on a larger data basis. Opposite to this, the levels turbine type or wind farm mostly have a high comparability because of the similar technical specifications of the considered WTs. However, the number of WTs included within these levels is significantly lower.

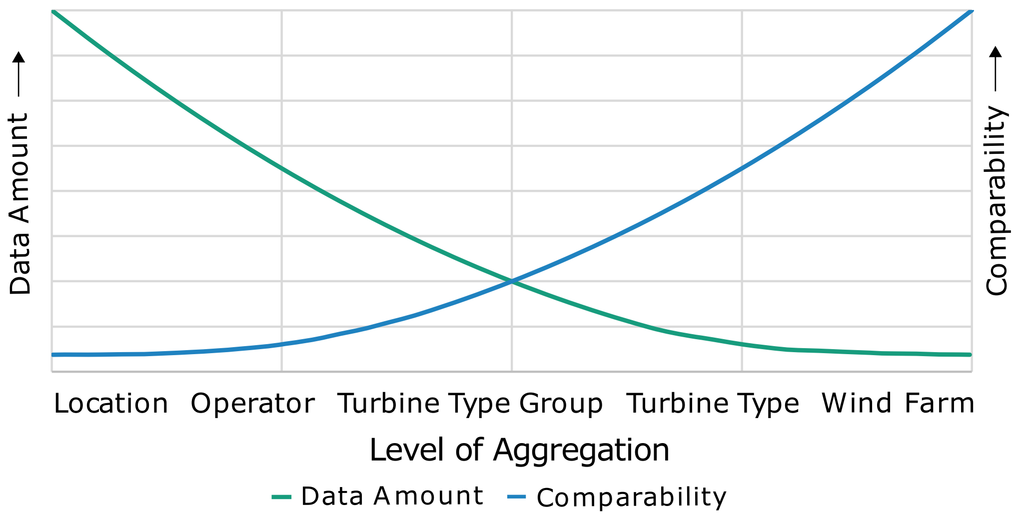


Figure 3.1: Level of aggregation - comparability and data amount

Benchmark structure

This section describes the definition and structure, required data and the thresholds of the applied benchmarks. The benchmark concept as well as the threshold for criticality are described and presented generally and applied individually for each KPI in section 3.2.

The assessment is built on a comparison of a measurement with a generated reference. For the WInD-Pool to be an industry wide database, the reference is based on its vast data amount. The KPI-dependent benchmark definition is based on the evaluation methodology and, therefore, includes the resulting values. The methodology is described in more detail with regard to its application in subsection 3.2. Each benchmark contains the aggregated KPI values, categorised to the levels described in subsection 3.1. Resulting, any plausible KPI value of the total WT performance is included within the benchmark. This information is then adapted to an empirical distribution that allows the classification of the KPIs. Figure 3.2 illustrates the distribution for the time-based availability benchmark aggregated to the level *location - onshore*. The accumulated percentage are quantiles that indicate the amount of data below the corresponding value. The course progression shows the availability assigned to the quantiles on the y-axis. As some of the distributions show both negative and positive deviations, the benchmarks are divided into the categories $< x$ and $\geq x$.

This method is applied on each level of aggregation to generate a comparability within different categories, cf. 3.1.

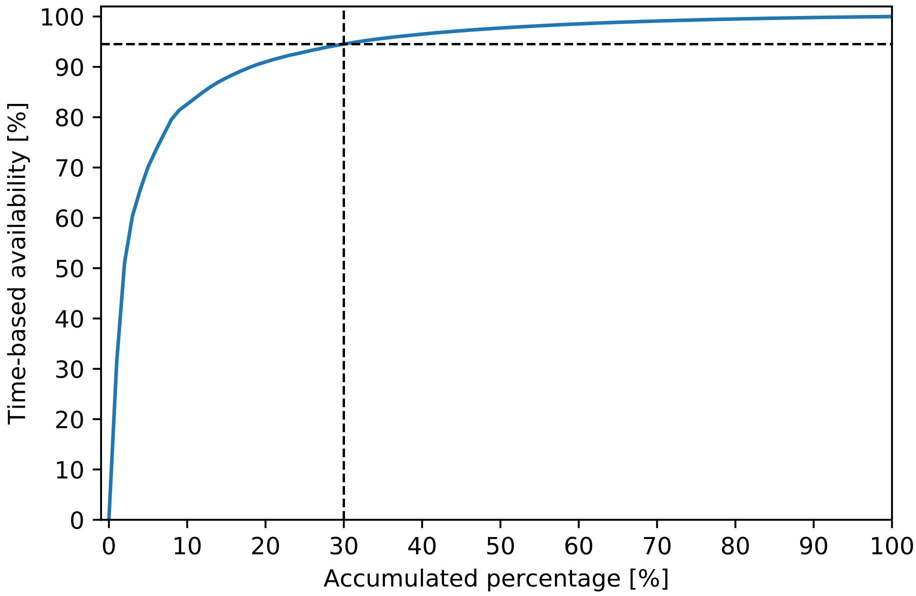


Figure 3.2: Benchmark distribution of time-based availability

The necessary data for the benchmarks consists of two main categories. On the one hand, the root data of the WTs is required as well as the processed operating data that implements the pre-calculated values of the KPIs.
The root data, defined in section 2.2.1, is used for the categorisation of the assets. As it contains information about e.g. the sites location or the turbine-type, the data can be clustered into the aggregation levels. The benchmarks are then generated for each level of aggregation, containing the assigned WTs. Furthermore, the root data contains general information, e.g. the WF sizes as well as the rated power of WTs, that are used later within the process.
The pre-processed operating data is included to create the benchmark reference. This reference is the total of the plausible values for the entire operating period, aggregated over the WTs assigned to the specific level. Therefore, the implied values either refer to the individual KPI definition or are processed from this definition to enable evaluability, e.g. the KPI wind speed. The benchmark accumulates the complete data to one distribution for every aggregation.
As the root and operational data contains information on the count of WTs within a WF as well as the total amount of operating months, it is used to validate the benchmark's robustness. To enable an anonymous assessment, the WInD-Pool has set thresholds in a confidentiality agreement for generating the benchmarks that were

applied and adapted within this thesis. Affected by this are the aggregation levels *wind farm*, *turbine type* and *turbine type group*. There are no thresholds for *location* and *operator* since they concern the entire WInD-Pool portfolio respectively only an individual related operator, which provides statistical robustness and anonymity.

Table 3.1: Necessary conditions for benchmark generation

Level of Aggregation	Number of operators ≥ 3	Min. number of WTs ≥ 5	Min. Number of operating months: n_{WT} x 12 months
Location			
Operator			
Turbine type	X	X	X
Turbine type group	X	X	X
Wind Farm		X	X

The in figure 3.1 shown thresholds are applied within the process of benchmark generation. Due to these thresholds, the robustness and comparability is provided by the extent of the data amount that is required for the benchmark's generation. Benchmarks that do not fulfill any of these conditions are not considered in the assessment.

Furthermore, the criticality of the assessed KPIs needed to be determined. Hence the definition of criticality is user-specific, it is variable and can be adjusted to match the individual expectations. The benchmarks are based on an empirical distribution function that contains the accumulated information of the measured values of the KPIs. From this, a quantile-specific approach was used to determine the threshold for criticality. Depending on the benchmark definition, it identifies each WT below or above the determined quantile as critical. This method sets the threshold globally for the entire assessment, because the number of data declared as critical is the decisive factor for criticality. Within this method, the individual expectations regarding the data amount declared as critical can be set by the operator itself without getting an extensive knowledge about the benchmark distributions.

3.2 Assessment

In this section, the assessment structure that contains the analysis period, the prerequisites, the connections of the KPIs and the possible outputs are going to be described in general.

Analysis Period
The period under consideration that is going to be assessed was selected with regard to the application repetition and minimum robustness of KPIs. In order to obtain relevant results, the data amount of the calculated KPIs needs to be as sufficient and current as possible. In order to achieve the objective of identifying performance weaknesses, it is designed to be repeated on a regular monthly basis. This decision is based on two reasons. On the one hand, the monthly period is the minimal duration for calculating the KPIs. On the other hand, the latest data can be examined on a data base that is robust enough against statistical uncertainties.

Assessment Structure
Within figure 3.3 the structure is presented and used to illustrate the weak point analysis that contains the benchmark oriented KPIs evaluation. It describes the required data, assessment structure and possible output.
The assessment is based on the KPIs provided by the WInD-Pool and refer to the performance areas *operation*, *downtime* and *environmental conditions*. Each of these KPIs is evaluated with regard to the, in relative terms, greatest possible informative value leading to the structure in figure 3.3. The evaluation process is similar for all KPIs and the main differences are the KPI and benchmark definitions. The evaluation was carried out according to the following principle. Firstly, the required data is provided. Afterwards these values are checked for presence, plausibility and criticality, which is applied for each aggregation level. In a final step, the assigned state is output for each WT, KPI and level of aggregation. In section 3.3, these steps are going to be explained for each KPI as well as their reference to other KPIs and, furthermore, underlined with an example.

