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TITLE: Wind energy generation systems – Part 9: Probabilistic design measures for wind turbines

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INTERNATIONAL ELECTROTECHNICAL COMMISSION

WIND ENERGY GENERATION SYSTEMS

Part 9: Probabilistic design measures for wind turbines

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The text of this Technical Specification is based on the following documents:

Draft	Report on voting
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Full information on the voting for its approval can be found in the report on voting indicated in the above table.

The language used for the development of this Technical Specification is English.

This document was drafted in accordance with ISO/IEC Directives, Part 2, and developed in accordance with ISO/IEC Directives, Part 1 and ISO/IEC Directives, IEC Supplement, available

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INTRODUCTION

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WIND ENERGY GENERATION SYSTEMS

Part 9: Probabilistic design measures for wind turbines

1 Scope

This Technical Specification sets out minimum requirements to the use of probabilistic design measures in order to ensure the structural and mechanical integrity of wind turbines. The TS shall be based on the general approach in ISO 2394, which also forms the basis for IEC 61400-1. In 61400-1 the design verification approach is based on deterministic design using safety factors. However, edition 4 opens for introduction of probabilistic design in an informative annex specifying requirements to the calibration of structural material safety factors and structural design assisted by testing. This TS provides appropriate methodologies and requirements for full probabilistic design by taking into account specific uncertainties on not only material properties but also on environmental conditions, design models and the degree of validation.

2 Normative references

The following documents are referred to in the text in such a way that some or all of their content constitutes requirements of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

IEC 61400-1, *Wind energy generation systems - Part 1: Design requirements*

IEC 61400-2, *Wind energy generation systems – Part 2: Design requirements for small wind turbines*

IEC 61400-3-1, *Wind energy generation systems – Part 3-1: Design requirements for offshore wind turbines*

IEC 61400-3-2, *Wind energy generation systems – Part 3-2: Design requirements for floating offshore wind turbines*

IEC 61400-4, *Wind energy generation systems - Part 4: Design requirements for wind turbine gearboxes*

IEC 61400-6, *Wind energy generation systems - Part 6: Tower and foundation design requirements*

IEC 61400-8, *Wind energy generation systems - Part 8: Design of wind turbine structural components* (CDV version)

IEC 61400-12-1, *Wind energy generation systems - Part 12-1: Power performance measurements of electricity producing wind turbines*

IEC 61400-13, *Wind energy generation systems – Part 13: Measurement of mechanical loads*

IEC TS 61400-31, *Wind energy generation systems – Part 31: Siting Risk Assessment* (DTS version)

IEC 61400-50-1, *Wind energy generation systems – Part 50-1: Wind measurement – Application of meteorological mast, nacelle and spinner mounted instruments*

ISO 2394, *General principles on reliability for structures, 2015.*

3 Terms and definitions

3.1

limit states

state of a structure beyond which the structure no longer satisfies the design criteria

[SOURCE: ISO 2394]

3.2

parked wind turbine

turbine being either in a standstill or an idling condition, depending on the design of the wind turbine

[SOURCE: IEC 61400-1]

3.3

reference wind speed

V_{ref}

basic parameter for wind speed used for defining wind turbine classes

Note 1 to entry: Other design related climatic parameters are derived from the reference wind speed and other basic wind turbine class parameters (see Clause 6).

Note 2 to entry: A turbine designed for a wind turbine class with a reference wind speed V_{ref} is designed to withstand climates for which the extreme 10 min average wind speed with a return period of 50 years at turbine hub height is lower than or equal to V_{ref} .

[SOURCE: IEC 61400-1]

3.4

site data

environmental, seismic, soil and electrical network data for the wind turbine site

Note 1 to entry: Wind data shall be the statistics of 10 min samples unless otherwise stated.

[SOURCE: IEC 61400-1]

3.5

standstill

condition of a wind turbine that is stopped

[SOURCE: IEC 61400-1]

3.6

support structure

part of a wind turbine comprising the tower and foundation

[SOURCE: IEC 61400-1]

3.7

turbulence intensity

I

ratio of the wind speed standard deviation to the mean wind speed, determined from the same set of measured data samples of wind speed, and taken over a specified period of time

[SOURCE: IEC 61400-1]

3.8

wind turbine site

location of an individual wind turbine either alone or within a wind farm

[SOURCE: IEC 61400-1]

3.9

component class

classification of the wind turbine structural components according to redundancy and safety requirements

Note 1 to entry: Refer to IEC 61400-1.

[SOURCE: IEC 61400-6]

3.10

reliability class

class of structures or structural members for which a particular specified degree of reliability is required

3.11

design situations

sets of physical conditions representing the real conditions occurring during a certain time interval for which the design will demonstrate that relevant limit states are not exceeded

[SOURCE: IEC 61400-6]

3.12

effect of actions

effect of actions (or action effect) on structural members or on the whole structure

Note 1 to entry: Internal force, moment, stress and strain are examples of action effect on structural members. Deflection and rotation are examples of action effect on the whole structure.

