A review of reliability-based methods for risk analysis and their application in the offshore wind industry

Mareike Leimeister[a,b,*], Athanasios Kolios[b]

[a] Fraunhofer Institute for Wind Energy Systems (IWES), Am Luneort 100, 27572 Bremerhaven, Germany
[b] Cranfield University, Energy and Power, Whittle Building, Bedfordshire MK43 0AL, United Kingdom

ABSTRACT

Offshore and marine renewable energy applications are governed by a number of uncertainties relevant to the design process and operational management of assets. Risk and reliability analysis methods can allow for systematic assessment of these uncertainties, supporting decisions integrating associated consequences in case of unexpected events. This paper focuses on the review and classification of such methods applied specifically within the offshore wind industry. The quite broad differentiation between qualitative and quantitative methods, as well as some which could belong to both groups depending on the way in which they are used, is further differentiated, based on the most commonly applied theories. Besides the traditional qualitative failure mode, tree, diagrammatic, and hazard analyses, more sophisticated and novel techniques, such as correlation failure mode analysis, threat matrix, or dynamic fault tree analysis, are coming to the fore. Similarly, the well-practised quantitative approaches of an analytical nature, such as the concept of limit states and first or second order reliability methods, and of a stochastic nature, such as Monte Carlo simulation, response surface, or importance sampling methods, are still common practice. Further, Bayesian approaches, reliability-based design optimisation tools, multivariate analyses, fuzzy set theory, and data pooling strategies are finding more and more use within the reliability assessment of offshore and marine renewable energy assets.

1. Introduction and outline

Offshore wind turbines are exposed to severe environmental conditions. Occurring failures could have environmental impacts, but definitely would lead to considerable financial losses. This is not only due to the lost production output because of the failure, but is especially amplified by the limited accessibility of offshore assets, located some distance from the coast and sometimes even in quite remote areas. Transport of offshore engineers and work on the asset can only be performed in acceptably safe sea states and at medium wind speeds. These prescribed working weather windows imply quite long delays sometimes, until the asset can operate in normal mode again. This moves the point of focus towards risk management and reliability assessment of offshore wind turbines.

According to BS ISO 31000, risk is the "effect of uncertainty on objectives…[and] is often expressed in terms of a combination of the consequences of an event (including changes in circumstances) and the associated likelihood…of occurrence" [1], p. 1. The latter can be influenced by the level of reliability. Reliability itself is defined, based on BS 4778 [2], as "the ability of a component or a system to perform its required functions without failure during a specified time interval" [3], p. 12, but "can also be denoted as a probability or as a success ratio" [4], p. xxvi. Several different techniques for obtaining qualitative or quantitative measures of reliability exist; however, not every method is

suitable to be applied to the assessment of offshore energy systems. Some may be more useful than others, and some have to be adjusted or combined to obtain valuable results.

The aim of this paper is to classify reliability methods used in the offshore and marine renewable energy industry. Other objectives are the analysis of these methods with respect to their applicability to offshore wind turbine systems, their benefits and limitations, as well as the elaboration of existing trends and further approaches required to overcome those limits still remaining. The paper is structured in such a way that first a classification of common reliability methods is given in Section 2. After this general overview, qualitative and quantitative reliability assessment procedures, specifically applied within the offshore wind and marine renewable energy industry, are presented and categorised (Sections 3 and 4). This is based on a systematic literature review, which primarily used the specific words "reliability" and "offshore", focused on the latest research work done, preferably from 2010 onwards, and aimed to concentrate on offshore wind turbines; however, some examples of other offshore industries and structures were also included due to the still low information density on offshore renewable energy devices. In total, more than 100 papers have been reviewed and further information was taken from recent conferences, as well as industrial experiences. Section 5 points out how offshore wind turbine systems challenge common reliability assessment methods, in which way and how far the presented techniques are already able to cope with this, as well as which limits are still existing and which theories will potentially develop further. Finally, a conclusion is provided in Section 6.

2. Classification of reliability methods

Reliability analyses (RAs) can be performed for different systems and components, such as mechanical, electronic, or software, as well as at various stages of the engineering process, for example design or manufacture [4]. Due to the broad application of reliability, attempts at categorisation are being made. Stapelberg [5] for example focuses on reliability in engineering design and distinguishes between reliability prediction, assessment, and evaluation, depending on the design stage conceptual, preliminary/schematic, or detailed, respectively. Furthermore, two different levels at which reliability can be applied are defined: component and system level. These already introduce the bottom-up and top-down approaches, which can be found in some reliability methods as well.

Considering the different reliability methods themselves, there are two main categories into which they can be grouped: qualitative methods and quantitative methods, depending on the availability and quality of data [5]. However, a comparison of different literature, such as O'Connor et al. [4] or Rausand and Høyland [6], shows some discrepancies in the assignment of certain reliability methods and indicates the need for a third intermediate category for such semi-quantitative reliability methods. The methods covered in the following, as well as the chosen categorisation, are visualised in the form of a Venn diagram, presented in Fig. 1. The abbreviations used will be explained in the following sections and are listed at the beginning of the paper.

Furthermore, it has to be noted that some of the presented methods are rather risk assessment tools than reliability methods. However, these risk assessment techniques are still included, as the awareness of the existing risks is the decisive basis for RAs. In the following, it is just stated whether the tool is strictly speaking used for risk or reliability. A detailed list of risk assessment methods can be found in BS EN 31010 [7].

2.1. Qualitative reliability methods

Missing or insufficient data does not allow for quantitative assessment of reliability. Nevertheless, relations within the system, covering hazards, failure causes, events, failure modes, faults, effects, and

consequences, can be shown and this way an estimate of reliability, failure probability, and consequence can still be obtained by using qualitative methods.

Before performing any qualitative RA, first the system structure and functions have to be identified and classified [6]. On this basis, a qualitative reliability assessment can be carried out. Some of the most common methods are briefly explained in the following, grouped into sheet-based, table-based, and diagrammatic techniques.

2.1.1. Sheet-based qualitative reliability methods

Typical sheet-based qualitative methods are checklists; they are used to assist engineers [6] in determining and examining influencing factors, and thus identifying risks, for design operation, maintainability, reliability, safety, and availability. Thus, for each stage there are different question sets, on which basis the contributing parameters can be studied [5].

2.1.2. Table-based qualitative reliability methods

The table-based qualitative methods focus either on hazards or failure modes (FMs).

The aim of hazard identification (HAZID) analysis is to determine potential hazards, as well as their causes and consequences. This risk identification method should be applied as early as possible, so that changes and adaptions, which may avoid the hazard or at least reduce the effects to the system, can be integrated in the early system design. A typical HAZID worksheet starts by naming the investigated component or area, followed by the potential incident. Then, the potential causes and consequences are determined and the severity of the latter is categorised. Finally, recommendations for corrections or precautions are given [5].