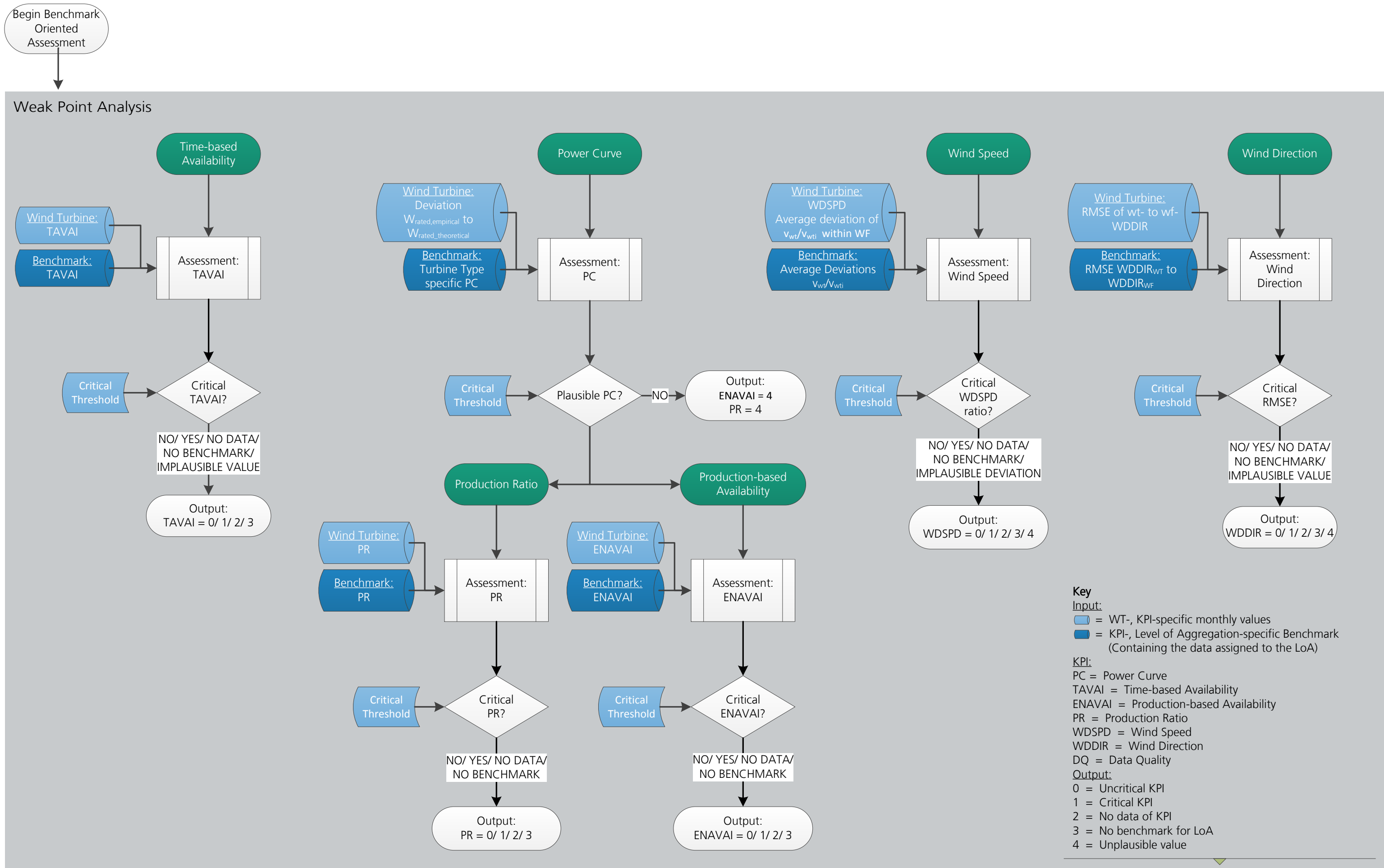


Figure 3.3: Analysis Structure

As a first step of the analysis, the data that is divided into two categories must be provided. These categories are on the one hand the relevant WT specific information, the root data, cf. 2.2.1, and on the other hand the KPI-specific values, cf. 3.2. To begin with, the use of the WT's root data, that is defined regarding its included information in section 2.2.1, is explained. It contains, on the one hand, the general WT information that is divided into technical attributes of the individual turbine type i.e. rated power, tower height, etc. and the associated operator, wind farm, turbine type group and location. This information, on the other hand, is implemented to be able to merge the data to the corresponding type of aggregation as well as within the process of processing KPIs to be assessed, i.e. creating a reference value for the power curve. Furthermore, the KPI specific data is implemented that contains the latest monthly values of the availabilities, wind speed, wind direction and data quality shares. The total WT specific power curve is, as already mentioned, adjusted respectively updated within a quarterly interval, which thus changes quarterly. Out of this, the KPIs are adapted to their determined definitions or directly assessed within the following step of the assessment. The methodology used for the weak point analysis is generally described in the following. The generated benchmarks as well as the input data for the evaluation play a decisive role in the execution of the assessment. Both are required in order to be able to evaluate the KPIs. The analysis itself is based on the comparison or classification of the monthly value of a WT in the context of the benchmark. However, a plausibility and presence check of the individual value is performed beforehand. First the existence is checked, whether the monthly value is available or can be calculated. For missing values, the state 2 is assigned to the according KPI. In the case of some KPIs, e.g. wind speed, the value's plausibility is checked on whether the calculation of it enables plausible results or if these are provided with too high an uncertainty. Afterwards it is checked if the benchmark provides a statistical robustness and guarantees the contractually regulated anonymity, cf. 3.1. If this is not ensured, state 3 is assigned. If all this is guaranteed, the criticality will be queried that assigns the state 0 as noncritical and state 1 as critical assets. Since benchmarks can be described by a distribution function, the difference between the value and the next higher or next lower quantile within the distribution is used as a measure. The defined limit value, i.e. the determined quantile, is the measure of the criticality and is used to define the WTs as critical or noncritical. The evaluation of the individual KPIs is applied to the implemented aggregation levels determined by the user leading up to five different evaluations per KPI. If the value is critical, the deviation of the quantile assigned

to the WT of the limit value is calculated to give a weighting of the relevance, cf. 3.3. From these queries, a state is assigned to each KPI, which represents the basis for further evaluation.
The main output of the assessment are the states that are categorised into five different possibilities resulting from the data. The categories are explained in the table 3.2.

Table 3.2: Defined output states

State	Description
0	Value is uncritical
1	Value is critical
2	No data available
3	No benchmark available
4	Implausible values

These output states are either further processed within the weighting function, cf. 3.3 or directly implemented into the results. States 0 and 1 are used to evaluate and classify the WT performance. Both values are available, plausible and can be assigned to a benchmark and thus be evaluated. States 2, 3 and 4 are not considered within the weighting function since either no evaluation of the KPI is possible, because the monthly value or benchmark is not available, or the evaluated or calculated value is implausible and therefore not considered further as well, cf. 4.1. The aim of this separation is to evaluate only that part of WT performance that is statistically reliable.

3.3 Implementation of the KPIs

Within this section, the application of the KPIs is described individually. To begin with, the status flags defined in the WInD-Pool are going to be described. They are used to get information on the current state of the asset, i.e. if it operates within certain technical and environmental conditions. Therefore, the collected 10-minute power and wind speed data needs to be assigned to predefined status-flags. The following table contains the implemented states that are used within the definitions of the KPIs. They are listed to enable a wholesome understanding of the evaluated KPIs regarding the extent of their definitions.

Table 3.3: Operating states defined in the WInD-Pool

Operating State	State	Description
1 Low Wind	08	WT is not running, wind speed below v_{Ci}
2 Low Power	10	WT is running with 0.1 - 10% w_r
3 Moderate Power	11	WT is running with 10.1 - 90% w_r
4 Rated Power	12	WT is running with > 90% w_r
5 High Wind	09	WT is not running, wind speed above v_{CO}
6 Switching Operation	01	WT has been switched on
	02	WT has been switched off due to unknown reasons
	03	WT has been switched off due to lack of wind
	04	WT has been switched off due to high wind speeds
	07	WT has been switched off, unknown wind
7 Downtime	05	WT is not running due to unknown reasons
	06	WT is not running, unknown wind
8 No Data	99	No information about power output available
	88	End of data gap
	77	Start of data gap

Time-based Availability

The time-based availability is, as one of the key figures of the WT performance, a substantial part of the weak point analysis. It is the ratio of the time in which the WT is available to operate to the total time of the duration. As mentioned before, the definitions of the availability vary depending on the actor. The WInD-Pool defines it regarding the IEC 61400-26-1 section B.2.3 (System operational availability) that contains the following specifications:

$$A_t = \frac{\sum\limits_{\substack{i=1 \\ s \in S_a}}^{n} P_{i,s}}{\sum\limits_{\substack{i=1 \\ s \in S_t}}^{n} P_{i,s}} \cdot 100 \tag{3.1}$$

where:

A_t	Time-based availability for considered period in [%]
n	Number of timestamps within considered period

i	i^{th} timestamp from n (averaging period usually 10 minutes)
$P_{i,s}$	Power for timestamp i in kW
s	State assigned to the timestamp
S_a	WT-states considered (available): 01, 03, 08, 10, 11, 12, 88
S_t	WT-states considered (total): States 1-12, 88

This information is generated through a assignment of each individual 10-minute power and wind speed value to the status-flags, section 3.3, that cover the possible operating state. The included status-flags regarding the unavailable time are as follows: *02, 05, 06, 07, 04* [1], *09*, while the available status-flags are the following: *01, 03, 08, 10, 11, 12, 88*. The data-quality states 77 and 99 are not included in the calculation, following the definition of the IEC-61400-26-1 section B.2.3, assuming the WT availability behaviour during the missing timestamps is the mean of the available timestamps. Therefore, S_t contains each existing timestamp of the WT performance within the period.
The input data of this KPI is the monthly value of the time-based availability, cf. 3.1. Within the assessment, the value is classified into the context of the benchmark that is illustrated in figure 3.4 and contains the accumulated time-based availabilities.

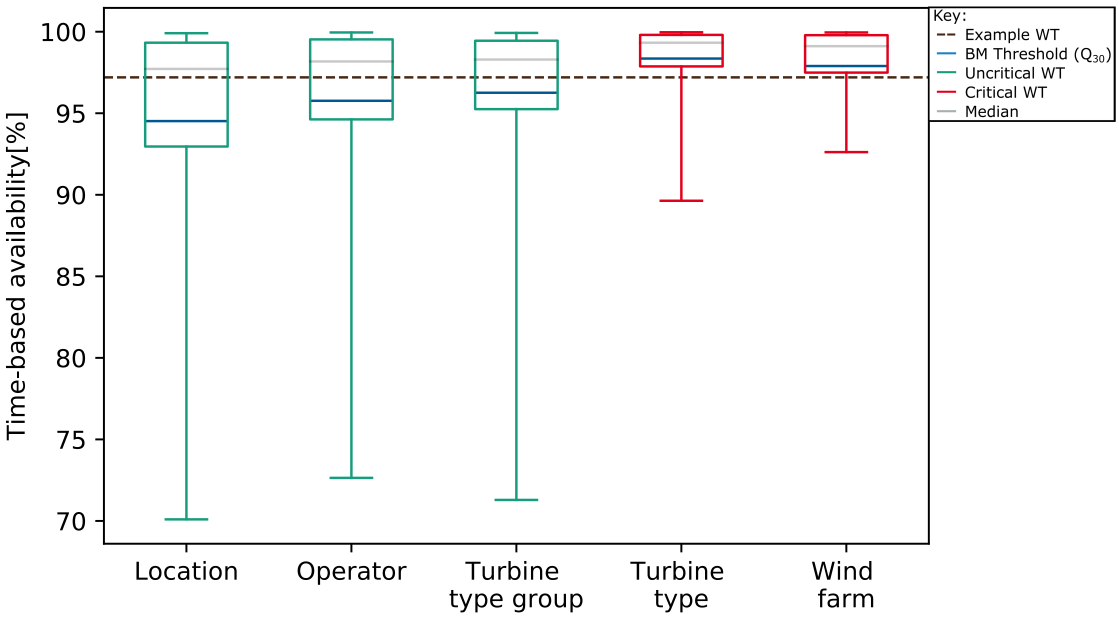


Figure 3.4: Benchmark boxplots time-based availability

1 The state 04 - 'switched off due to high wind speeds' is defined as unavailable as the WT performance is limited by its technical specifications

The figure shows the benchmarks of the time-based availability for the different levels of aggregation. The boxplots are specified to match the assessment structure and the whiskers are assigned to the quantiles Q_5 and Q_{95}. Therefore, the blue line describes the threshold of criticality defined individually by the user, while the dashed brown line provides the availability of the example WT. This illustration has been applied to each of the following benchmarks. Within the turbine type and the WF benchmark, the WT value would be considered critical if it fell below both of them. Both would be assigned with the state 1. Within the assessment, the availability is classified into the benchmark by assigning it to the lower percentile regarding its value. This is done to ensure that the WT lies within the data amount of the assigned percentile.
The threshold of criticality default is set to the 30% quantile. This equals a time-based availability of around 97% of the total operating time.
The output of this evaluation can contain the states 0, 1, 2 or 3. The plausibility check is not necessary since implausible values are filtered within the calculation of the KPI. In addition to the state, the quantile is output as well, since both are used within the weighting function, which would lead to the following states:

Table 3.4: Example output time-based availability

Location	Operator	Turbine type group	Turbine type	Wind farm
0	0	0	1	1

Power Curve

To assess the production-based availability and the production ratio, the power curve needs to be validated regarding major influences of e.g. down-regulation. The *power curve* is generated individually for each WT to an overall characteristic curve and updated on a quarterly duration. It relates to the entire operating period of the WT. The IEC 61400-12-2 - Method of bins describes the power curve calculation for the WInD-Pool, that has been further adapted [34]. To generate the power curve, a wind speed time series of the WT is created using the plausible data as well as representative substitute values. The wind speed is then categorised into bins with width of 0.2 $\frac{m}{s}$ and the median of the power values is determined for each bin. The adjustments refer to the smaller bin width and the use of the median instead of the mean, since this method is more robust against outliers. Furthermore, non-linear piece-by-piece interpolation is applied within the partial load range [35], while linear interpolation of missing or implausible interpolation support points is applied within the nominal load range. The power curve is not turbulence or air density corrected. Relevant for the assessment is the plausibility of the generated power curve. For this, the WT's measured rated power is compared to its theoretically possible value regarding the turbine type specifications. To get the empirical rated power, the empirical rated wind speed needs to be found. This is done by calculating the power gradient of all neighboured wind speed bins within the interval of 8 to maximum $20\frac{m}{s}$. The first wind speed bin and its corresponding wind speed value, that shows a power gradient of ≤ 0.001, is determined as the rated wind speed. The average ratio of the empirical power curve's power values and the theoretical (OEM) power curve's power values within the defined rated wind speed and 20m/s is used as an indicator for assessing the plausibility of a calculated empirical power curve, cf. figure 3.5.