[SOURCE: IEC 61400-6]

3.13

fatigue limit state

structural failure due to damage accumulation under effects of repeated loading

[SOURCE: IEC 61400-6]

3.14

serviceability limit state

state which corresponds to conditions beyond which specified service requirements for a structure or structural element are no longer met

[SOURCE: IEC 61400-6]

3.15

ultimate limit state

limit states which generally correspond to the maximum load bearing capacity

Note 1 to entry: This generally corresponds to the maximum load-carrying resistance of a structure or structural element but in some cases to a strain or deformation limit.

[SOURCE: IEC 61400-6]

3.16**reliability**

ability of a structure or structural member to fulfil the specified requirements, during the working life, for which it has been designed.

Note 1 to entry: Reliability is often expressed in terms of probability.

Note 2 to entry: Reliability covers safety, serviceability, and durability of a structure.

[SOURCE: ISO 2394]

3.17**structural safety**

ability (of a structure or structural member) to avoid exceedance of ultimate limit states, including the effects of specified accidental phenomena, with a specified level of reliability, during a specified period of time

[SOURCE: ISO 2394]

3.18**reliability-based design**

design procedure that is subjected to prescribed reliability level of the structure

[SOURCE: ISO 2394]

3.19**member reliability**

reliability of a single structural member which has one single dominating failure mode

[SOURCE: ISO 2394]

3.20**system reliability**

reliability of a system of more than one relevant structural member or a structural member which has more than one relevant failure mode

[SOURCE: ISO 2394]

3.21**resistance**

ability of a structure (or a part of it) to withstand actions without failure

[SOURCE: ISO 2394]

3.22**target reliability**

specified average acceptable failure probability that is to be reached as close as possible

Note 1 to entry: Reliability targets are generally model dependent and need to be set for each case considered based on the models used.

[SOURCE: ISO 2394]

3.23

reliability-based design

A design procedure that is subjected to prescribed reliability level of the structure.

[SOURCE: ISO 2394]

3.24

risk-informed design

design optimized with due consideration of the total risks, including loss of lives and injuries, damages to the qualities of the environment, and monetary losses

Note 1 to entry: Risk-based design is presently not generally accepted by all national standards and codes.

[SOURCE: ISO 2394]

3.25

robustness

ability of a structure to withstand adverse and unforeseen events (like fire, explosion, impact) or consequences of human errors without being damaged to an extent disproportionate to the original cause

[SOURCE: ISO 2394]

3.26

hazard

unusual and severe threat, e.g. a possible abnormal action or environmental influence, insufficient strength or stiffness, or excessive detrimental deviation from intended dimensions

[SOURCE: ISO 2394]

3.27

limit state

state beyond which a structure no longer satisfies the design criteria

[SOURCE: ISO 2394]

3.28

serviceability limit states

limit state concerning the criteria governing the functionalities related to normal use

[SOURCE: ISO 2394]

3.29

limit state function

function $g(X_1, X_2, \dots, X_n)$ of the basic variables, which characterizes a limit state when $g(X_1, X_2, \dots, X_n) = 0$

[SOURCE: ISO 2394]

3.30

basic variables

variables representing physical quantities which characterize actions and environmental influences, material and soil properties, and geometrical quantities

204 [SOURCE: ISO 2394]

205 **3.31**

206 **design service life**

207 assumed period for which a structure or a structural member is to be used for its intended
208 purpose with anticipated maintenance, but without substantial repair being necessary

209 [SOURCE: ISO 2394]

210 **3.32**

211 **model uncertainty**

212 basic variable related to the accuracy of physical or statistical models

213 [SOURCE: ISO 2394]

214 **3.33**

215 **aleatory uncertainty**

216 inherent variability typically associated with the loading environment, the geometry of the
217 structure, and the material properties

218 [SOURCE: ISO 2394]

219 **3.34**

220 **epistemic uncertainty**

221 lack of knowledge that, in principle, can be reduced by measurements or improved theories

222 Note 1 to entry: The exact borderline between aleatory and epistemic is not always unambiguous.

223 [SOURCE: ISO 2394]

224 **3.35**

225 **hierarchical modelling of uncertainty**

226 random variable is a function of other random variables

227 [SOURCE: ISO 2394]

228 **3.36**

229 **probabilistic methods**

230 verification methods in which the relevant basic variables are treated as random variables,
231 random processes, and random fields, discrete or continuous

232 [SOURCE: ISO 2394]

233 **3.37**

234 **reliability index**

235 β

236 substitute for the failure probability $\beta = \Phi^{-1}(P_f)$ where Φ^{-1} is the inverse standardized normal
237 distribution

238 [SOURCE: ISO 2394]

239 **3.38**

240 **structural model**

241 idealisation of the structure, physical, mathematical, or numerical, used for the purposes of
242 analysis, design, and verification

[SOURCE: ISO 2394]

3.39

First/Second Order Reliability Methods - FORM/SORM

numerical methods used for determination of the reliability index β

[SOURCE: ISO 2394]

3.40

reference period

period of time used as a basis for assessing the design value of variable and/or accidental actions

[SOURCE: ISO 2394]

3.41

load effect

effect of actions (loads) is a result of actions on a structural member (e.g. internal force, moment, stress, strain) or on the whole structure (e.g. deflection, rotation)

[SOURCE: based on ISO 2394]