A hazard and operability (HAZOP) study, another risk assessment tool, is also used for the identification of hazards, their potential causes and effects; however, this analysis rather focuses on deviations from the normal operation mode as initiating event. Special guide words, such as NO or NOT, MORE, LESS, LATE, or BEFORE, are used for describing these deviations. The HAZOP procedure itself could either start with the guide word or the considered element. A HAZOP worksheet contains, besides the guide word and element, the explicit meaning of the deviation, the potential causes and consequences, already existing safeguards, as well as recommended necessary actions and further comments [8].

More adaptable tools for identifying risks are the what-if analysis or structured what-if technique (SWIFT). The SWIFT starts with collecting potential hazards and uses in addition a checklist, containing typical errors and failures that could also make up hazards. The hazards are then organised in a worksheet, comprising the hazard itself, mentioned in the column headed What-if?, its potential causes and effects, as well as presenting safeguards and giving recommendations, similarly to HAZID and HAZOP [9].

Not only focusing on hazards, the failure mode and effects analysis (FMEA) aims to identify FMs in the system function or equipment, their potential impacts and causes, as well as determining existing controls and precautions. Thus, while being originally a risk assessment tool, FMEA can also be used for RA. Three different types of FMEA exist: concept/functional FMEA, design/interface FMEA, and detailed/updated FMEA, implying that FMEA can be used throughout the entire life cycle of an asset [6].

2.1.3. Diagrammatic qualitative reliability methods

Qualitative reliability methods in the form of a diagram can be structured from the top down or the bottom up. Such a top-down approach is used in the cause and effect diagram, which is also called the fish-bone diagram due to its shape. The top event, a failure or incident, makes up the head of the fish on the right side. Different cause categories, containing several specific factors, are then added in form of fish-bones to the diagram, allowing a structured risk assessment [6].
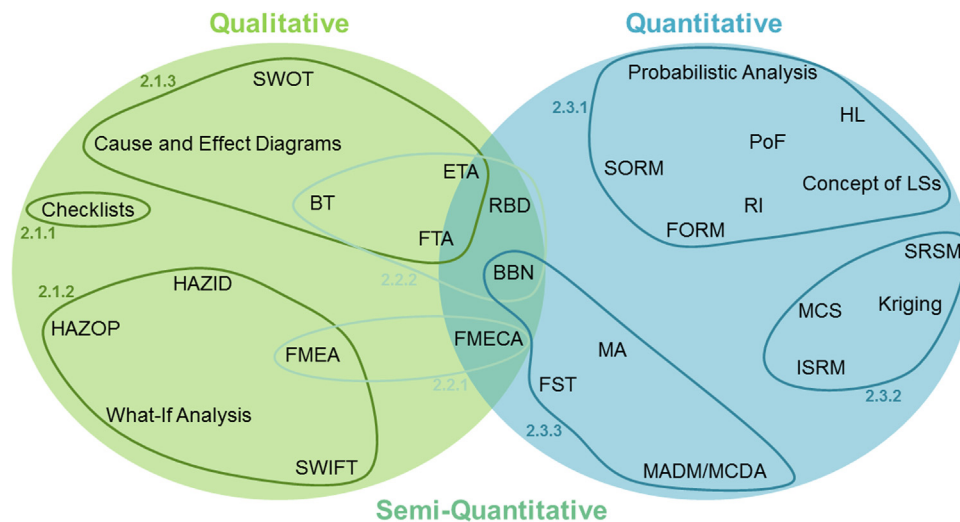
Fig. 1. Venn diagram for the classification of the presented reliability methods.

The same deductive (top-down) approach is used in the fault tree analysis (FTA), strictly speaking a risk assessment tool, which is visualised in a fault tree diagram (FTD). The tip of the tree is the incident or failure which is then broken down into immediate, intermediate, and basic causes. The relationship between causes and the top event are represented by logical gates, such as AND and OR [6].

An event tree analysis (ETA), also a risk assessment technique, is performed in the opposite direction, meaning from the bottom up. Such an inductive approach uses the incident or failure as the starting point for identifying all potential event sequences which may result from the initial event. The different levels in the corresponding event tree diagram (ETD) can directly represent safeguards and the two branches of that part of the tree are the options for the success or failure of this safety barrier [5].

A combination of risk assessment methods FTA and ETA is given in the bow-tie analysis (BTA). The diagrammatic form of such a BT has the failure or incident in the middle, which is then broken down to the left into its causes, representing the FTA, and to the right into its consequences, such as in the ETA. In both directions safety barriers can be included, safeguards for control and precaution in the FT-part, and safety functions for mitigation in the ET-part [10].

Besides those linear diagrammatic methods, the strengths, weaknesses, opportunities, and threats (SWOT) technique analyses influence factors and identifies risks in two dimensions. Based on the shape of a compass rose or four-quadrant format, the internal factors i.e. strengths and weaknesses are in the north, while the external factors i.e. opportunities and threats are in the south. In the east-west direction, the factors are distributed such that the positive factors lie in the west and the negative ones in the east [11].

2.2. Semi-quantitative reliability methods

Some of the qualitative reliability methods can be extended with some quantitative approximate measures and thus also be used for quantitative reliability assessment. These tools can again be grouped into table-based and diagrammatic methods, as presented in the following.

2.2.1. Table-based semi-quantitative reliability methods

In Section 2.1.2, FMEA has already been introduced as a qualitative risk assessment methods, which however can also be used for RA. If this is combined with a criticality analysis, a semi-quantitative reliability method, the so-called failure mode effects and criticality analysis (FMECA), can be obtained. The additional parameters are three rating

values: for the severity of the effects, the occurrence of the FM, and the detectability of the failure cause. Different tables with recommendations for rating those parameters and assigning a ranking number to them do exist but can also be defined individually. Having determined the severity, occurrence, and detection ratings, the risk priority number (RPN) is computed as a product of these three rating values. This can finally be used to rank the criticality of risks and FMs. As for the FMEA, the worksheet for the FMECA can also either be focused on the component/equipment or on the requirement/function. Furthermore, it is possible to distinguish between product and process FMEA, depending on the items or system under consideration [6,12].

2.2.2. Diagrammatic semi-quantitative reliability methods

The tree-shaped risk assessment techniques FTA, ETA, and BT, mentioned in Section 2.1.3, can also be used for a quantitative assessment of reliability if probability values are added to the branches. Those numbers indicate the occurrence probability of a causal event, in the case of an FT, and the conditional probability of a safety function being functional or not, in an ET, respectively. Multiplication of all probability values along one cause or consequence path yields the total probability of this happening. This calculation can be performed in measures for either failure or success; the latter directly represents the reliability value, while in the first case the reliability has to be computed as complementary to the failure probability [6].

Comparable to FTDs and cause and effect diagrams, however, more general are the Bayesian belief networks (BBNs). Similar to the FTA, a BBN uses the top-down approach, starting with the initiating event and breaking this down into different causes or cause categories. Arrows indicate the relationships between the undesired event and the causes, which could result in a quite complex network [6]. By assigning probabilities to the contributing factors, BBNs can not only be used for risk identification, but also for quantitative reliability assessment. With the help of the Bayes theorem, existing data can be inter- or extrapolated, but also newly available information can be incorporated in the BBN and the reliability estimation updated [5].