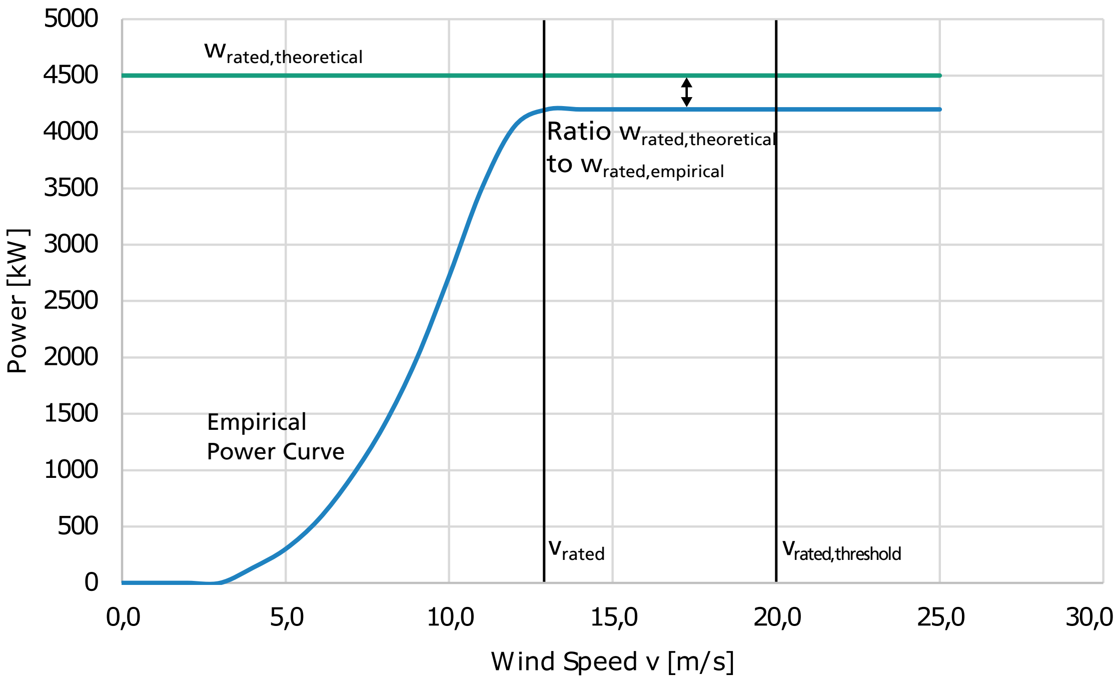


Figure 3.5: Power curve assessment - calculation methodology

Figure 3.6 illustrates these deviations aggregated for the entire WInD-Pool. There is no differentiation of the levels of aggregation. The thresholds are set to deviations of -5% and +10%[2] that determine plausible deviations of the power curve within rated wind speed range. Since only the deviation of the nominal loads of each

2 The thresholds were set on the empirical knowledge of another project in the labour process within the Fraunhofer IEE and can be seen as consistent for this evaluation.

other is evaluated, no result state is generated. Thus, the result of the power curve assessment has a direct influence on the output of the production-based availability as well as the production ratio. If the deviation is beyond the thresholds, the output set for the KPIs is state 4 as the deviation of the rated power indicates missing statistical robustness of the generated power curve. This can be explained by the fact that there is no reliable theoretical reference for the KPIs' calculation and therefore, they cannot be evaluated.

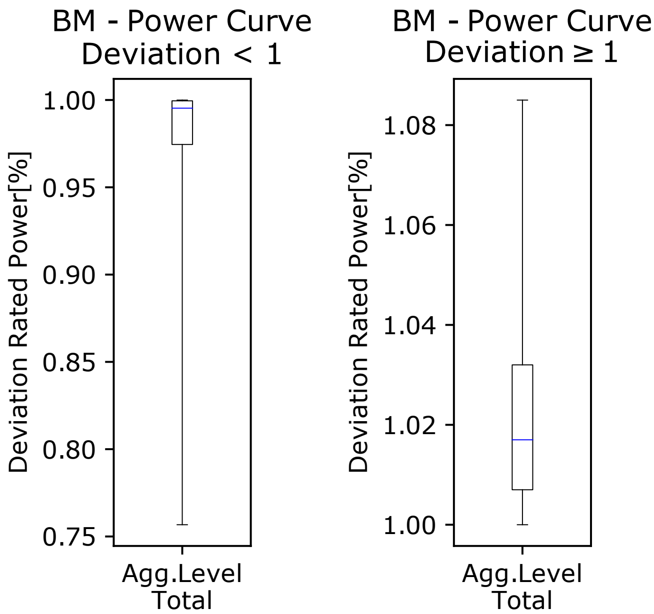


Figure 3.6: Benchmark boxplots power curve

Production-based Availability

The production-based availability is defined similarly to the time-based availability. In general, it is defined as the ratio of the actual to theoretical power output and, therefore, assesses the energy loss from the operational phase. For this definition, the lost energy of the status-flags 02, 05,06, 07, 04, 09 is considered. Furthermore, the states 77 and 99 are not considered, which leads to the assumption that the energy loss during the missing time stamps is equal to the mean of the existing data. This leads to the following equation:

$$A_w = \frac{\sum\limits_{\substack{i=1\\ s\in S_t}}^{n} P_{i,s}}{\sum\limits_{\substack{i=1\\ s\in S_t}}^{n} P_{i,s} + \sum\limits_{\substack{i=1\\ s\in S_{le}}}^{n} (P_{PC}(v_{i,s}) - P_{i,s})} \cdot 100\,\% \tag{3.2}$$

where:

A_w	Production-based availability for considered period in [%]
n	Number of timestamps within considered period
i	i^{th} timestamp from n (averaging period usually 10 minutes)
$P_{i,s}$	Power for timestamp i in kW
S_{le}	WT-states considered in lost energy calculation: 02, 05, 06, 07, 04, 09
S_t	WT-states considered (total): 1-12
s	State assigned to the timestamp
P_{PC}	Median power for timestamp i in kW
$v_{i,s}$	Mean wind speed for timestamp i in $\frac{m}{s}$

The production-based availability is assessed in the same terms as the time-based availability. The availability A_w [%] is used as the input of the benchmark creation as well as of the classification into these.

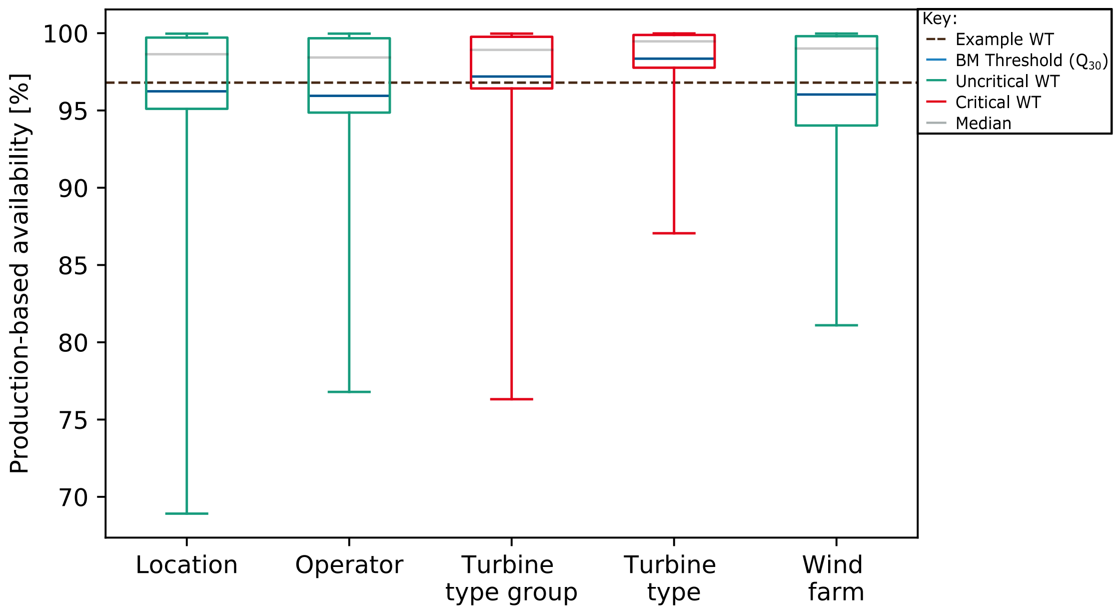


Figure 3.7: Benchmark boxplots production-based availability

The benchmark is structured with the limits 0% and 100%. The boxplot structure is equal to the time-based availability and the brown dotted line shows the WT's availability. As the threshold is set globally for the whole assessment, it is determined to the 30% quantile. Within the example, the WT falls below the turbine type benchmark and is therefore considered as critical. The possible output states are all mentioned, since the assessment is either non-/ critical (0,1), there is no existing data (2) or generated benchmark (3) as well as the implausibility of the power curve (4). Applied to the example, the output would be as the following:

Table 3.5: Example output production-based availability

Location	Operator	Turbine type group	Turbine type	Wind farm
0	0	1	1	0

Production Ratio

In contradistinction to the production-based availability, the production ratio is assessed. It is used to evaluate the operational performance of an asset and, therefore, the lost energy of the states 10, 11 and 12 is considered within the analysis. The WT's specific total power curve is used to generate the theoretical reference. It is compared to the actual operational data. Therefore, the production ratio examines the WT performance to its empirical, long-term operation and can be used to identify deviations within the level of performance. The following equation states the definition of the KPI:

$$A_p = \frac{\sum\limits_{\substack{i=1 \\ s\in S_t}}^{n} P_{i,s}}{\sum\limits_{\substack{i=1 \\ s\in S_t}}^{n} P_{i,s} + \sum\limits_{\substack{i=1 \\ s\in S_{le}}}^{n} (P_{PC}(v_{i,s}) - P_{i,s})} \cdot 100\,\% \tag{3.3}$$

where:

A_p	Production ratio for considered period in [%]
n	Number of timestamps within considered period
i	i^{th} timestamp from n (averaging period usually 10 minutes)
$P_{i,s}$	Power for timestamp i in kW
S_{le}	WT-states considered in lost energy calculation: 10, 11, 12
S_t	WT-states considered (total): 1-12, 88
s	State assigned to the timestamp
P_{PC}	Median power for timestamp i in kW
$v_{i,s}$	Mean wind speed for timestamp i in $\frac{m}{s}$

The production ratio deviates from the production based availability in terms of the values extent. This means, the production ratio can deviate, depending on former down-regulations or degradation, into positive as well as negative direction. Due to the fact that the power curve is built on empirical data, it can deviate in its partial load range, e.g. due to the missing turbulence and air density correction, etc. Furthermore, since influences on the nominal load range through, e.g. down regulations, production ratios of over 100% can occur. Out of this definition, it is possible to assess the systematic deviations from a WT to its empirical operational performance. To prevent countervailing effects within the benchmark generation, it is split into values $< 100\%$ and $\geq 100\%$.