4 Symbols and abbreviations

4.1 Symbols and units

TO BE COMPLETED FOR THE FINAL VERSION OF THE TEXT

C	scale parameter of the Weibull distribution function	[m/s]
c	environmental conditions	[-]
D	rotor diameter	[m]
D_{adm}	admissible damage level	[-]
$D(t)$	accumulated damage at time t	[-]
E	event	[m]
I_{ref}	reference value of the turbulence intensity corresponding to the 70 % quantile at 15 m/s	[-]
I_{eff}	effective turbulence intensity	[-]
k	shape parameter of the Weibull distribution function	[-]
m	Wöhler curve exponent	[-]
n_i	counted number of fatigue cycles in load bin i	[-]
$N(.)$	number of cycles to failure as a function of the stress (or strain) indicated by the argument (i.e. the characteristic S-N curve)	[-]
N	return period for extreme situations	[years]

p	air pressure	[N/m ²]
$P(-)$	probability	[-]
P_f	probability of failure	[-]
ΔP_f	annual probability of failure	[-]
$P_{f E}$	probability of failure conditional on event E	[-]
$P_{f E,v,c}$	probability of failure conditional on an event E , mean wind speed v and specific wind conditions c	[-]
$g(.)$	limit state equation	[-]
$F_X(x)$	probability distribution function for a stochastic variable X	[-]
$f_X(x)$	probability density function for a stochastic variable X	[-]
X	stochastic variable	[-]
K	material parameter of the SN-curve	[-]
θ	statistical parameters in probability distribution functions $F_X(x \theta)$	[-]
Y	stochastic variable in hierarchical stochastic model	[-]
P_s	survival probability	[-]
S	load effect	[-]
L	load effect	[-]
N_{ref}	reference number of cycles for the equivalent load	[-]
L_E	is the extreme load effect during event E	[-]
R	resistance	[-]
R	stress ratio	[-]
T_L	design lifetime	[y]
v	mean wind speed	[-]
s_i	the stress (or strain) level associated with the counted number of cycles in bin i	[-]
T	gust characteristic time	[s]
t	time	[s]
V	wind speed	[m/s]
$V(z)$	wind speed at height z	[m/s]
V_{ave}	annual average wind speed at hub height	[m/s]
V_{cg}	extreme coherent gust magnitude over the whole rotor swept area	[m/s]
V_{eN}	expected extreme wind speed (averaged over three seconds), with a recurrence time interval of N years. V_{e1} and V_{e50} for 1 year and 50 years, respectively	[m/s]
V_{gust}	largest gust magnitude with an expected return period of 50 years	[m/s]
V_{hub}	wind speed at hub height	[m/s]
V_{in}	cut-in wind speed	[m/s]
V_{50}	extreme wind speed (averaged over 10 minutes) with a recurrence interval of 50 years	[m/s]

V_{100}	extreme wind speed (averaged over 10 minutes) with a recurrence interval of 100 years	[m/s]
V_{out}	cut-out wind speed	[m/s]
V_r	rated wind speed	[m/s]
V_{ref}	reference wind speed	[m/s]
$V_{\text{ref,T}}$	reference wind speed for tropical-like conditions	[m/s]
$V(y,z,t)$	longitudinal wind velocity component to describe transient horizontal wind shear	[m/s]
X_M	random variable representing a model uncertainty for M	[-]
W_X	random variable representing an environmental parameter X	[-]
x, y, z	co-ordinate system used for the wind field description; along wind (longitudinal), across wind (lateral) and height respectively	[m]
z_{hub}	hub height of the wind turbine	[m]
z_r	reference height above ground	[m]
z_0	roughness length for the logarithmic wind profile	[m]
α	wind shear power law exponent	[-]
β	parameter for extreme direction change model	[-]
β	Reliability index	[-]
γ_f	partial safety factor for loads	[-]
Δ	Uncertainty on the Palmgren-Miner damage summation model	[-]
γ_M, γ_R	partial safety factor for resistances	[-]
λ_F	annual failure rate	
λ_E	rate of events	
$\theta(t)$	wind direction change transient	[deg]
θ_{cg}	angle of maximum deviation from the direction of the average wind speed under gust conditions	[deg]
θ_{eN}	extreme direction change with a return period of N years	[deg]
Λ_1	turbulence scale parameter defined as the wavelength where the non-dimensional, longitudinal power spectral density, $fS_1(f)/\sigma_1^2$, is equal to 0,05	[m]
ρ	air density	[kg/m ³]
σ_1	hub-height longitudinal wind velocity standard deviation	[m/s]
Φ	standardized normal probability distribution function	[-]
φ	standardized normal probability density function	[-]
σ_{lim}	Component capacity (e.g. yield strength, tensile strength) in terms of limiting stress level	MPa
σ_m	Mean stress	MPa
σ_R	stress range	MPa
S_u	ultimate limit strength	MPa

σ_Y yield strength of the material

MPa

4.2 Abbreviated terms

COV	coefficient of variation
DLC	design load case
ECD	extreme coherent gust with direction change
EDC	extreme wind direction change
EOG	extreme operating gust
ETM	extreme turbulence model
EWM	extreme wind speed model
EWS	extreme wind shear
FMEA	failure mode and effect analysis
FORM	First Order reliability Method
FRT	fault ride through
IFORM	Inverse First-Order Reliability Method
SORM	Second Order reliability Method
NWP	normal wind profile model
NTM	normal turbulence model
ULS	ultimate limit state
FEM	Finite Element Method
LSE	Limit State Equation
LVRT	Low Voltage Ride Through
PSF	Partial Safety Factor
RNA	Rotor Nacelle Assembly
S-N	Stress- Cycle Curve for fatigue of materials
PSHA	probabilistic seismic hazard analyses

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5 Principal elements

5.1 General

The following clauses specify essential requirements to the use of probabilistic design measures in order to ensure the structural and mechanical integrity of wind turbines. The specification of requirements applies to the design, siting and reassessment of a wind turbine system and its components, accounting for validated influences of the manufacturing, operations, and maintenance, and site-specific environmental conditions.