An alternative way of presenting an FTD or ETD is a reliability block diagram (RBD), which is - as the name already suggests - a reliability assessment tool. The different components are more or less aligned on one common line with the input on the left end and the output on the right end. This way, systems with a flow can also be represented very well. Instead of the AND and OR gates, used in FTDs and ETDs, parallel and series connections are incorporated in the RBD to describe the relationships of the single components, as well as to represent dependencies. If the probabilities of each event or system function,
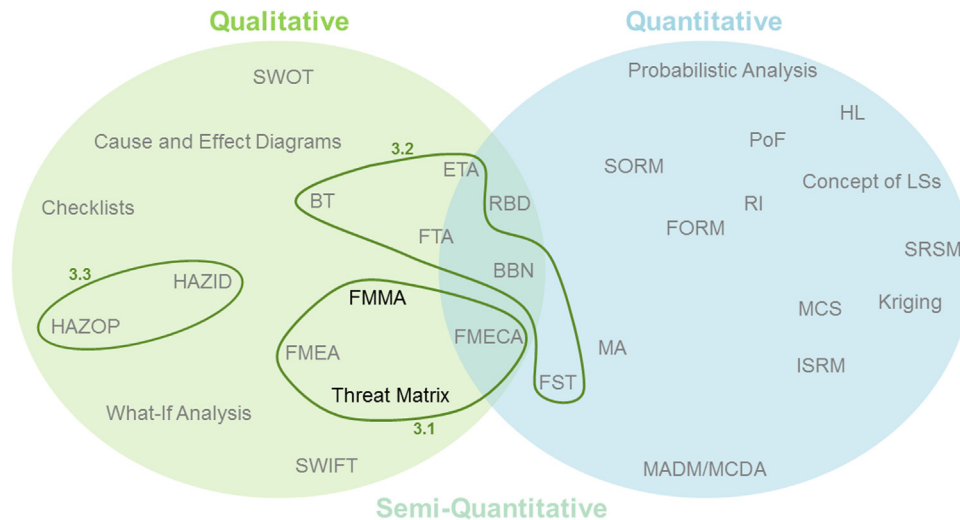
Fig. 2. Venn diagram for the presented qualitative reliability approaches.

illustrated by the blocks in the diagram, are known, the system reliability can be computed based on the algebraic rules for parallel and series systems [5].

2.3. Quantitative reliability methods

For a detailed assessment of the reliability, including ranking of risks as well as the prioritisation of where to focus on and thus integrate corrections or precautions, quantitative methods are needed. Typical techniques for quantitative reliability assessment are presented in the following, grouped into analytical, stochastic, and some sophisticated methods.

2.3.1. Analytical quantitative methods

Analytical approaches for quantitative reliability assessment are based on load-strength interference. The difference between the resistance of the system and the acting load is known as performance or also called limit state function (LSF). Some guidelines, e.g. DNV-OS-C101 [3] and DNVGL-CG-0128 [13], provide definitions of LSs and analytical expressions for certain failure criteria. Some of the parameters used in these expressions are uncertain and thus have to be represented by stochastic or random variables. The performance function is used to show the area of failure, which is the case for negative results. For evaluating the reliability, the LSF has to be solved, which can be done in different ways [4].

As the computation of the reliability, based on the condition that the LSF must be positive, could be very complex, the first order reliability method (FORM) or second order reliability method (SORM) are often used for simplifying the analytical expression by applying a first or second order Taylor expansion [14]. Based on FORM, an iterative approach for determining the reliability index (RI) is given by Hasofer and Lind (HL). The cumulative distribution function relates the RI to the probability of failure (PoF); the latter is just complementary to the reliability [15].

2.3.2. Stochastic quantitative methods

As in the analytical quantitative methods, described in Section 2.3.1, the stochastic Monte Carlo simulation (MCS) reliability assessment technique is based on the equation for the LSF. In the MCS, several cases are simulated, in which the uncertain variables are randomly sampled based on the defined probability distribution functions and corresponding key parameters, such as mean value and variance. Using direct MCS, conditional expectation, or importance sampling reduction methods (ISRMs) [16], the reliability or PoF can be estimated based on

the results of the iterated simulation calculation [5].

Unlike in the previous techniques, surrogate modelling methods, such as kriging, or stochastic response surface methods (SRSMs) only use an approximated LSF instead of the real one. While SRSM just uses some sample points for interpolating and approximating the response surface, surrogate modelling methods meet all initial data points and are therefore a more accurate method for approximating the LSF, which is then solved for the PoF and reliability by means of FORM, SORM, or MCS. Besides the advantage of SRSMs to reduce the computational effort for solving the iterations, obtained by simplification of the simulation expressions, SRSMs can also link input and output variables [17,18].

2.3.3. Sophisticated quantitative methods

Even more sophisticated system conditions can be handled with quantitative reliability methods. Multi-attribute decision making (MADM), also called multi-criteria decision analysis (MCDA), can support selecting the best option when having multiple criteria within an analysis process, whereas fuzzy set theory (FST) can deal with incomplete information or fuzzy data. Both tools can also be combined in the case of several alternatives being vague in nature. [19]

Finally, dynamic systems can be approached using Markov Analysis (MA). This diagrammatic risk and reliability assessment method allows the inclusion of transitions between different states [4].

3. Qualitative approaches for the analysis of offshore wind turbine systems

The qualitative reliability assessment methods, applied to offshore and marine energy devices, which are presented in this chapter are categorised, based on the classification given in Section 2, into FM analyses, tree and diagrammatic analyses, and hazard analyses. The techniques and their grouping are shown in Fig. 2.

3.1. Failure mode analyses

FM analyses are already frequently applied to offshore wind turbines and used in both qualitative and quantitative ways, but also in other variations.

3.1.1. FMMA, FMEA, and FMECA

An entire RA of the 5 MW wind turbine REpower 5 [20] was performed in [21]. This consisted of a failure mode and maintenance analysis (FMMA) for determining the system components that required

focused monitoring, a semi-quantitative FMEA including a criticality rating indicating the risk, based on the two factors of probability and consequence, and an FMECA for identifying those system components which are very prone to failures.

Failure mode identification, based on FMEA, FMECA, as well as FTA, is performed in [22] to analyse different end of life scenarios for offshore wind turbines.

3.1.2. Quantitative FMEA

Similarly to the work of Bharatbhai [21], mentioned in Section 3.1.1, Arabian-Hoseynabadi et al. [23] deal with FMEA for wind turbines; however, they focus on a quantitative FMEA. The three factors (severity, occurrence, and detectability) of a traditional FMECA were adhered to, but the rating scales were modified and adapted to a wind turbine system. Furthermore, the software Relex Reliability Studio 2007 V2 [24] was also adjusted and the component FMEA was chosen to be the most suitable type of FMEA for performing a reliability assessment of a wind turbine. Finally, the benefits of an FMEA, especially for offshore wind turbine systems but also for further improvements towards higher economic efficiency and competitiveness of wind energy, are pointed out.