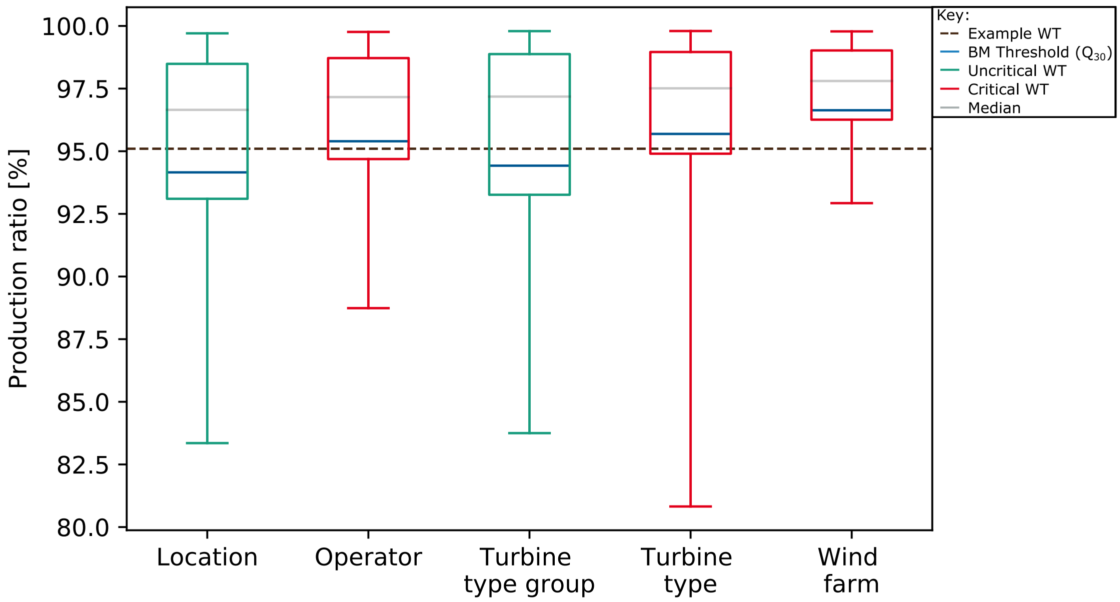


Figure 3.8: Benchmark boxplots production ratio

The boxplot illustrate the benchmarks below 100%, corresponding to the WT. The operational performance of the benchmark is critical as well as noncritical, since the WT's production ratio lies above only two of the benchmarks. This would lead to the following output of the KPI:

Table 3.6: Example output production ratio

Location	Operator	Turbine type group	Turbine type	Wind farm
0	1	0	1	1

The thresholds are equal in the amount of data considered as critical when applied on both benchmarks. Therefore, the threshold of the benchmark beneath 100% is the 30% quantile, while it is the 70% quantile for the benchmark $\geq$ 100%. The output states can either be 0, 1, 2, 3 or 4.

Wind Speed

The assessment of the wind speed deviates from the former ones. While the previous KPIs evaluated the performance and the downtime, the evaluation of the wind speed aims at the plausibility check of the measurement system. For this purpose, deviations of the measured values within a WF are evaluated. The input data are the WTs' mean wind speeds within a WF. This leads to the following equation:

$$WDSPD = \frac{1}{n_{WT}} \sum_{i=1}^{n_{WT}} \frac{v_{WT}}{v_{WTi}} \tag{3.4}$$

where:

$WDSPD$	Wind speed assessment result
n_{WT}	Number of WTs within WF
v_{WT}	Wind speed of considered WT
v_{WTi}	Wind speed of WT i in WF
i	i^{th} WT from n_{wt}

First, the values are tested for plausibility by checking whether its position is within the wind speed range of $3 - 20\frac{m}{s}$. WTs whose mean wind speed exceeds this range are assigned to state 4, implausible value. After this, for each plausible value the wind speed ratios of the WTs of a WF are calculated. Out of this, a matrix is generated that is used to average these results individually for each WT. This mean value is then used as the assessed measurement as well as for the development of the benchmarks. As figure 3.9 illustrates, the benchmark is split into the two ranges values < 1 and ≥ 1. The example WT has a value of 1.41, i.e. on average the mean wind speed is 1% higher compared to the WTs within the WF. The thresholds are the 30% quantile for the benchmark below 1, while the other is determined to the 70% quantile. The possible output states of the assessment are 0, 1, 2, 3 and 4. The example WT is stated critical for the levels location, turbine type and turbine type group, while the wind farm and operator benchmark are classified noncritical. The output are shown in figure 3.7

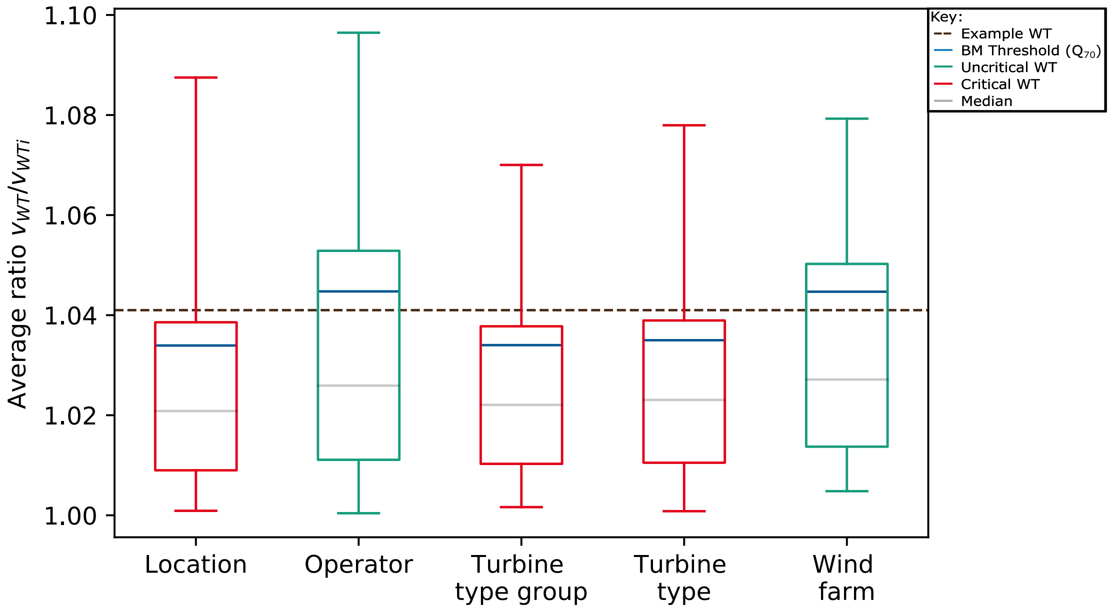


Figure 3.9: Benchmark boxplots wind speed

Table 3.7: Example output wind speed

Location	Operator	Turbine type group	Turbine type	Wind farm
1	0	1	1	0

Wind Direction

The KPI wind direction indicates the wind direction distribution of a WT or WF. Within the assessment, it is used to measure the deviation of the WT's to its WF's wind direction distribution. This method is applied to create a measurability. It aims on the identification of weak points either within the nacelle alignment or within the wind measurement system. Therefore, the input data are the quantified direction distributions of the WF and its included WTs. The aggregation to the WF-level is generated through averaging the regarding WT distributions. To calculate the deviation of the wind direction distribution, the RMSE is applied between a WT and its WF distribution. The RMSE results are then used to generate the benchmark. The characteristics of the RMSE lead to the following structure of the benchmark. The value 0 is filtered as implausible due to the fact that in reality two identical distributions are extremely unlikely. Furthermore, a lower RMSE indicates a lesser deviation of the distributions.

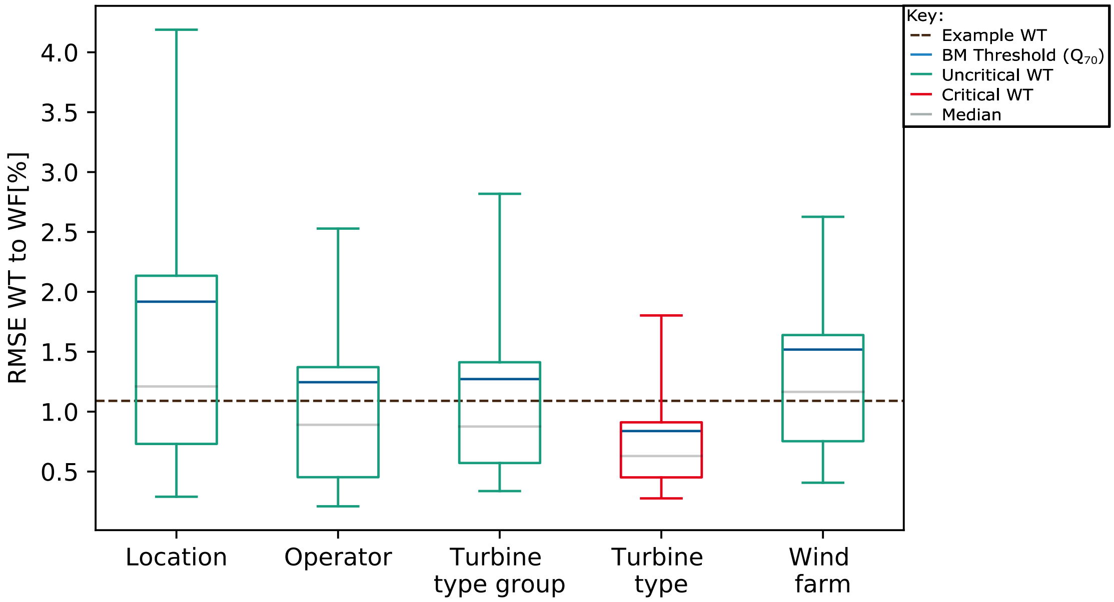


Figure 3.10: Benchmark boxplots wind direction

The possible output states are 0, 1, 2, 3 and due to implausibilities, e.g. RMSE = 0, state 4 cannot be avoided. The example WT has a RMSE of 1.01 and lies above the turbine type benchmark, while the other levels of aggregation are considered as noncritical. This leads to the following output list:

Table 3.8: Example output wind direction

Location	Operator	Turbine type group	Turbine type	Wind farm
0	0	0	1	0

Data Quality

As the assessment relies on a robust data set, the data quality needs to be included into the assessment. The KPIs are dependent on the data quality of following measures. Table 3.9 lists the assigned measures that have an influence on the KPI. They are implemented into the assessment as a measurement of the robustness. The method of the data being applied is explained within the following section.