This document provides appropriate methodologies, probabilistic models, and requirements for probabilistic assessment of components in line with IEC61400-1. Probabilistic assessment is an alternative to the semi-probabilistic (deterministic) assessment procedures given in IEC 61400-1. The reliability assessment is performed for individual components and failure modes, and the resulting system reliability is implicitly accepted. The designer may select components and failure modes for probabilistic assessment, while the remaining failure modes shall be verified using traditional semi-probabilistic methods. It is allowed to do a full probabilistic analysis, or use probabilistic methods to calibrate specific partial safety factors for use in semi-probabilistic assessment. Specific partial safety factors for a subset of limit states should be calibrated such that the average reliability over the subset is as close to the target reliability as possible. In IEC 61400-1, the same partial safety factors are applied for a range of load cases, components, and environmental conditions, and as a result the obtained reliability level may deviate from the target reliability specified in this document. Deviations from the methodologies, probabilistic models, and requirements are allowed if properly justified.

The main steps in a reliability assessment for a selected component and failure mode are the following:

- a) Determine appropriate consequence class and target annual reliability index (see 5.2)
- b) Model specification
 - i) Formulate limit state equations (see 7)
 - ii) Develop appropriate probabilistic models for the variables in the limit state equations (see 6 and additionally 9 for siting)
- c) Reliability analysis
 - i) Perform a reliability analysis and compute the annual reliability index (see 8)
 - ii) Assess the accuracy of the computation and perform sensitivity studies (see 8)
- d) Assessment
 - i) For design situations: Perform a design optimization loop over steps b)-c) until a design is found where the target reliability is reached or exceeded in all years of the planned lifetime.
 - ii) For siting: The component has sufficient reliability on a site if the target reliability is reached or exceeded in all years of the planned lifetime.
 - iii) For reassessment: The component has sufficient reliability for continued operation for as many years as the target reliability is reached or exceeded.

The reliability model and assessment procedure should undergo verification by comparing the results of the reliability analysis with the result of a deterministic analysis for a baseline model.

5.2 Target Reliability Level and Component Classes

In Table 1 target reliability levels are given dependent on the consequence of failure (component class)¹ for ultimate limit states. The target reliability level may be achieved through a combination of design, prescribed scheduled maintenance and parts replacement, and health monitoring. For fatigue limit states, the target is given for the annual reliability index in the last year of the design lifetime. For limit states related to the ultimate strength, the target is given for the year with the largest annual failure probability, typically the first year of operation. Exceptions to these target reliabilities should be permitted if justified based on ISO 2394². Reliability targets for serviceability limit states should be defined based on their consequences, see ISO 2394 and JCSS PMC. Target reliabilities for special safety class wind turbines should be agreed between the manufacturer, customer and relevant authorities.

Table 1 – Target reliability levels.

Component class	Annual target probability of failure	Annual target reliability index
Component class 1	$2 \cdot 10^{-3}$	2.9
Component class 2	$5 \cdot 10^{-4}$	3.3
Component class 3	$5 \cdot 10^{-5}$	3.9

5.3 Limit States

For the failure modes selected for probabilistic assessment, limit state equations should be formulated based on the deterministic design equation, representing variables by their probability distributions, instead of using characteristic values and partial safety factors. Uncertainties related to external conditions, load assessment, and resistance (as described further in chapter 6) should be included either directly (e.g. the input variable is represented directly as a random variable in the limit state equation) or indirectly (e.g. the effect of uncertainty on one or more variables is represented as a model uncertainty multiplied on the load effect) in the limit state equation.

Reliability assessments may be performed for ultimate and serviceability limit states such as:

- Exceedance of the ultimate strength
- Fatigue failure
- Static Instability
- Dynamic Instability
- Component interference due to deformation
- Extreme vibrations
- Loss of control functionality
- Permanent deformations

5.4 Data Validity

Probabilistic models for physical quantities should be based on representative data, and model uncertainties should be assessed to the degree possible through a combination of tests and measurements such as:

- Material tests
- Test of sub-components / scaled components

¹ If human health and/or environment is at risk, a site-specific risk assessment with failure modes of tower collapse and throwing parts is to be performed, as defined in IEC TS 61400-31.

² Changes to the target reliability for specific cases can be motivated by e.g. the consequence of failure, cost of safety measure, or the level of uncertainties.