Shafiee and Dinmohammadi [25], as well as Kahrobaee and Asgarpoor [26], elaborate the limitations of a traditional FMEA or FMECA, when being applied to the assessment of a wind turbine or wind farm, especially offshore. The RPN, used for prioritisation, has very little informative value when comparing different wind turbine types and is also difficult to determine accurately due to deficient failure data. Furthermore, economic aspects, which are becoming more relevant offshore, are not considered in the standard approaches. Thus, a modified FMEA, or in [26] called risk-based FMEA, is proposed which includes both qualitative and quantitative measures. In addition, the cost priority number (CPN) is computed based on the PoF, the cost consequences of a failure, and the detectability. This economic measure is more tangible than the abstract and poor RPN, and allows a better and more realistic comparison of different wind turbine systems with respect to criticality.

3.1.3. Correlation-FMEA

When dealing with complex systems, such as a floating offshore wind turbine, FMEA could be extremely extensive due to the amount of FMs and the prioritisation could become more difficult as many RPNs could have the same order of magnitude. Furthermore, if some FMs are correlated, a direct isolated analysis of each single FM would be more difficult but also less accurate. Thus, Kang et al. [27] and Bai et al. [28] propose a correlation-FMEA for the risk assessment of offshore assets. While [27] applies just the traditional FMECA and uses those FMs with the highest RPN, [28], modifies the FMECA and determines the RPN based on the ALARP (as low as reasonably practicable) principle, which is also mentioned in [29] as a common approach for defining target safety levels. In both procedures by Kang et al. [27] and Bai et al. [28], the correlation of different FMs is then incorporated by means of the reliability index vector (RIV) method. The RIV contains the reliability indices and correlation coefficients of the FMs. The final ranking of these correlated FMs happens through the probability network evaluation technique (PNET) and the most crucial FMs can be determined in this way.

3.1.4. Threat matrix and FMECA

A preparatory action for an effective FMECA is described in [30]: the threat matrix. This is meant to be used to estimate the operational expenditure early in the design stage, to identify the most critical components with respect to reliability and maintainability, as well as to be able to optimise the design with respect to cost-efficiency. Using the example of a wave or tidal energy system, a threat matrix is set up by collecting all potential threats or FMs and corresponding failure mechanisms, which are listed on the x-axis, while the y-axis contains all

components obtained by a system breakdown. Within the matrix it is marked which threats could occur to which component. This can be used afterwards as a basis for an FMECA in which the possibility of a failure mechanism is supplemented by the probability measure.

3.2. Tree and graphical analyses

Just like FM analyses, tree and diagrammatic reliability methods are applied in many cases for the assessment of offshore energy devices; however, these methods are rarely used separately but rather in combination with other tools or in a modified version.

3.2.1. FTA, ETA, and BBN

Several techniques are integrated in a complete risk analysis for collision impact on offshore wind turbines, performed in [31]. First, the causes or sequence of events are determined based on FTA or ETA, respectively. Secondly, data for frequencies and probabilities are required. At this stage it is emphasised that in the offshore renewable energy industry sufficient data are often missing; however, existing data from other similar industries, such as offshore oil and gas, with already long-lasting experiences can be taken as a basis. In the third step, potential risk influencing factors (RIFs) affecting event or barrier failure probabilities need to be estimated. With these RIFs, complex BNs can be created, on which basis the RIFs can be ranked. Finally, the probabilities of undesired events are computed based on the RIFs. For further evaluation of the risk, the consequences and their severity have to be analysed and then both proactive and reactive actions can be proposed and ranked according to their importance and degree of necessity.

3.2.2. Dynamic FTA

A qualitative RA with additional quantitative assessments for complex systems with dynamic characteristics, such as floating offshore wind turbines, is presented in [32]. System grading for dealing with the complex composition of the asset is performed in two respects: focused on the system function, and based on the structure. For the qualitative assessment of the FMs, dependencies, sequences, and redundancies are taken into account by adapting the traditional FTA to a dynamic FTA, which uses special dynamic logic gates. The quantitative analysis, based on the dynamic FTDs, requires failure rates data, which however are not or just insufficiently available for such a floating wind turbine system. Based on databases for onshore wind turbines and offshore energy assets, which will be covered in more detail in Section 4.6.1, the failure rates for a floating wind turbine are approximated by the inclusion of marine environmental influences.

3.2.3. BTA

The combination of FTA and ETA, in the form of a BTA, is used in [33] for the assessment of offshore terminals and ports. In the first step, the risk factors are determined by means of HAZID. However, due to vague and imprecise data for failure rates and event occurrences, FST using the fuzzy analytical hierarchy process method with triangular fuzzy numbers is applied for prioritising these identified risk factors. The highest ranked risk factors are then assessed via BTA.

Adjusted BTAs for quantitative and dynamic reliability assessment can be found in [34–37]. The quantitative aspect is covered by FST or evidence theory for dealing with uncertain and vague data, and is applied after the creation of the BT based on expert knowledge as input for the event probabilities [34]. With such a quantitative BTA, the likelihood of consequences can be set in relation to failure rates of system components and safety barriers [35]. But in order to include dynamics, dependencies, and common causes [37] as well, or also update the probability estimates based on newly available data [34,35], Bayesian updating approaches [35,34] and BNs [36], which could also be object-oriented [37], are also used.

3.3. Hazard analyses

Contrary to FM, tree, and diagrammatic analyses, hazard analysis techniques are more rarely found to be applied for the reliability assessment of offshore and marine renewable energy assets. HAZID was mentioned once in [33] for identifying the risk factors of an offshore system. HAZID is more likely to be used preparatory to an FMEA, compared to HAZOP, as the latter requires that the entire design is already fixed and everything is in place. Thus, those two hazard analysis tools are more suitable for reviewing the final design [38] or within integrity management for scheduling inspection and maintenance, based on the determined hazards [39].

4. Quantitative approaches for the analysis of offshore wind turbine systems

The quantitative reliability assessment methods, applied to offshore and marine energy devices, which are presented in this chapter are categorised, based on the classification given in Section 2, into analytical methods, stochastic methods, Bayesian approaches, reliability-based design optimisation methods, multivariate analyses, and data foundations. The techniques and their grouping are shown in Fig. 3.

4.1. Analytical methods

The analytical quantitative reliability methods, found to be used for the assessment of offshore wind turbines, are mainly based on performance functions and focus on the determination of the RI.

4.1.1. Concept of LSs

LSFs, RI, and PoF are mentioned frequently as a basis for assessing the reliability of whole offshore systems or single components [40–48]. Furthermore, the hazard rate function is used in [49] for developing an availability growth model, which accounts already in the early design stage for innovations and later changes.

In the IRPWind-project [46], safety factors are used for creating the equations for the LSFs in a study into the reliability of support structures for offshore wind turbines, focusing on degradation due to operational and environmental impact. The benefits of partial safety factors, thus the LS method, are also emphasised in [47] by pointing out the applicability of this reliability-based design concept to novel offshore structures, where existing standards may only be used to a limited extend, as well as the upside of having optimisation possibilities and other advantages over global safety factor approaches.