Table 3.9: KPIs with assigned data quality shares

KPI	DQ-shares
Time-based availability	Power
Power curve	Arithmetic mean of power and wind speed
Production-based availability	Arithmetic mean of power and wind speed
Production ratio	Arithmetic mean of power and wind speed
Wind speed	Wind speed
Wind direction	Wind direction

Weighting Function

The weighting function is used at the end of the assessment to rank the results of the individual KPIs. It is based on the weighted arithmetic mean method, that is used when a distinction is made between the relevance of variables. Within this concept, a distinction between the relevance of the availabilities and environmental conditions is made. For this purpose, the time-based availability and the production-based availability as well as the production ratio are assigned to the value 1. The wind speed's and wind direction's weighting value is 0.5. The weighting is a variable and can be adjusted to the individual expectations by the stakeholder. The implemented values are the developed default values. Currently, within the different aggregation levels no distinction of relevance is applied, which can be, however, extended by a corresponding sensitivity analysis. Further information can be found within the discussion, cf. 5. The definition leads to the following equation:

$$c = \frac{\sum_{i=1}^{n_{KPI}} w_i(KPI) \left[\left(\frac{1}{n_{DQ}(KPI)} \sum_{j=1}^{n_{DQ}(\mathrm{KPI})} DQ_j(KPI) \right) \left(\frac{1}{n_{AL}(KPI)} \sum_{k=1}^{n_{AL}(KPI)} \frac{\Delta Q_k(KPI,AL)}{Q_{crit}} \right) \right]}{\sum_{i=1}^{n_{KPI}} w_i(KPI)} \tag{3.5}$$

where:

c	Measurement of criticality with regard to the considered KPIs
i	i^{th} KPI from n_{kpi}
n_{kpi}	Number of considered KPIs with the assigned states 0 or 1
$w_i(KPI)$	KPI specific weight
$n_{DQ}(KPI)$	Number of data quality values assigned to the KPI

j	j^{th} data quality share from $n_{DQ}(KPI)$
$DQ_i(KPI)$	Data quality value of i in n_{DQ}
$n_{AL}(KPI)$	Number of considered levels of aggregation
k	k^{th} level of aggregation from $n_{AL}(KPI)$
$\Delta Q_i(KPI, AL)$	Quantile deviation between Q_{value} and Q_{crit}
Q_{crit}	Critical quantile (individually defined by user)
Q_{value}	Quantile value of WT k

In the equation, Δ Q represents the deviation of the WT quantile from the limit value of criticality. Case distinctions are defined in order to be able to determine and normalise the difference between the quantiles, which is structured as the following:

$$\Delta Q = \begin{cases} Q_{value} - Q_{crit.}, & Q_{crit.} < Q_{value} \\ Q_{crit.} - Q_{value}, & Q_{crit.} > Q_{value} \end{cases} \tag{3.6}$$

To illustrate the weighting function, the resulting matrix of the example WT is presented in 3.10.

Table 3.10: Weighting function - result matrix

KPI	State | Q_{Loc}	State | Q_{Op}	State | Q_{TTG}	State | Q_{TT}	State | Q_{WF}	$Q_{Threshold}$
Time-based availability	0	1 | 19	0	1 | 22	0	30
Production-based availability	0	1 | 20	1 | 28	0	0	30
Production ratio	0	1 | 25	0	1 | 11	0	30
Wind speed	1 | 77	1 | 77	1 | 79	0	0	70
Wind direction	0	1 | 83	0	0	0	70

Table 3.11: Weighting function - data shares

Data Quality Shares		
Power [%]	Wind speed [%]	Wind direction [%]
99	99	97

The tables 3.10 and 3.11 contain all the information required to calculate the c-value. The upper table shows the KPIs and the states assigned to the aggregation

levels. The critical states are appended to their corresponding quantile, since these are relevant for the later calculation. As can be seen, the states 2, 3 and 4 are not included since the evaluation could be carried out on the specific levels of aggregation for the KPIs. Furthermore, the thresholds of the respective KPIs are shown. The second table shows the data qualities of the shares included. The calculation is carried out according to the following scheme.
First, the mean value of the criticality indicator of each row is calculated. For each KPI, which is defined as critical according to its respective aggregation level, the corresponding quantile is assigned to the underlying, aggregation level specific distribution. Then, the deviation between this quantile value and the threshold quantile (e.g. 30%) is calculated and normalised. The ratio is calculated for each aggregation level which meets the conditions described in table 3.1. These ratios are averaged over the number of assessable aggregation levels and multiplied with the data quality assigned to the considered KPI according to table 3.9. If a KPI depends on multiple data quality measures, the arithmetic mean of those values is used for described multiplication. For each KPI an individual weighting factor can be defined to adapt the formula according to user specific conditions. The weight is then multiplied with the previously calculated and described value. This procedure is done for each KPI individually and summed over all available KPIs. This represents the function's numerator and is divided by the sum of the weights of the included KPIs. This results in the following c-value for the example above: c = 0.1202.
At last, the influence of the data quality on the c-value needs to be further explained, since it can vary from a minimal ($DQ_{W,WDSPD,WDDIR}$= 100%) to a maximal ($DQ_{W,WDSPD,WDDIR} \ll 100\%$) influence on the c-value. The definition implies a more uncritical behavior of the WT for lower data qualities, since the data quality lowers the c-value. This approach has been developed with regard to the decision support through relevance ranking. If the influence of data quality would not be considered, assets with high c-values but low data qualities would have the same relevance as critical assets with high data qualities. To avoid this, a positive influence on the relevance is assigned to the data quality, arguing that no statement can be made about the performance during the data gaps and the WTs are, therefore, less critical.

4 Results

This chapter deals with the results of the thesis. Since the objective of this thesis is the development of a concept of a weak point analysis, the results of the executed analysis and the reporting of the results is described as well as an indication of the time expenditure. To begin with, the assessment's results are illustrated exemplary in a report template. It is used to present the relevant information of the evaluation and as a basis for the discussion. In addition, the generated results are presented and described regarding their robustness. Eventually, the time saving through the automation, which was determined on the basis of an example calculation, is described.

Report Template

The illustrated report template is an example of how the result might be presented within the later process. It is intended to give an example of how the result report can be structured and the information included. It is divided into three main categories that include the title page, the list of the ranked WTs and the individual results of each included WT. Figure 4.1 shows the title page of the report. It includes the stakeholders' name and logo and an executive summary of the KPIs of their portfolio. The executive summary gives an overview of the general monthly performance of the stakeholders' assets. Therefore, the specific values are illustrated as well as compared to the WInD-Pool benchmark mean and to the monthly development.

The second chapter of the report, cf. 4.2, contains the generated WT list. It includes the assessment results of each WT with a summary of the assessed KPIs. The column c presents the resulting values calculated by the described weighting function, cf. 3.3, and is used to rank the assets. Furthermore, an overview of the KPI results that provides general information about the states assigned to each level of aggregation within the analysis is given. Therefore, the cells are coloured regarded their assigned state. The green colouring illustrates that the states assigned to the

aggregation levels of a WT are uncritical. Contrary to that, the red colouring indicates that each level of aggregation is determined as critical. The orange colouring contains diverse states and includes at least two of the states 0, 1 and 3. At last, the grey colouring illustrates missing or implausible data and, therefore, contains the states 2 and 4. The results stated are a shortened version of the WInD-Pool results for January 2019 and are not operator specific for this example report.
The third and last section of the report contains the individual evaluations of the analysed WTs. The evaluations of the included KPIs are displayed. This is illustrated by the presentation of the benchmarks of the different aggregation levels, the determined limit values of the analysis and the classification of the WT into the system. The state assigned to the individual evaluation is colourised to simplify the examination.

Figure 4.1: Report template, page 1, cover

WIND pool
Windenergie-Informations-Datenpool

Betreiber Report *Test Wind*
Version *Date*

Fraunhofer IEE

Betreiber Report

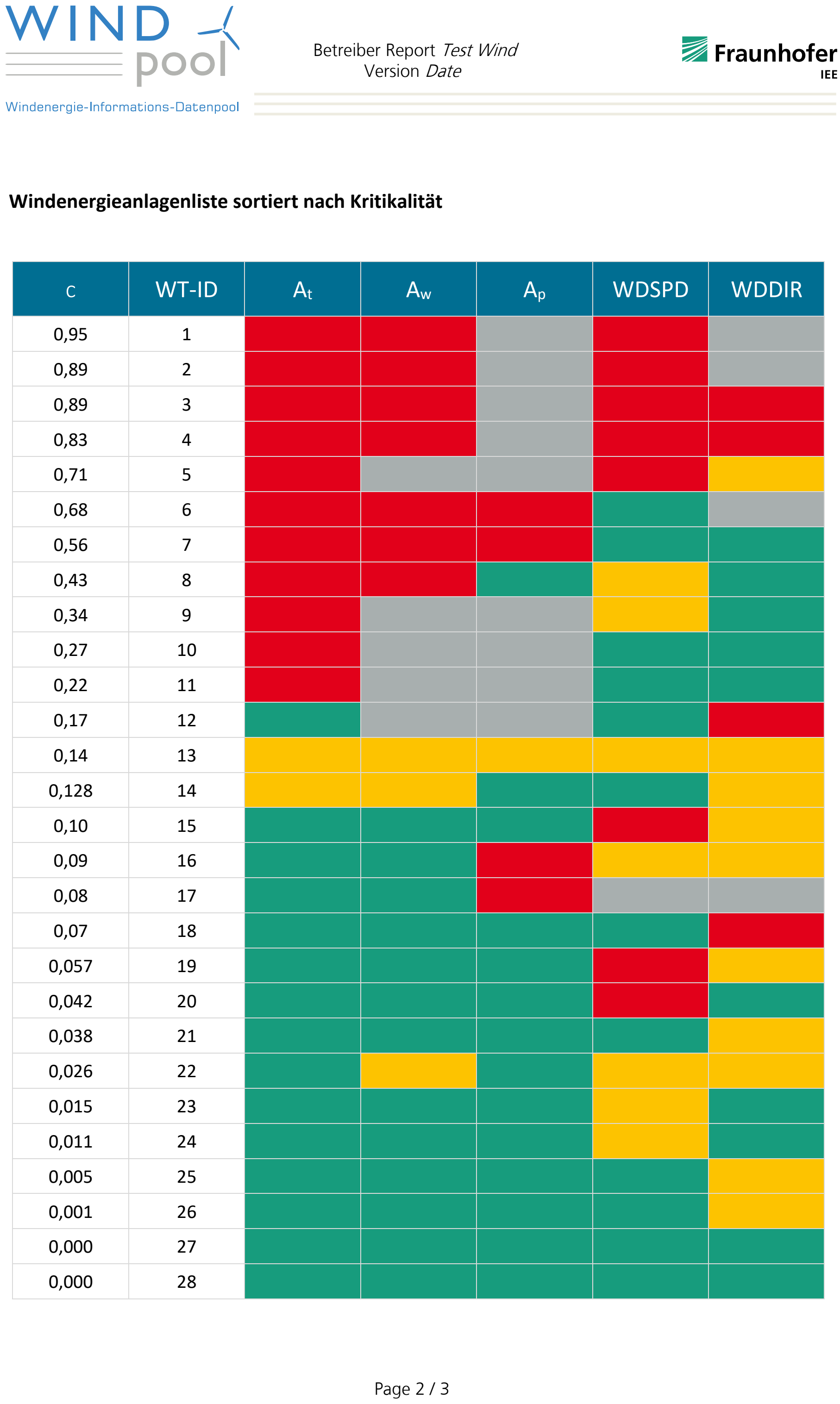
Betreiberlogo
Test Wind

Betrichtszeitraum: Monat / Jahr
ExecutiveSummary:

	Onshore		Offshore	
	WInD-Pool	Betreiber	WInD-Pool	Betreiber
Kapazitätsfaktor [%]	19,47 % ↘	● 15,79 % ↗	21,13 % ↗	● 14,39 % ↗
Energetische Verfügbarkeit [%]	88,84 % ↘	● 91,36 % ↘	88,98 % ↗	● 86,04 % ↘
Zeitbezogene Verfügbarkeit [%]	95,58 % →	● 97,74 % ↘	89,56 % →	● 94,51 % ↘
Mittlere Windgeschwindigkeit [m/s]	5,92 m/s ↗	● 5.31 m/s ↗	5,95 m/s ↗	● 5.51 m/s ↗
Datenqualität [%]	91,79 % →	● 98,09 % ↗	86,91 % ↗	● 98,43 % ↘

Page 1 / 3

Figure 4.2: Report template, page 2, ranked wt-list


Betreiber Report *Test Wind*
Version *Date*

Windenergie-Informations-Datenpool

Fraunhofer IEE

Windenergieanlagenliste sortiert nach Kritikalität

c	WT-ID	A_t	A_w	A_p	WDSPD	WDDIR
0,95	1					
0,89	2					
0,89	3					
0,83	4					
0,71	5					
0,68	6					
0,56	7					
0,43	8					
0,34	9					
0,27	10					
0,22	11					
0,17	12					
0,14	13					
0,128	14					
0,10	15					
0,09	16					
0,08	17					
0,07	18					
0,057	19					
0,042	20					
0,038	21					
0,026	22					
0,015	23					
0,011	24					
0,005	25					
0,001	26					
0,000	27					
0,000	28					

Figure 4.3: Report template, page 3, individual assessment WTs

WIND pool

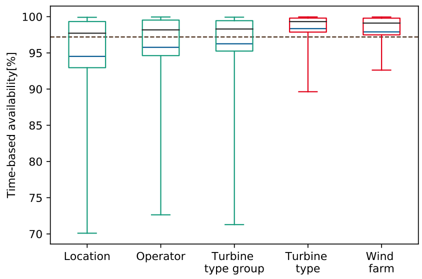
Windenergie-Informations-Datenpool

Betreiber Report *Test Wind*
Version *Date*

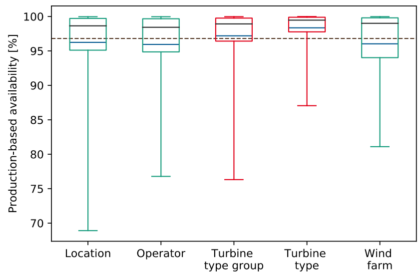
Fraunhofer IEE

Individualergebnisse Windkraftanlage: *WT-Name/-ID*

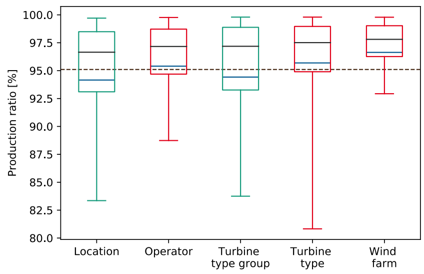
Boxplot Zeitbasierte Verfügbarkeit



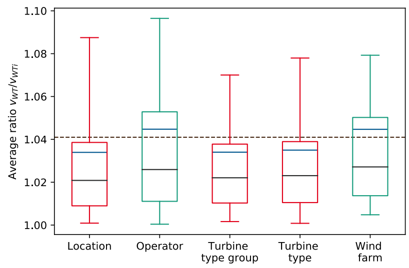
Boxplot Energetische Verfügbarkeit



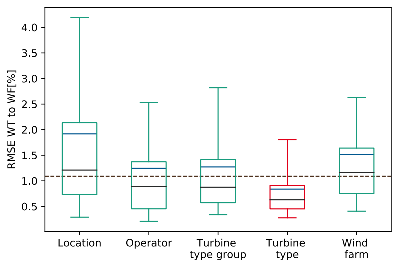
Boxplot Erzeugungsverhältnis



Boxplot Windgeschwindigkeitsauswertung



Boxplot Windrichtungsauswertung



Key:
- Example WT
- BM Threshold ($Q_{30,70}$)
- Uncritical WT
- Critical WT
- Median

Detail Result Examination

This chapter describes the detailed examination of an example WT within the automated weak point identification. Table 4.1 shows the results of the evaluation for the WT with the highest c-value in the sample report. To begin with, the robustness of the evaluation is examined through the data quality influence. During this examination, it can be concluded that the data quality has an deviating influence only on the wind direction since the calculation of the KPI is not possible. For the other KPIs the data quality is sufficiently robust. Afterwards, the KPI values are going to be examined. To begin with, the low availability values are particularly striking. For both time-based and production-based availability the value is critical respectively an extreme value. This is also reflected in the quantiles of the individual aggregation levels, which are significantly below the critical value and close to or equal to zero. Furthermore, the non-existent value of the production ratio is also notable. This has not been calculated despite the sufficient data quality. Last but not least, the wind speed is striking and significantly below the critical value.

Table 4.1: Example WT assessment

c = 0.95			Levels of aggregation (quantile)				
KPI	Value	Q_{crit}	Q_{Loc}	Q_{Op}	Q_{TTG}	Q_{TT}	Q_{WF}
$A_t[\%]$	11.4	30	0	3	2	2	3
A_w [%]	0	30	0	0	0	0	0
A_p [%]	n/a	30					
WDSPD [-]	0.87	30	0	5	3	3	5
WDDIR[%]	n/a	70					

Table 4.2: Example WT assessment - data quality

Data Quality Shares		
Power [%]	Wind speed [%]	Wind direction [%]
100	100	72.32

As a result, the following statements can be made. The value of the time-based availability indicates an extremely high downtime rate of the WT. Furthermore, it is noticeable that the production-based availability is zero and the production ratio is not calculated. This leads to the assumption that the asset did not generate any power during the period under consideration. The wind speed measurement of the

WT deviates clearly from the mean value of the WF.
Thus, the asset shows extreme weak points in different areas and is therefore assigned to the highest priority.
In order to fully verify the plausibility of the results, the SCADA-data of the database were considered. In the process, a striking operational behaviour of the WT was also be determined. This methodology was carried out on multiple WTs throughout the WInD-Pool portfolio to examine the analysis concept for plausibility.

Temporal Advantages

The extensive expenditure of time is one of the main issues of the analyses of the current WInD-Pool Operator-Portal. Firstly, the time expenditure per WT for the manual analysis is going to be determined. The average observation time of a WT was determined on the basis of the methodology of the guideline for assessing the operator portal. Out of this, an average time expenditure of about five minutes per asset could be ascertained. This includes a learning curve, which contains the transition from initial seven minutes per asset to four minutes in the later progress. This learning curve is partly explained by the fact that a fundamental part of the analysis consists of a comparison with other WTs of the portfolio which gives an overview of the different analyses. This time expenditure mainly depends on the analysis' extension and on the manual interpretation of the results regarding their criticalities. Furthermore, the external influences, e.g. the user environment, need to be mentioned. Loading times of the evaluations have an equal influence on the time expenditure as the manual selection of the variables.
For the described concept, the expenditure is considerably low. On the one hand this is due to the relevance ranking of the portfolio and the accumulative analyses within the individual considerations. On the other hand, the analysis is carried out and the report is generated beforehand which decreases the effort of the analysis. Out of this, the time expenditure per asset can be averaged to around 2 minutes, which leads to time savings of approximately 60%.
This calculation is applied to an average operator portfolio in order to represent the time savings qualitatively. For this, the average portfolio size of the WInD-Pool is used, which corresponds to 324 WTs. The manual analysis is thus equivalent to a time expenditure of approximately 27 hours if the entire portfolio is examined for weak points. In comparison, the analysis of automation takes approximately 10.8 hours, which equals a time saving of 16.2 hours per months.

5 Discussion

During the development of the concept some discussion topics arose which are explained in the following.
First, the applied observation period is discussed. This was determined in the course of the concept development to one month. The intention was to define a value that is actual, but robust enough to allow an analysis. The monthly level is the limit value for calculating the KPIs. This procedure is supported by the actuality of the KPIs meaning that an evaluation is carried out in temporally proximity to the operating period. Additionally, the data basis is relatively small compared to extended periods, which decreases the robustness of the KPIs. Therefore, a further approach would be to evaluate quarterly, half-yearly or annual values. However, even though the underlying data amount would increase the robustness, the currency would decrease and a performance improvement based on found weak point would be more difficult.
The next issue to be discussed provides a critical review of the evaluated KPIs. The concept is based on the KPIs within the WInD-Pool calculation concept and procedure, which are partly connected to certain requirements that decrease the comparability of the KPI. This concerns in particular the production ratio as it uses the empirical, WT-specific power curve during the calculation of the theoretical power output. This procedure defines the production ratio as a measure of the operational performance of a WT in comparison to its long-term operational behaviour. As a result, the comparison of the WTs within the aggregation levels is not possible, since the reference for the calculation of the production ratio differs for each WT. By calculating an aggregation level specific turbine type power curve, the comparability would increase. This would lead to the following power curve versions:

Table 5.1: Level of aggregation specific power curves

Aggregation level	Power curve type
Location	Turbine type power curve
Operator	Operator specific turbine type power curve
Wind farm	Wind farm specific turbine type power curve
Turbine type group	Turbine type power curve
Turbine type	Turbine type power curve

Therefore, the turbine type power curve is implemented in the different aggregation levels. The current application of the comparison of different turbine types within the aggregation levels leads to higher uncertainties and thus, to a deterioration of significance despite a growing number of WTs. By defining one specific turbine type for the different aggregation levels, the comparability is given and the differences in the underlying data quantity can be used as a reference for the evaluation.