- 367 – Full-scale component tests
- 368 – Load measurement campaigns (e.g. prototype testing)
- 369 – Environmental data (e.g. met-mast data)
- 370 – Operational data
- 371 The availability of data depends on whether the reliability assessment is made in relation to
- 372 design, siting, or reassessment. Examples of typical situations and available data are:
- 373 – Design of RNA components for an IEC class or class S turbine (tests on material and sub-
- 374 components, data from other wind turbine models)
- 375 – Site-specific design of tower, sub-structure and/or foundations, or site assessment of an
- 376 IEC class or class S turbine for a specific site (tests on material and components, load
- 377 measurement campaigns, environmental data)
- 378 – Re-assessment of a wind turbine during or near the end of the operational phase (tests on
- 379 material and components, load measurement campaigns, environmental data, operational
- 380 data, condition
- 381 – monitoring data)
- 382 – The possible influence of the following sources of uncertainty should be included in the
- 383 analysis where relevant: Deviation in raw material quality
- 384 – Nonconformity of finished parts to quality control specifications
- 385 – Unknown part defects outside the scope of QC specifications (i.e., incomplete CTQ
- 386 specifications due to incomplete knowledge)
- 387 – Nonconformity of installation procedures to specifications
- 388 – Site environmental conditions
- 389 – Variability in operational practices, including controller issues
- 390 – Variability in maintenance practices
- 391 – Nonconformity of component repairs with specifications or standard industry practice.

392

393

6 Uncertainty representation and modelling

6.1 General

The uncertainties associated with the external conditions, load assessment, structural resistance and electrical / mechanical component reliability related to wind turbine control or safety system should be modelled for the wind turbine lifetime as part of a reliability analysis.

6.1.1 Types of uncertainty

Various sources of uncertainty as for example natural / physical variability, statistical uncertainties, measurement uncertainties and model uncertainties exist.

The natural / physical uncertainties are typically uncertainties related to the external conditions, the geometry of the structure and the material properties and are often referred to as aleatory uncertainties.

The statistical uncertainties originate from limited information and data about external conditions, material properties, load validation etc. and are often referred to as epistemic uncertainties.

The measurement uncertainties originate from uncertainty in measurement setup, equipment, calibration or analysis of tests and are often referred to as epistemic uncertainties. The list of contributions to measurements uncertainty should be as complete as reasonable for the application and reflect the information available about accuracy.

The model uncertainties originate from idealizations and imperfections associated with describing a physical phenomenon using mathematical models. This includes the formulation of the models (M), that attempt to represent the real world (Y) based on a given input (X), as well as the parameters (θ) of the model that are subject to uncertainty, see Figure 1. Model uncertainty is e.g. associated with aeroelastic models, finite element models, reduced-order representations, simplifications in failure criteria definitions and are often referred to as epistemic uncertainties.

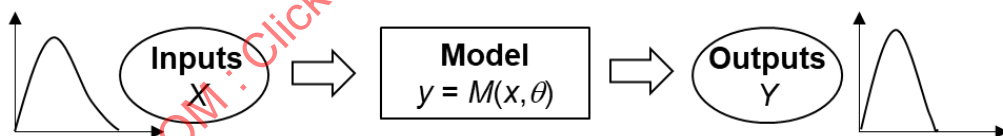


Figure 1 – Application of a mathematical model to estimate an output based on a given input.

Uncertainties can be aleatory or epistemic and can change nature in different phases of the lifetime of a wind turbine. For example, a material property can be considered as aleatory before the manufacturing of a wind turbine, once the wind turbine is manufactured, it can be considered as an epistemic uncertainty.

6.1.2 Interpretation of probability and treatment of uncertainty

In structural reliability analysis, the Bayesian interpretation of probability should be considered as the most adequate basis for the consistent representation of uncertainties, independent of their sources. It facilitates the joint consideration of analytically assessed uncertainties, evidence as obtained through observations and subjectively assessed uncertainties (expert knowledge).

Subjective information can e.g. be used to quantify the expected variation for a very limited test sample based on previous test samples or to quantify physical or model uncertainties which either cannot or are not practically possible to measure. However, subjectively assessed uncertainties should be used with caution and the information used should be documented and preferable obtained through a structured process as e.g. Cooke (1991).

In Bayesian probability theory, the values for probabilities are estimated based on an adequate combination of data, theoretical arguments, and judgment. There is no distinction in the treatment between aleatory and epistemic uncertainty. If large amounts of data are available, the Bayesian interpretation coincides with the frequentist one.

Considering the probabilistic modelling of a random basic variable X , the principle in Bayesian probability analysis is to model one or more of the parameters θ (e.g. the mean and standard deviation) of the probabilistic model (e.g. the probability distribution function) as random variables themselves. The frequentist or subjective information available about X can then be used in the probabilistic modelling of θ .

All uncertainties that are of importance for the reliability analysis of a wind turbine or parts thereof should be considered in the analysis using the theory of probability. A systematic approach based on a hierarchy of uncertainties can support the identification of contributions to uncertainty.

6.1.3 Probabilistic model

Depending on the nature of the reliability problem, basic variables can be represented as random variables, random processes and random fields, discrete as well as continuous.

The probabilistic models should describe the uncertainties of individual random basic variables, but also accommodate the consideration of the dependencies among them.

Dependencies often arise due to causality, spatial and/or temporal correlations and/or ergodic states of underlying phenomena, as well as statistical and/or model uncertainties that commonly affect the uncertainties of the individual variables.