4.1.2. Analytical probabilistic analyses

FORM and/or SORM are frequently applied for the reliability assessment of different assets, such as floating offshore wind turbines [40,41], mooring lines for a floating device [45], offshore support structures [43,44], or the welded tubular joints of an offshore structure [50]. Kolios et al. [41] emphasise the capability of those indirect methods to estimate joint probability density functions, as well as their advantage over MCS regarding the computational effort. A direct comparison in [51] of the results from FORM and SORM with those obtained by MCS was satisfactory. Furthermore, Rendón-Conde and Heredia-Zavoni [45] applied FORM to show how the reliability is affected by uncertainties in system parameters. Finally, Kolios et al. [40] indicate the HL method as an example for FORM and point out the higher accuracy of SORM, which can also handle non-linear LSFs.

Different methods, however, related to FORM and SORM, as they are also based on derivatives of the LSF, are the first order second moment approach [42] and the method of moments [48]; the latter was used for estimating the reliability sensitivity. The computational efficiency of the moment-based reliability assessment, and its applicability to systems with several FMs is underlined by Lu et al. [48]. Furthermore, Llado [52] mentions the advanced mean value method as a tool for reliability assessment and reliability-based design optimisation.

4.2. Stochastic methods

Besides the above mentioned analytical quantitative reliability methods (Section 4.1), stochastic techniques, such as MCS, ISM, or SRSM, are also applied for the reliability assessment of offshore wind turbine systems.

4.2.1. MCS

Kolios et al. [40,41], Llado [52], Lee et al. [53], Yang et al. [54], and Scheu et al. [55] all refer to MCS as a method for assessing system reliability. One reason for using this method is the demanding approximation of the PoF, as stated in [40], especially when complex systems such as floating offshore wind turbines are considered. However, Kolios et al. [41] also point out the corresponding disadvantage of MCS, which often comes with high computational effort. The number of iterations is lower for Latin hypercube sampling (LHS) [53], while uncertainties can still be accounted for in the design [54].

A specific category within MCS is ISM, which only samples a selected region of interest. Thus, Thöns et al. [56] first identifies the converged design point based on an adaptive RS algorithm, which will be introduced in Section 4.2.2, and then carries out the RA with the
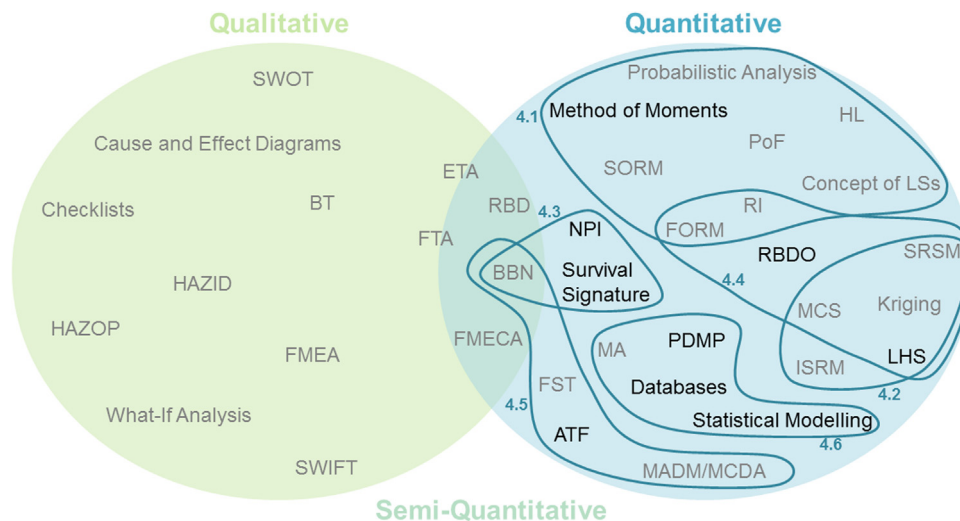

Fig. 3. Venn diagram for the presented quantitative reliability approaches.

help of an IS Monte Carlo scheme to determine the PoFs. Due to the preceding RS-based approach, this IS algorithm only requires the LSs and corresponding uncertainties as input. Similarly, IS follows the surrogate modelling within the stochastic simulation in [57] to quantify the importance of uncertain parameters.

4.2.2. SRSM

RAs of offshore (wind turbine) support structures are also conducted by means of SRSM, as for example in [43] for obtaining the RI. A special approach in this reliability assessment has to be mentioned: due to the time-consuming analysis of systems with dynamic characteristics, as prevailing in the environmental conditions of an offshore wind turbine support structure, the dynamic response is approximated by applying a peak response factor for the dynamic amplification to the static response.

Similarly to [43], Thöns et al. [56] examine the reliability of an offshore wind turbine support structure. An adaptive RS algorithm is proposed for obtaining the design point, which is later used for the RA based on IS, covered in SubSection 4.2.1. First, an experimental design is created, which is used for finite element computations. Afterwards, a regression analysis is performed and the design point is determined. This is an iterative process until the design points converge.

RSM and regression analysis are also used in [58], while Yang et al. [54] apply the kriging RSM for building an approximate model including uncertainties, and Taflanidis et al. [57] use moving least squares response surface approximations within the surrogate modelling approach for obtaining higher computational efficiency.

4.3. Bayesian inference

The system reliability can be investigated in more detail by means of the Bayesian approach. This combines and processes expert knowledge, providing prior distributions, and test data, representing sample distributions [59]. Bayesian inference can also be used for dealing with uncertainties or conflicts in the prior probability distributions [60–62].

4.3.1. Bayesian updating

In [63], the Bayesian approach is used for updating the reliability and the resulting maintenance schedule of a floating offshore structure. However, not all parameters are updated after each inspection - only those which are very prone to uncertainties. Nielsen and Sørensen [64] also make use of previous experiences, inspections, and Bayesian pre-posterior decision theory in order to optimise maintenance planning.

A non-parametric Bayesian updating approach is presented in [65] for the reliability assessment of a support structure for an offshore wind turbine. For integrating uncertainties in the RA, a polynomial chaos expansion approximation, based on Hermite polynomials and Gaussian variable, is applied. Furthermore, discrete semi- or non-conjugated updating is recommended for multi-parametric updating.

4.3.2. Survival/system signature

A kind of Bayesian inference can also be obtained by combining the survival signature, which is equal to the system signature if only one type of component exists, with non-parametric predictive inference (NPI). NPI does not provide exact probabilities, but a lower and upper bound for the survival probability function [59].

The survival signature can also be used within optimisation models for more efficient opportunistic condition-based maintenance strategies [66].

4.4. Reliability-based design optimisation

Several quantitative reliability methods are used together in reliability-based design optimisation (RBDO) processes. The structure of RBDO is always quite similar. However, three different approaches for the design optimisation of offshore wind turbine support structures are presented in the following.