Another point of discussion is the inclusion of data quality in the assessment. Currently, the data quality is included quantitatively in the evaluation. For this purpose, the value in the range $0 \leq DQ \leq 1$ of the share is included. Thereby, different data parts are used for the calculation of the KPIs. To determine the influence of the data quality shares both in the calculation of the KPIs and the weak point analysis, a sensitivity analysis should be carried out. The aim would be to establish an appropriate measure of the influence on the data quality to the weighting function. The current method includes the influence of the data and has a positive effect on the c-value, as it decreases with low data quality. This method was used to decrease the relevance of the assessed WTs as the uncertainty of the analysis increases with missing data shares. Therefore, another possibility would be not to include missing data in the evaluation and thus not to attribute any influence to them. The advantage of this approach is the evaluation of the available data only and, therefore, it has a minor uncertainty for the available time period. However, this can lead to WTs with extremely low data qualities and critical evaluation results being assigned a greater relevance even though the uncertainty is high. Another approach would be to include data quality with a negative impact on the c-value. This approach assigns a higher relevance for low data qualities, since there the WT is assigned with a noticeable performance. However, this would also lead to data gaps having a similar relevance to the evaluation results of KPIs.

Resulting from the aforementioned issues, the implementation of the aggregation levels can also be discussed. Currently, within the weighting function the levels of aggregation are equally weighted. However, since the aggregation levels are based on different data sets and have different relevance, depending on the KPI, a more precise assessment of the influence is necessary. This becomes apparent when looking at the above discussed production ratio. Therefore, the levels of aggregation could also be assigned to different weights. These weights could depend on the robustness, i.e. of the underlying data amount, of the aggregation level as well as on their comparability regarding the evaluated KPI.

6 Summary

The key statements of the chapters methodology, cf. 3 and of the results, cf. 4, are presented in the following.

Benchmarking Concept
The methodology (cf. 3) describes the structure and framework of the concept of benchmark based weak point analysis. Firstly, the definition of the benchmark is described. The benchmark is created by accumulating the KPIs, that are pre-calculated within the WInD-Pool Operator-Portal, of each in the level of aggregation included WTs throughout the entire operating period. It is applied to different aggregation levels to vary the reference in terms of data volume and significance. The benchmarks are used as the reference within the evaluation in which the KPIs are classified. The chapter concludes with a description of the limit values and framework conditions for the benchmarks with regard to the statistical robustness and contractual framework conditions. The determined threshold default to identify weak points is set globally for each KPI to the 30, respectively 70 quantile. This declares 30% of the assessed data as critical. The thresholds to generate the benchmark are applied on the one hand to avoid a comparability of the assets and on the other hand to ensure a statistical robustness of the evaluation through determined minimum operating periods and WT quantities.

Weak Point Analysis Concept and Implementation
Section 3.2 deals with the structure of the analysis. First of all, the structure of the evaluation is presented. Therefore, the implemented data, the assessment execution and the possible output states are described. The necessary input data contains the WTs' root data as well as the pre-calculated KPIs. During the assessment execution, these values are either directly classified into the benchmark or adjusted in advance with regard to their evaluation methodology, e.g. for the wind speed or wind direction evaluation. Out of this, in section 3.3, the assessment applied to the KPIs is described. This includes the considered data, the KPIs' definitions

and, further on, their possible output states. The KPIs that are assessed are the time-based as well as the production-based availability and production ratio with a previously applied plausibility test for the power curve. These KPIs assess the operational performance of the WT performance. Furthermore, the wind speed and wind direction are considered, to evaluate the environmental conditions and the installed measurement system. Therefore, for each WT the specific KPIs are tested for existence, availability of the benchmark and partly plausibility. Out of this, the values are classified into the benchmark and examined for criticality. During this process the corresponding output states are assigned to WTs. These outputs generate a matrix which is further implemented into the weighting function.

Weighting and Ranking

Within subsection 3.3, the weighting function is defined. It is used to rank the WTs according to the significance of their results. For this purpose each assessable result of the evaluation of the KPIs' aggregation levels is used. This includes the critical as well as the uncritical states, cf. 3.2. The critical states are evaluated with regard to their position in the benchmark distribution. For each KPI, the average criticality for each level of aggregation is determined by calculating the deviation to the critical quantile and normalising it. Further on, the data quality assigned to the specific KPI definition is multiplied to this. Afterwards, the result is implemented in a weighted mean value function that is used to differentiate the relevance of the examined KPIs' by applying different weights. The generated result is then used as the factor for criticality and for the ranking of the WT.

Report Template and Time Savings

The results generated from the execution of the python script are presented. The script was created with regard to the assessment methodology, are presented in the following. These consist of two main components, the sample report and the time savings of automation. The result of the weak point analysis concept is shown in the ranked WT list. Therefore, a report template was generated to illustrate the results as well as providing the results of the individual assessments. The structure of the template is divided into two major areas and the title page. The title page summarises the monthly KPI values aggregated to the operator portfolio compared to the last month as well as to the WInD-Pool benchmark mean value. After that, the main part of the report begins, which contains the listed WTs of the operator. Individually for each WT, the list includes the calculated c-value and an indication of the states assigned to the KPIs of the evaluation. This list serves as a decision

support for the recommended action. For each of the assets an individual analysis is displayed in the second main area of the report. This contains the various benchmarks of the evaluated KPIs and is presented with regard to a more in-depth analysis.
To illustrate the time savings of automation, an example calculation was carried out in chapter 4, which is based on an empirical analysis and represents an approximate time saving. Therefore, the WInD-Pool Operator-Portal was analysed regarding weak points, the time expenditure was measured and the mean expenditure per WT calculated. Additionally, an average number of WTs per portfolio was calculated that relies on the WInD-Pool database. These values are used to estimate the time expenditure per portfolio and are compared to the created concept. A time saving of approximately 60% could be determined, which is, however, still error-prone and is rather considered as a rough estimate.

7 Outlook

The concept for the development of an automated weak point analysis currently represents a basic model, which can be extended by further evaluations, e.g. the monetary-based availability, and made more robust by the validation of variables, e.g. for the determined weights. Currently, the monthly KPI values of the corresponding WTs are evaluated and sorted by relevance within the analysis. This method evaluates the KPIs within the conditions of the previously determined interval. Seasonal fluctuations of the KPIs are not taken into account and should be extended. Furthermore, the monthly analysis of the KPIs neglects the occurrence of possible trends in the short, medium and long-term development. The inclusion of trend analyses, which is carried out on the c-values, can be used to put the generated results of the evaluation into context. The implementation of trend analyses on the c-value is currently being developed and the basic concept includes the calculation of three variants. The present concept includes the calculation of a short-, medium- and long-term trend, which evaluates the WTs operating time between a one year up to the total period of operation.
In addition to the trend analysis, further evaluations could be added. The monetary-based availability, for which a definition was created within the WInD-Pool project, could be included as a KPI. The influence of this analysis on the weighting would have to be determined with regard to a partially occurring negative correlation in relation to the production-based availability.
A sensitivity analysis of individual parts of the assessment is another component that could be applied. This analysis refers, on the one hand, to the inclusion of data quality and its influence. It should be identified which influence missing data components have on the calculation of KPIs and the uncertainties they are concerned with. This procedure can be used to better estimate the robustness of the individual evaluations. On the other hand, an analysis of the robustness and the informational value of the aggregation level can be carried out. This aims at the weighting of the aggregation levels with regard to the individual KPIs. As an exam-

ple, the production ratio analysis is carried out on each of the levels of aggregation. As aforementioned in section 5, the difficulties of the comparability of this KPI are discussed. This issue could be solved by assigning different weighting values to the aggregation levels, depending on the comparability and the robustness of the specific level and its influence on the KPI. Another approach would be to calculate different turbine type power curves that vary in their assigned level of aggregation to increase the comparability.

These steps would increase the informational value of the evaluation by reducing uncertainties and increasing the significance of the KPIs under consideration. After these validations, the further process would include the implementation of the assessment structure and results in the WInD-Pool Operator Portal. This application can help operators to identifying weak points within their WT portfolio with greater efficiency and a reduced time expenditure and, thus, transforming the optimisation potential into an additional revenue.

Bibliography

[1] Behem, Guillaume ; Berkhout, Volker ; Buchmann, Elisabeth ; Callies, Doron ; Cernusko, Robert ; Dobschinski, Jan ; Durstewitz, Michael ; Faulstich, Stefan ; Grashof, Katherina ; Hahn, Berthold ; Jäger, Florian ; Keller, Sarina ; Lutz, Marc-Alexander ; Meyer, Julian ; Ortega, Andres ; Pfaffel, Sebastian ; Pfennig, Maximilian ; Puchta, Matthias ; Rehwald, Florian ; Rettenmeier, Andreas ; Dalla Riva, Alberto ; Röpnack, Andreas ; Rohrig, Kurt: *Windenergie Report Deutschland 2017*. Stuttgart : Fraunhofer Verlag, 2018. – ISBN 9783839613580

[2] Anna-Kathrin Wallasch, Silke Lüers, Dr.-Ing. Knud Rehfeldt, Kerstin Vogelsang ; DEUTSCHE WINDGUARD (Hrsg.): *PERSPEKTIVEN FÜR DEN WEITERBETRIEB VON WINDENERGIEANLAGEN NACH 2020*. https://www.wind-energie.de/fileadmin/redaktion/dokumente/publikationen-oeffentlich/themen/02-technik-und-netze/06-betrieb/perspektiven-fuer-den-weiterbetrieb-von-wea-nach-2020-v3c.pdf

[3] Bundesministerium für Wirtschaft und Energie: *Fragen und Antworten zum EEG 2017*. https://www.bmwi.de/Redaktion/DE/FAQ/EEG-2017/fragen-und-antworten-zum-eeg-2017.html

[4] RES LEGAL - LEGAL SOURCES OF RENEWABLE ENERGY (Hrsg.): *Feed-in tariff (EEG feed-in tariff)*. http://www.res-legal.eu/search-by-country/germany/single/s/res-e/t/promotion/aid/premium-tariff-i-market-premium/lastp/135/

[5] Marcus Franken, Ahnen & Enkel: Windkraft setzt Big Data ein. (2017). https://www.windindustrie-in-deutschland.de/fachartikel/windkraft-setzt-big-data-ein/

[6] Sebastian Pfaffel, Stefan Faulstich, Kurt Rohrig: Performance and Reliability of Wind Turbines: A Review. In: *Energies* 10 (2017), Nr. 11, S. 1904. http://dx.doi.org/10.3390/en10111904. – DOI 10.3390/en10111904. – ISSN 1996–1073

[7] Stefan Faulstich: *WInD-Pool*. https://wind-pool.iee.fraunhofer.de/wind_pool_de/projekt-details/

[8] Hau, Erich: *Windkraftanlagen: Grundlagen, Technik, Einsatz, Wirtschaftlichkeit*. 5., neu bearb. Aufl. Berlin : Springer Vieweg, 2014. http://dx.doi.org/10.1007/978-3-642-28877-7. http://dx.doi.org/10.1007/978-3-642-28877-7. – ISBN 978–3–642–28877–7

[9] Gasch, Robert ; Twele, Jochen ; Bade, P. ; Conrad, W. ; Heilmann, C. ; Kaiser, K. ; Kortenkamp, R. ; Kühn, M. ; Langreder, W. ; Liersch, J. ; Maurer, J. ; Reuter, A. ; Schubert, M. ; Sundermann, B. ; Stoffel, A.: *Windkraftanlagen: Grundlagen, Entwurf, Planung und Betrieb*. 4., vollständig überarbeitete und erweiterte Auflage 2005. Wiesbaden and s.l. : Vieweg+Teubner Verlag, 2005. http://dx.doi.org/10.1007/978-3-322-99446-2. http://dx.doi.org/10.1007/978-3-322-99446-2. – ISBN 978–3–519–36334–7