The uncertainty in the basic variables and the dependencies among them can normally be modelled by probability distribution functions $f_X(X|\theta)$ and correlation coefficients ρ focussing on the application of interest (e.g. extreme values).

A dependent or hierarchical modelling is recommended, where applicable. The dependent or hierarchical model assumes that a random quantity Y can be written as a function of several variables, each one representing a specific type of variability:

$$Y_{ijk} = f(X_i, X_{ij}, X_{ijk}) \quad (1)$$

The variables X_i , X_{ij} , X_{ijk} represent various origins, time scales of fluctuation, or spatial scales of fluctuation. This modelling approach is for example relevant for the wind conditions, where the wind speed standard deviation σ_1 (turbulence) is dependent on e.g. the 10min mean wind speed V_{hub} and terrain roughness.

The probabilistic models should when relevant also accommodate the updating of the models by additional information, which can become available with, for example, experiments, tests, inspections, and monitoring. The Bayesian updating formula provides the operational basis for this.

The description of uncertain quantities by probabilistic models should correspond to well-defined outcome spaces (or populations) and the results of the reliability analysis are only valid for the same sets.

The probabilistic models can be determined based on information from different e.g. wind turbine types, design concepts or site conditions. In these cases, it should be justified that the probabilistic model is representative and potential residual uncertainty should be covered by model uncertainty.

6.1.4 Uncertainties for wind turbines

The typical flow chart and uncertainties which should be considered in probabilistic design for wind turbines are shown in Figure 2 and the principles for assessment of the individual uncertainties are described in the following sub-sections.

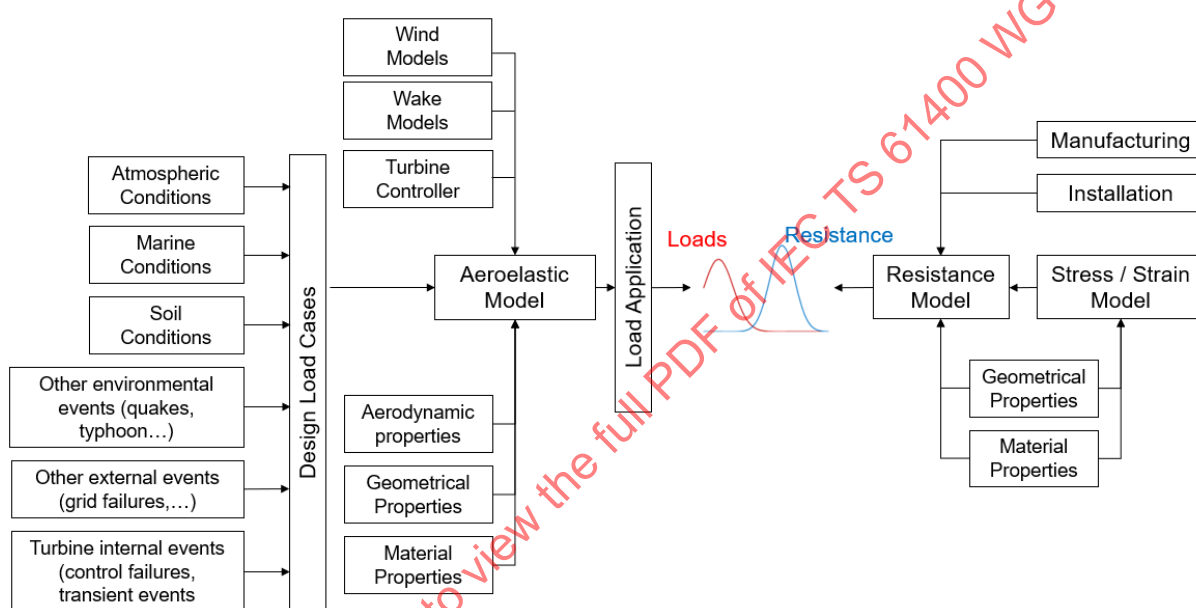


Figure 2 – Typical flow chart and uncertainties to be considered in probabilistic design of wind turbine components.

The *design load cases* defined in IEC 61400-1, IEC 61400-3-1 and IEC 61400-3-2 specify the minimum number of design situations which should be considered. The uncertain input to the design load cases is listed in the following:

- *Atmospheric conditions* represent the uncertainty in e.g. mean wind speed, extreme wind speed (incl. tropical cyclones), turbulence, wind shear, air density and gust events.
- *Marine conditions* represent the uncertainty in e.g. wave conditions, current, tides and storm surge.
- *Other environmental events* represent the uncertainty in e.g. temperature, lightning, ice conditions and earthquakes.
- *Other external events* represent the uncertainty in e.g. grid fault, loss of electrical network, low voltage ride through.
- *Turbine internal events* represent the uncertainty in e.g. controller failures (primary and secondary layer protection functions), overspeed, actuators and braking systems.

499 The *aeroelastic model* is normally relying on a number of sub-models:

- 500 • *Wind models* represent the uncertainty in e.g. the Mann or Kaimal turbulence models.
- 501 • *Wake models* represent the uncertainty in e.g. the added wake turbulence method or
- 502 dynamic wake meandering model.
- 503 • *Turbine controller* represents the uncertainty in e.g. a simplified controller
- 504 implementation.