4.4.1. RBDO vs. deterministic optimisation

The comparison of RBDO and deterministic optimisation (DO) is shown in [53]. The optimisation procedures aim at reducing the mass of the structure by taking reliability into account. For both approaches, first, design loads are determined by conducting a dynamic response analysis with a finite element model. The DO, based on progressive quadratic RSM optimises the mass and fulfills the LS requirements; however, the reliability of the structure is not necessarily ensured. In contrast, RBDO yields an optimised design and achieves the target reliability at the same time. In the RBDO procedure, the mean values of the random design variables are processed. The boundary conditions for the computations are given by the LSFs and required reliability. The iterative calculation procedure consists of an inner loop for the reliability and structural analyses, applying LHS, and the outer optimisation process, including RA and using a micro genetic algorithm. With this RBDO procedure, a reliable and cost-effective design is aimed to be obtained.

4.4.2. Dynamic RBDO

A dynamic RBDO is elaborated in [54]. Due to the integrated dynamics, these RBDO processes have a quite high computational effort. Commonly, deterministic techniques are used in optimisation procedures; however, these do not account for uncertainties, for which probabilistic methods are required. The proposed dynamic RBDO process also starts with a finite element model of the considered structure. With the focus on the inclusion of uncertainties in the RBDO approach and the reduction of computational effort, an approximate metamodel is created by means of kriging RSM or LHS, based on the generated finite element model. This approximate model is used within the iterative optimisation process, incorporating uncertainties and focusing on the weight of the structure. For comparative purposes, MCS is used to estimate the reliability of the resulting optimum design. This shows higher reliability values than are obtained by deterministic optimisation.

4.4.3. Integrated RBDO

For the realisation of RBDO, an integrated algorithms system is presented in [67]. This integrated RBDO algorithm consists itself of three interacting numerical algorithms for structural analysis, RA, and the optimisation process. By means of the structural analysis, which is based on a finite element model and performed with the stochastic analysis program for offshore structures, the LSF, as well as the cost or weight and their gradients are computed as function of the design variables. LSF and its gradient, as well as the probabilistic data are given as input to the RA algorithm. Using FORM, the RI is determined iteratively and for the converged value also the gradient is calculated. These parameters, together with the cost/weight function and its gradient from the structural analysis, are integrated into the optimisation process, using sequential quadratic programming. The iterative loop computes the objective function, thus cost/weight, based on the provided design variables, proves the requirements for reliability, and is iterated until convergence, and thus the optimised design is achieved. This integrated RBDO algorithm requires an initial estimate for the optimisation design variables as input and then runs in a closed loop until the final optimum design variables are found. Despite the functionality and applicability of this integrated RBDO algorithm, it also brings the disadvantage of high computational effort.

4.5. Multivariate analyses

The category of multi-variate quantitative reliability assessment methods comprises analyses, which contain various criteria, handle several hazards, or deal with complex systems.

4.5.1. FST in MADM

MADM is commonly used to find a preferred solution from a pool of

Table 1
Wind turbine databases, based on [80,81].

Name	Country	Period	# Turbines	Reliability-relevant collected data
WMEP	Germany	1989–2006	1500	Maintenance and repair events, disruptions, malfunctions, failures, downtimes
LWK	Germany	1993–2006	241	Failures, downtimes
Windstats WSD	Germany	1995–2004	4285	Failures, downtimes
Windstats WSDK	Denmark	1994–2003	904	Failures, downtimes
VTT	Finland	2000–2004	92	Failures, downtimes
Elforsk	Sweden	1997–2004	723	Failures, downtimes
ReliaWind	Europe	2004–2010	~350	Failures, downtimes, FMEA

alternatives. Different MCDA methods are applied and compared in [68] for determining the most suitable support structure for wind turbines at specific locations, while Lozano-Minguez et al. [69] focus on the technique for order preference by similarity to ideal solution (TOPSIS), which is one typical method within MADM [70]. This was also applied in [71] to select the best barrier for offshore wells with respect to costs and benefits. In order to deal with fuzzy data, a fuzzy analytical hierarchy process is integrated in MADM. Similarly, an intuitionistic fuzzy entropy method within an MCDA model allowed to choose the most appropriate wind energy technology for a specific site under consideration of vagueness and uncertainties in environmental, economic, and social factors [70]. Kolios et al. [72] apply as well a fuzzy-TOPSIS method for prioritisation of FMs of a subsea control module, while Kolios et al. [73] and Martin et al. [74] extend the TOPSIS method to take stochastic inputs and uncertainties into account.

Besides these more traditional applications of MADM, Okoro et al. [75] use TOPSIS for risk-based prioritisation of offshore energy asset components. The proposed multi-criteria risk assessment approach is similar to FMEA; however, it overcomes the disadvantageous subjective ranking of FMs within FMEA, as each single variable of one FM is weighted instead. The entire risk assessment contains, as usual, risk identification, risk analysis (with collection of information, multi-criteria analysis, and final integration to an overall ranking), and risk evaluation. Within the multi-criteria RA, first, all FMs are investigated and broken down into all risk parameters, which are finally weighted, as already mentioned. In a second step, all relevant FMs of each system component are determined. Based on these estimates, FMs and risk parameters are ranked by means of the TOPSIS method.

Apart from TOPSIS, the analytic hierarchy process (AHP) and the analytic network process (ANP) are two further MCDAs which can be applied within risk and reliability assessments. While the hierarchical approach in AHP only shows the relation between elements, the network view in ANP provides a more sophisticated analysis which takes dependencies and feedbacks into account [76]. This capacity benefits the utilisation of ANP in multi-criteria decision tasks within complex systems, for which reason it was applied in [77] in the field of offshore wind energy in order to find the best strategy for mitigating operational risks.

4.5.2. Multi-hazard reliability assessment

Also, for supporting the decision-making process within the planning and design of offshore wind energy projects, Mardfekri and Gardoni [78] present a multi-hazard reliability assessment method. A finite element model for an offshore wind turbine is set up to represent the dynamic response by taking aero-elastic coupling and soil-structure interaction into account. Probabilistic demand models for the support structure are obtained in a deterministic procedure, which is supplemented by adjustment terms to consider uncertainties in the statistics, as well as model errors and uncertainties. These demand models are

updated by incorporating existing data, using the Bayesian approach. With wind and seismic hazard data for a particular site, the fragility curves are estimated, based on LSFs. These fragility curves give information about the expected structural damage, but also the degree of sensitivity of single random variables, which could then provide a measure of importance.

4.5.3. Artificial transfer function

Structural RA of offshore structures, evaluated with respect to fatigue behaviour and considering each single failure scenario, could be computationally intensive and time-consuming. To deal with this, an artificial transfer function (ATF) is used in [79]. The real transfer function, used in the fatigue calculations, is approximated by a two-parameter ATF with a predefined shape, similar to the Pierson-Moskowitz spectrum. The two parameters are determined by evaluating the real and ATF at two points. With these parameters and the eigenperiod of the structure, the wave scatter, and the in-service life time, the RIs of different components can be determined and thus used as a measure of the structural reliability.