[10] Fichtner, prognos ; Fichtner, prognos (Hrsg.): *Cost Reduction Potentials of Offshore Wind Power in Germany - Short Version*. https://www.prognos.com/publikationen/alle-publikationen/338/show/fc3cf511f301128c92ad2988517d79bc/. Version: 2013

[11] Ehrmann, Robert S. ; Texas A & M University (Hrsg.): *Effect of Surface Roughness on Wind Turbine Performance*. https://oaktrust.library.tamu.edu/handle/1969.1/153342https://oaktrust.library.tamu.edu/handle/1969.1/153342. Version: 2014

[12] Bundesnetzagentur, Bundeskartellamt ; Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen [BNETzA] (Hrsg.): *Monitoringbericht 2014*. https://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Allgemeines/Bundesnetzagentur/Publikationen/Berichte/2014/Monitoringbericht_2014_BF.pdf?__blob=publicationFile&v=4. Version: 14. November 2014

[13] Faulstich, S. ; Hahn, B. ; Tavner, P. J.: Wind turbine downtime and its

importance for offshore deployment. In: *Wind Energy* 14 (2011), Nr. 3, S. 327–337. http://dx.doi.org/10.1002/we.421. – DOI 10.1002/we.421. – ISSN 10954244

[14] Hahn, Berthold ; Ringhandt, Axel, Schubert, Alexander ; Schulz, Volker ; Sucrow, Walter ; AKIDA Institut für Bergwerks- und Hüttenmaschinenkunde, RWTH Aachen (Hrsg.): *Instandhaltung von Windkraftwerken: Können konventionelle Kraftwerke Vorbild sein?* https://8p2.de/index.php/de/downloads/know-how/wind/36-instandhaltung-von-windkraftwerken-koennen-konventionelle-kraftwerke-vorbild-sein/file. Version: 2006

[15] Böttcher, Jörg (Hrsg.): *Handbuch Offshore-Windenergie: Rechtliche, technische und wirtschaftliche Aspekte.* München : Oldenbourg, 2013 (BWL 10-2012). http://www.degruyter.com/doi/book/10.1524/9783486717761. – ISBN 9783486715293

[16] WInD-Pool (Hrsg.): *WInD-Pool - Application.* https://wind-pool.iee.fraunhofer.de/opencms/opencms/wind_pool_en/WInD-Pool/Anwendung/

[17] WInD-Pool (Hrsg.): *WInD-Pool - Your benefits.* https://wind-pool.iee.fraunhofer.de/opencms/opencms/wind_pool_en/WInD-Pool/Nutzen_und_Auswertungen/

[18] WInD-Pool (Hrsg.): *WInD-Pool - Homepage.* https://wind-pool.iee.fraunhofer.de/opencms/opencms/wind_pool_en/WInD-Pool/index.html

[19] Steiner-Dicks, Katherine ; NewEnergyUpdate (Hrsg.): *Benchmarking platforms: why more knowledge means more leverage: Greater plant owner demand for high speed computing and benchmarking data analysis platforms will cause rapid development of power upgrade packages and create a basis for further OEM innovation.* http://newenergyupdate.com/wind-energy-update/benchmarking-platforms-why-more-knowledge-means-more-leverage. Version: 2015

[20] DNV-GL ; DNV-GL (Hrsg.): *Wind power benchmarking.* https://www.dnvgl.com/services/wind-power-be

[21] Wind Energy Benchmarking Services Limited (Hrsg.): *WEBS - WIND ENERGY BENCHMARKING SERVICE*. https://www.webs-ltd.com/

[22] CATAPULT - Offshore Renewable Energy (Hrsg.): *SPARTA: A UK offshore wind performance data benchmarking platform, transforming wind turbine operational performance*. https://ore.catapult.org.uk/stories/sparta/. Version: June 2018

[23] WinJi ; DKB, WinJi True P. (Hrsg.): *DKB und WinJi bieten digitale Performance-Benchmarking-Lösung für Betreiber von Wind- und PV-Anlagen*. https://www.win-ji.com/news-dkb. Version: 25th March 2019

[24] Greenbyte ; Greenbyte (Hrsg.): *Breeze - Wind farm management system*. https://www.greenbyte.com/de/produkt/breeze/

[25] WInD-Pool (Hrsg.): *WInD-Pool - Operator Portal: Capacity Factor - Comparison of wind turbines: Username: Seminar_PAW , PW: 123456*. https://wind-pool.iee.fraunhofer.de/windpool-portal/login.jsf

[26] British Airways: *Our Key Performance Indictors*. https://www.britishairways.com/cms/global/microsites/ba_reports0809/our_business/kpi3.html

[27] MacNair, Carol J. ; Leibfried, Kathleen H. J.: *Benchmarking: A tool for continuous improvement*. London : Harper Collins, 1994 (The Coopers & Lybrand performance solutions series). – ISBN 0004990064

[28] Lindberg, Carl-Fredrik ; Tan, SieTing ; Yan, JinYue ; Starfelt, Fredrik: Key Performance Indicators Improve Industrial Performance. In: *Energy Procedia* 75 (2015), S. 1785–1790. http://dx.doi.org/10.1016/j.egypro.2015.07.474. – DOI 10.1016/j.egypro.2015.07.474. – ISSN 18766102

[29] SETIS ; SETIS - EPIA – ESTELA (Hrsg.): *Key Performance Indicators for the Solar Europe Industrial Initiative*. https://setis.ec.europa.eu/set-plan-process/european-industrial-initiatives-eiis/eii-key-performance-indicators

[30] Gonzalez, Elena ; Nanos, Emmanouil M. ; Seyr, Helene ; Valldecabres, Laura ; Yürüşen, Nurseda Y. ; Smolka, Ursula ; Muskulus, Michael ; Melero, Julio J.: Key Performance Indicators for Wind Farm Operation and

Maintenance. In: *Energy Procedia* 137 (2017), S. 559–570. http://dx.doi.org/10.1016/j.egypro.2017.10.385. – DOI 10.1016/j.egypro.2017.10.385. – ISSN 18766102

[31] SETIS - TPWind ; SETIS - TPWind (Hrsg.): *Key Performance Indicators for the European Wind Industrial Initiative.* https://setis.ec.europa.eu/implementation/eii/eii-key-performance-indicators/KPIs_Wind/view

[32] Artigao, Estefania ; Colone, Lorenzo ; Gonzalez, Elena ; Nanos, Emmanouil ; Pandit, Ravi ; Reder, Maik ; Seyr, Helene ; Tautz-Weinert, Jannis ; Valldecabres, Laura ; Yildirim, Nurseda ; Ziegler, Lisa ; Melero, Julio ; Muskulus, Michael ; Smolka, Ursula: *1st Joint Industry Workshop Scientific report.* https://www.researchgate.net/publication/312627620_1st_Joint_Industry_Workshop_Scientific_report

[33] Hau, Erich: *Windkraftanlagen: Grundlagen. Technik. Einsatz. Wirtschaftlichkeit.* 6th ed. Berlin, Heidelberg : Springer Berlin Heidelberg, 2017 https://ebookcentral.proquest.com/lib/gbv/detail.action?docID=4818780. – ISBN 9783662531532

[34] International Electrotechnical Commission: *Wind turbines – Part 12-2: Power performance of electricity-producing wind turbines based on nacelle anemometry (IEC 61400-12-2:2013).* February 2014

[35] Liu, Xian: An Improved Interpolation Method for Wind Power Curves. In: *IEEE Transactions on Sustainable Energy* 3 (2012), Nr. 3, S. 528–534. http://dx.doi.org/10.1109/TSTE.2012.2191582. – DOI 10.1109/TSTE.2012.2191582. – ISSN 1949–3029

[36] International Electrotechnical Commission: *Wind turbines – Part 12-1: Power performance measurements of grid connected wind turbines (IEC 61400-12-1:2002).* 2002

[37] International Electrotechnical Commission: *IEC 61400-26-1 TS Ed. 1: WIND TURBINES – Part 26-1: Time based availability for wind turbines.* 2011

[38] DNV-GL (Hrsg.): *Definitions of Availability Terms for the Wind Industry.* https://www.dnvgl.com/publications/definitions-of-availability-terms-for-the-wind-industry-98846. Version: A

[39] International Electrotechnical Commission: *IEC 61400-26-2 TS Wind turbines – Part 26-2: Production-based availability for wind turbines.* 2014

[40] Ammonit Measurement GmbH ; Ammonit Measurement GmbH (Hrsg.): *Professional Wind Measurement: WindMeasurement_Brochure.* https://www.ammonit.com/en/support/downloads/217-ammonit-windinfo. Version: 2019

[41] Oxford University Press (Hrsg.): *© The Oxford Pocket Dictionary of Current English 2009.* 2009

[42] Merriam-Webster.com Dictionary ; Merriam-Webster, Inc. (Hrsg.): *Trend - The Merriam-Webster Dictionary.* https://www.merriam-webster.com/dictionary/trend

[43] Siebert, Gunnar ; Kempf, Stefan: *Benchmarking: Leitfaden für die Praxis.* 1. Aufl. s.l. : Carl Hanser Fachbuchverlag, 2012. – ISBN 978–3–446–41569–0

[44] Zairi, Mohamed ; Leonard, Paul: *Practical benchmarking: The complete guide.* London : Chapman & Hall, 1994 http://www.loc.gov/catdir/enhancements/fy0902/95130576-d.html. – ISBN 0412574101

[45] Straub, Rolf: *Benchmarking. Eine Darstellung des Benchmarking als modernes Instrument zur Leistungsverbesserung: Dissertation zur Erlangung der Würde eines Doktors der Wirtschaftswissenschaften der Universität Zürich.* Zürich, 1997

[46] Weisstein, Eric W. ; MathWorld–A Wolfram Web Resource (Hrsg.): *Standard Deviation.* http://mathworld.wolfram.com/StandardDeviation.html

[47] Rottmann Horst ; Auer, Benjamin R. ; GABLER WIRTSCHAFTLEXIKON (Hrsg.): *mittlerer quadratischer Vorhersagefehler.* https://wirtschaftslexikon.gabler.de/definition/mittlerer-quadratischer-vorhersagefehler-52088/version-275237. Version: 19.02.2018 - 16:03

[48] Dodge, Yadolah (Hrsg.): *The concise encyclopedia of statistics.* [Updated ed.]. New York, NY : Springer, 2010 (Springer reference). http://

dx.doi.org/10.1007/978-0-387-32833-1. http://dx.doi.org/10.1007/978-0-387-32833-1. – ISBN 978–0–387–31742–7

[49] Weighted Arithmetic Mean. Version: 2008. http://dx.doi.org/10.1007/978-0-387-32833-1{_}421. In: *The Concise Encyclopedia of Statistics*. New York, NY : Springer New York, 2008. – DOI 10.1007/978–0–387–32833–1_421. – ISBN 978–0–387–32833–1, 565–566

[50] Weiss, Georg ; GABLER BANKLEXIKON (Hrsg.): *Gewichtetes arithmetisches Mittel*. https://www.gabler-banklexikon.de/definition/gewichtetes-arithmetisches-mittel-58415/version-342976. Version: 05.11.2018 - 21:31