505 Additionally, the *aeroelastic model* is based on some input parameters which normally are

506 constant for the different design load cases:

- 507 • *Aerodynamic properties* represent the uncertainty in e.g. lift and drag coefficients.
- 508 • *Geometrical properties* represent the uncertainty in e.g. thickness and length.
- 509 • *Soil / Material properties* represent the uncertainty in e.g. stiffness.

510 The aero-elastic simulations are normally post-processed in order to determine the input to the

511 resistance model:

- 512 • *Load application* represent the uncertainty in e.g. extrapolation, contemporaneous
- 513 loads, rainflow cycle counting and Miner's rule.

514 The *resistance model* or failure criteria is based on the following input parameters:

- 515 • *Manufacturing* represents the uncertainty in e.g. the manufacturing quality.
- 516 • *Installation* represents the uncertainty in e.g. the installation process and quality.
- 517 • *Geometrical properties* represent the uncertainty in e.g. thickness and length.
- 518 • *Material properties* represent the uncertainty in e.g. stiffness and strength.

519 Additionally, the resistance model is often dependent on a sub-model

- 520 • *Stress / Strain model* represent the uncertainty in stress and strain assessment for a
- 521 load application e.g. through a finite-element model.

522 The individual physical, model, measurement and statistical uncertainties can be quantified

523 directly and propagated through the flow chart in order to determine the resulting uncertainty in

524 the load or resistance. Alternatively, the resulting uncertainty on load or resistance can be

525 determined directly by other means.

526 **6.2 External condition uncertainty modelling**

527 **6.2.1 General**

528 The external conditions refer to the environmental and electrical conditions which affect the

529 wind turbine or parts thereof. Environmental conditions can in general be separated into wind,

530 marine, soil and other conditions.

The individual environmental conditions should be modelled by stochastic models established based on the standard conditions used for IEC class verification as defined in IEC 61400-1, IEC 61400-3-1 and IEC 61400-3-2 or representative measurements for the quantity and application of interest. The term “representative” should be considered in relationship to the measurements available and expert knowledge used for defining the standard conditions used for IEC class verification.

The standard conditions cover along with the design load cases in IEC 61400-1, IEC 61400-3-1 and IEC 61400-3-2 the relevant design situations for a wind turbine for which stochastic models may be established.

Uncertainty representation and modelling for site specific conditions are described in chapter 9.

6.2.2 Wind conditions

The atmospheric conditions can in general be separated into the standard wind conditions and other conditions defined in IEC 61400-1. The standard wind conditions are generally established by determining a characteristic value (typically 50 year value) for a single wind parameter or wind event e.g. turbulence or gust. The potential interaction of the individual wind conditions and non-linear interaction of the wind turbine controller can influence the wind turbine response and should if relevant be considered when the stochastic models are established.

Probabilistic models established for IEC class type certification (I-III & A+-C) should be based on the probabilistic models defined in IEC 61400-1 when available. Other wind conditions may be modelled by probabilistic models when these are in alignment with the general design philosophy in IEC 61400-1. As an example, the air density can be modelled by a probabilistic model with mean value equal to 1.225 kg/m^3 as specified in IEC 61400-1 and other parameters determined based on a few reference sites. Probabilistic models established for IEC class “S” should be specified by the designer.

Alternatively, probabilistic models may be established based on representative wind or turbine measurements from a few reference sites. The probabilistic models may be developed by identifying the standard wind conditions (e.g. gusts or wind direction changes) from IEC 61400

-1 in wind or turbine measurements with a sufficient resolution to cover the spatial and time fluctuations. The probabilistic models should beyond the physical uncertainty in the wind conditions also represent the measurement and statistical uncertainty in the wind measurements used to establish them.

The turbulence model describes the spatial and time variation in the wind velocity field established through longitudinal, lateral and upward vector components, generally consistent with a specified 10-min average wind speed at hub height and reference turbulence intensity, see IEC 61400-1 Annex C. The model and statistical uncertainty related to the turbulence model should be quantified e.g. as part of the load uncertainty modelling, see section 6.3.

6.2.2.1 Normal wind conditions

The normal wind conditions are represented by the mean wind speed distribution, the Normal Wind Profile (NWP) and the Normal Turbulence Model (NTM) in IEC 61400-1.

The mean wind speed distribution $F_{V_{hub}}(V_{hub})$ for the wind speed at hub height V_{hub} (10min reference period) is according to IEC 61400-1 defined as a Rayleigh distribution for the different IEC classes.

$$F_{V_{hub}}(V_{hub}) = 1 - \exp \left[-\pi \left(\frac{V_{hub}}{2 V_{ave}} \right)^2 \right] \quad (2)$$

where V_{ave} is the annual average wind speed. The Rayleigh distribution is a special case of the more general Weibull distribution which normally is used to characterize the mean wind speed distribution in probabilistic models.

$$F_{V_{hub}}(V_{hub}) = 1 - \exp \left[- \left(\frac{V_{hub}}{A} \right)^k \right] \quad (3)$$

where A and k are the scale and shape parameter. The NWP represent a deterministic wind profile (no turbulence) modelling the variation of mean wind speed over the rotor using average (near-neutral boundary layer) conditions for wind shear and air density. The NWP is used in combination with specific controller actions like start-up or shutdown and serves as the basis upon which other wind events are added. Uncertainty modelling for the NWP is therefore normally not relevant or replaced by other specific wind conditions as e.g. the NTM model.