4.6. Data foundations

Quantitative reliability methods depend, as their name suggests, on quantitative measures. The required data do not always exist, are complete, or accurate enough. Thus, data often have to be modelled based on available information or estimates.

4.6.1. Databases

Several long-term surveys have been performed in different countries for collecting data on installed wind turbines, as summarised in Table 1. These could be of various types, such as fixed or variable speed wind turbines, with geared or direct drives. Furthermore, the amount and concrete type of collected data depend on the specific survey [80].

These data, however, are only for onshore wind turbines and thus show an example for a case where data of similar, but not the finally considered, assets are available. Faulstich et al. [81] already mentioned a transfer of the existing data to offshore wind turbines, which are however affected by the concrete type of asset, as well as the different environmental conditions, and thus require a very rich database. WMEP is quite extensive but not broad enough, therefore a new research project for an Offshore-WMEP has been undertaken in Germany. In accordance and cooperation with the Offshore-WMEP, Great Britain has set up the offshore wind data platform SPARTA, which focuses on availability and reliability to improve the system performance [82]. Within another recent research project, WInD-Pool [83], a broad database is provided by amalgamating compatible data, including among others also the Offshore-WMEP. Similar to the databases presented in Table 1, however, considering offshore wind turbines, Carroll et al. [84] have analysed and collected failure rate, repair time, and operation and maintenance data of around 350 offshore wind turbines in Europe.

The need for a database for offshore wind turbines is also emphasised in [85]. With respect to offshore energy industries, there is a reliability, availability, maintainability, and safety (RAMS) database existing for the oil and gas industry, called offshore reliability data (OREDA). However, comprehensive data collections for reliability and safety of offshore and marine renewable energy assets are lacking. Thus, it is proposed to make use of already existing databases, such as OREDA, and transfer this knowledge to other industries for setting up RAMS databases for offshore renewable energy systems, such as offshore wind turbines. The structure of the RAMS database, proposed in [85], is inspired by the concept of the offshore-WMEP presented in [81]. Thus, Hameed et al. [85] construct a RAMS database, which uses operational, equipment, failure, and maintenance data, as well as condition monitoring information as input. Furthermore, already existing experiences from OREDA, as well as from onshore and offshore wind turbines, are used as information sources. Directly linked to the

RAMS database is the analysis of the data, which provides outputs that are valuable for design and manufacturing, self-maintenance machines, operation and maintenance strategies, life cycle cost and profit estimates, as well as the assessment of qualifications for new technologies. Despite the suspected powerfulness of this RAMS database, Hameed et al. [85] also mention challenges which come with the data collection. Besides cost factors, information protection and specific client needs, as well as data quality and management, technological changes, and optimisation strategies have to be faced.

The method of using existing reliability databases from other energy industries as a basis for assessing reliability data for offshore wind turbines has already been applied in [86]. By transferring the existing data to the specific offshore environmental and operational condition of the considered asset, a so-called surrogate data portfolio is generated. The factor of dealing with different environmental conditions is considered by applying a failure rate estimate approach. By means of reliability modelling and prediction analysis, which is a combination of diagrammatic and analytical models, the reliability of the system and its components can be assessed.

4.6.2. Statistical modelling

In case of a lack of failure rate data, statistical modelling techniques can be applied. The Weibull distribution is commonly used [59,87] for estimating the failure rate of a system. By changing the shape parameter of the Weibull distribution, the entire life cycle can be covered and the bathtub curve of the failure rate represented. As this power law process is very suitable for complex repairable systems, it can also be utilised to assess the reliability of large (offshore) wind turbines [87].

4.6.3. Markov chain approach for data modelling

The capability of MA to deal with transitions between states, mentioned in Section 2.3.3, can be utilised for modelling developing data such as environmental conditions or degradation and maintenance processes. Thus, Hagen et al. [88], Castro Sayas and Allan [89], as well as Scheu et al. [90], used the Markov chain for modelling the sea state parameters of wave height and wind speed. In [88,91], Markov chain weather models, also representing seasonal characteristics, are generated. Furthermore, deterioration processes are sometimes modelled by using the Markov property, as done in [92]. This presented Markov chain maintenance model considers degradation of components, but also includes inspection processes. An alternative to this are Petri net models combined with MCS, which can also take degradation, inspection, and maintenance into account, and provide information about condition, failure estimates, as well as basic details helpful for planning maintenance strategies [93].

Alternative applications of the Markov property can be found in [94,95]. Strauss [94] uses a Markov chain model and semi-Markov chain model for assessing the fatigue reliability of concrete structures, including Bayesian updating for considering actual information from monitoring activities. Broader capabilities of the Markov property are opened up with a piecewise deterministic Markov process (PDMP), as applied in [95]. With PDMP, discrete failure events, as well as continuous processes, can be modelled. Due to this ability, PDMP combined with MCS can make a quite powerful tool for the reliability assessment of offshore systems.

5. Discussion

Some challenges that come with the reliability assessment of offshore wind turbine systems are already mentioned in Sections 3 and 4. The main ones, as well as the customised proposed solution methods, are collated and presented in the following.

- **RPN and ranking of FMs:**
  The ranking of FMs within an FMECA is often quite subjective [75] and the RPN does not always provide meaningful information,

especially when different technologies and types of wind turbine systems have to be compared [25]. Thus, Okoro et al. [75] recommend subdividing the FMs into their risk factors and applying the weights directly to these parameters, and Kolios et al. [72] use a fuzzy-TOPSIS MCDA method in addition to FMEA and RPN to prioritise FMs. Shafiee and Dinmohammadi [25], as well as Kahrobaee and Asgarpoor [26], on the other hand, introduce the CPN for inclusion of economic aspects and in order to work with a more tangible monetary ranking value within the prioritisation process.

- **Complex and novel systems:**
  Offshore wind turbines are often very complex systems and prone to several different, correlated, and dynamic FMs. Kang et al. [27], Bai et al. [28], and Onoufriou and Forbes [29] propose a correlation-FMEA, based on the ALARP principle and using RIV as well as PNET, to cope with this difficulty, while Zhang et al. [32] use system grading and a dynamic FTA. An additional challenge, especially within the relatively recent offshore renewable energy technologies, is that of novel designs, to which existing standards can only be applied to a limited extend. The concept of LSs [47], as well as RBDO procedures (Section 4.4) could be a helpful support.

- **The problem with the data:**
  Missing, insufficient, and vague data, especially in the offshore wind energy industry, is a big issue in detailed and meaningful reliability assessment of such assets. FST and evidence theory can help dealing with vague data [33,34]. However, this does not replace the need for a RAMS database for offshore wind turbines. Existing data from other offshore industries, such as oil and gas, or even onshore renewable energy equivalents, which already have long-lasting experience, can serve as a basis for setting up a useful RAMS database for these assets [31]. Besides the need for modifications to take different (environmental) conditions into account [32], further challenges, such as cost aspects, richness of data, or fast developing technologies, have still to be faced [85].

These above mentioned challenges are still current working areas within the reliability assessment of offshore wind turbines. The most recent theories show that computational simplifications, through FORM or SORM, are still of interest; however, the main research focus has shifted towards more comprehensive and adjusted approaches for complex, dynamic systems with correlated FMs, multivariate problems, as well as data collection and modelling. Based on this existing trend and including the characteristics of offshore wind turbine systems, as well as the specific capabilities of different reliability methods, Bayesian approaches, MCDMs, Markov analyses, and especially combined theories, are likely to come more to the fore.

A summary of the presented methods, their applicability with respect to stage, specific challenges, and aimed outcomes, as well as their limitations, is presented in Table 2. The considered stages are divided into design (D), construction (C), operation (O), maintenance (M), and life cycle planning (LC).

It can clearly be seen that for the early stages of the process life cycle qualitative methods are more suitable than quantitative methods, as not sufficient data is yet available. However, when proceeding towards later stages in which more and more data is already gained and available, more quantitative methods can be used and are also favoured due to their more comprehensive capabilities. Thus, qualitative methods are mostly used in the design stage and some also in the construction stage. Only a few qualitative methods, such as dynamic FTA or BTA, are utilised in operation and maintenance when it comes to monitoring. Furthermore, advanced qualitative methods, such as correlation-FMEA, threat matrix, and FMECA, can support life cycle planning. On the other hand, quantitative methods are mostly used in operation, maintenance, and life cycle planning, while only a few, e.g. analytical methods, RBDO, and some multi-variate analyses, can be applied in the design stage for the purpose of design optimisation.

Table 2
Applicability of presented reliability methods, in summary.

Type	Category	Method	Stage D	C	O	M	LC	Results	Capabilities	Limitations	References
Qualitative	Failure Mode Analyses	FMMA, FMEA, and FMECA	X					FMs	Easy implementation; employable from the beginning of the project	Competent facilitator for reaching consensus in scoring is required	[20,22]
		Quantitative FMEA	X	X				Prioritisation of FMs	Straightforward application due to well-defined bands of scores	Appropriate scoring for different classes of application	[25,23,24]
		Correlation-FMEA	X				X	Weak points	Coping with mutual correlated FMs	Complexity in case of multiple FMs	[27–29]
		Threat Matrix and FMECA	X				X	Components requiring high reliability or good maintainability	Visual representation of FMs and associated consequences	No incorporation of detectability factor in 2D representation	[30]
	Tree and Graphical Analyses	FTA, ETA, and BBN	X	X				Decision making	Visual representation of interdependencies of events	Cumbersomeness in case of highly granulated system analysis	[31]
		Dynamic FTA	X	X	X	X		Maintenance references	Coping with sequentially dependent and redundancy failures	Effect of inappropriate sequencing of events on analysis results	[32]
		BTA			X	X		Real time risk monitoring	Efficient link of ETA and FTA; visualisation of dependencies	Common cause and dependency failures	[33,36,35,37]
	Hazard Analyses	HAZID/ HAZOP	X		X	X		Monitor integrity; operational risk factors	Structured description of hazards and system effects of deviations from design intent	Extensive documentation; only to be applied to well-defined system	[39,38,33]
	Analytical Methods	Concept of LSs	X	X			X	Design optimisation and novel designs	Systematically considered uncertainties; no global safety factors	Combined FMs vs. their individual contributions	[40,42,44–47,49]
		Analytical Probabilisitc Analyses	X	X	X		X	Reliability sensitivity	Robust consideration of input uncertainties	Complex derivation of joint probability distribution functions	[42–45,48,51,50]
	Stochastic Methods	MCS		X		X		Decision making	Easy to implement due to direct simulations	Large computational effort	[52,41,55]
		SRSM		X				Computational efficiency	Time-varying and dependent variables	Sensitive to initial assumption of RS shape	[43,54,56,58,57]
		ISM		X				Computational efficiency	Overcome limitations of direct MCS	Performance in multiple variables; modelling requirements	[56,57]
	Bayesian Inference	Bayesian Updating	X	X				Optimised/updated inspection planning	Uncertainty in prior; application with condition monitoring	Appropriate data to update probabilities	[60,59,61,62,65,63,64]
		Survival/ System Signature		X	X	X	X	System survivability	Incorporation of condition monitoring	Resilience and maintenance effects	[60,59,66]
	RBDO	(Dynamic, integrated) RBDO	X					Optimised design (reliability, mass, performance, cost)	Consideration of uncertainties	Computational effort	[53,54,67]
	Multi-Variate Analyses	FST in MADM	X	X	X	X	X	Decision making; prioritisation of interventions	Easy implementation due to intuition-based input data	Skewness of results due to extreme values	[70,71,75,77,68,69,73,74,72]
		Multi-Hazard Reliability Assessment	X					Design optimisation	Consideration of uncertainties; level of importance of variables in LSF	Complex derivation of joint probability density functions in case of correlated hazards	[78]
		ATF			X		X	Inspection planning	Approximation of complex processes	Lost information further from expected value	[79]
	Data Foundations	Databases	X	X				Data collection; optimised operation and maintenance	Availability of generic occurrence frequencies	Processed data; different sources and reporting protocol forms	[80,81,85,86]
		Statistical Modelling			X			Optimisation (design, operation and control strategies)	Failure prediction in complex and repairable systems	Sufficiently accurate system modelling required (e.g. supervised learning)	[87]
		Markov Chain Approach for Data Modelling		X		X		Sensibility to parameter variations	Coping with dynamic reliability problems, degradation, and maintenance processes	Non-explicit expression of dependencies between hidden states; computational effort	[88–90,92,95,93]

6. Conclusion

This paper presents a review of reliability-based methods for risk assessment, which have been most used so far for the assessment of offshore wind and marine renewable energy systems. Based on the current practices in offshore applications, a comprehensive sub-categorisation of qualitative and quantitative techniques is carried out. The represented qualitative methods are mainly structured as failure mode analyses, tree and graphical analyses, as well as the more rarely used hazard analyses. The quantitative methods are differentiated between analytical and statistical as well as Bayesian approaches, reliability-based design optimisation tools, multivariate analyses, and strategies for data pooling.

It should be noted that offshore wind turbine systems are very complex with dependent, repairable, or redundant components, dynamic characteristics, and non-linearities; furthermore, they require special consideration regarding the severe offshore site conditions, implying several uncertainties in the motion and stress response of the system due to unknown and complex environmental effects, as well as non-linearities; though, there is little experience with novel structures and lack of reliability data; and last but not least, ethical and economic aspects, such as data confidentiality, as well as time and computational efficiency, have to be preserved. These factors challenge the reliability assessment of offshore wind turbines.

The trend towards more complex, efficient, and flexible tools, as well as the approach of combining different techniques is developing and should advance further, also including more advanced sensitivity analysis tools to systematically consider uncertainties which will govern the design and operation of offshore wind turbine systems.

Acknowledgements

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