The NTM represent normal stochastic wind (turbulence) conditions using a distribution for the turbulence and average conditions for wind shear and air density to model normal operating conditions. The stochastic representation of the NTM should according to IEC 61400-1 be based on a Weibull distribution $F_{\sigma_1}(\sigma_1)$ for the wind speed standard deviation σ_1 (10min reference period) for IEC class verification.

$$F_{\sigma_1}(\sigma_1) = 1 - \exp \left(- \left(\frac{\sigma_1}{C} \right)^k \right) \quad (4)$$

$$k = 0.27 V_{hub}(\text{s/m}) + 1.4 \quad (5)$$

$$C = I_{ref}(0.75 V_{hub} + 3.3\text{m/s}) \quad (6)$$

where C and k are the scale and shape parameter and I_{ref} is the reference turbulence intensity according to IEC 61400-1. The uncertainty modelling for the NTM should cover the natural variation of mean wind speed and turbulence. Additionally, the uncertainty modelling may cover variations in wind shear, air density and wind direction along with the potential dependence / correlation between these due to different atmospheric stability conditions.

6.2.2.2 Extreme wind conditions

The extreme wind conditions are in IEC 61400-1 represented by the Extreme Wind Model (EWM), Extreme Operation Gust (EOG), Extreme Turbulence Model (ETM), Extreme Direction Change (EDC), Extreme Coherent gust with Direction change (ECD) and Extreme Wind Shear (EWS). These events are defined to cover all relevant extreme wind conditions for a wind turbine and are defined by extrapolation of a single wind parameter or wind event. The events should therefore in general not be combined with variations in other wind conditions.

The stochastic models for the extreme wind conditions should correspond to an annual reference period when combined with specific operational states e.g. grid-loss, start-up or shutdown. This ensures consistency with the target reliability level specified in 5.

The EWM represents conditions with extreme wind speeds. The EWM is in IEC 61400-1 defined by the maximum 10min mean wind speed with a return period of 1 year and 50 years, which represent the characteristic value.

$$V_{50} = V_{ref} \quad (7)$$

The uncertainty modelling for the EWM should represent the physical uncertainty in the annual maximum wind speed which for extratropical storms can be modelled by a Gumbel distribution with a typical coefficient of variation equal to 12% for IEC class verification.

The EOG represents the extreme gust which occurs together with a specific operation event such as a start-up, shut-down or electrical fault to give a combined return period of 50 years. The EOG can according to IEC 61400-1 be replaced with the NTM model for DLC 2.3 and by the ETM model for DLC 3.2 and 4.2 offering an easier combination with specific operational states.

The EOG is in IEC 61400-1 defined by a gust profile expressed in space over the event duration and described by the gust magnitude V_{gust} (which for current wind turbine design is defined by the second term in equation (9)) and duration T .

$$V_{gust} = \beta \left(\frac{\sigma_1}{1 + 0.1 \left(\frac{D}{\Lambda_1} \right)} \right) \quad (8)$$

$$V(z, t) = \begin{cases} V(z) - 0.37V_{gust} \sin(3\pi t/T)(1 - \cos(2\pi t/T)) & \text{for } 0 \leq t \leq T \\ V(z) & \text{otherwise} \end{cases} \quad (9)$$

The uncertainty modelling for the EOG should represent the uncertainty in the annual maximum gust magnitude and duration. The gust profile can be considered deterministic along with the parameters Λ_1 , D and σ_1 (90% quantile). The gust magnitude and duration can be assumed fully correlated and can be modelled by a Gumbel distribution based on the return periods defined in Table 2. A simplified uncertainty model for the EOG can be obtained by only modelling the gust magnitude probabilistically, while assuming the duration is deterministic ($T=10.5s$).

Table 2 – EOG parameters for different return periods.

Return Period	Gust Magnitude (V_{gust})	Duration (T)
IEC 61400-1 Ed.4	$\beta = 3.3$	$T = 10.5s$
1 year	$\beta = 4.8$	$T = 10.5s$
50 year	$\beta = 6.4$	$T = 14.0s$

The ETM represents the 50 year extreme turbulence conditions at a given mean wind speed V_{hub} , based on the Inverse First Order Reliability Method (IFORM) using the models for the normal wind conditions in 6.2.2.1, see Annex B. Alternatively, the uncertainty model for the ETM can be represented by the conditional distribution for the annual extreme turbulence at a given mean wind speed.

The EDC represent the extreme direction change which occur together with a specific operation event such as a start-up with a return period of 50 years. The EDC is in IEC 61400-1 defined by a wind direction variation, expressed over the event duration, which is described by the extreme direction change magnitude θ_e and duration T .

$$\theta_e = \pm \beta \arctan \left(\frac{\sigma_1}{V_{hub} \left(1 + 0.1 \left(\frac{D}{A_1} \right) \right)} \right) \quad (10)$$

$$\theta(t) = \begin{cases} 0^\circ & \text{for } t < 0 \\ \pm 0.5 \theta_e (1 - \cos(\pi t/T)) & \text{for } 0 \leq t \leq T \\ \theta_e & \text{for } t > T \end{cases} \quad (11)$$

634 The uncertainty modelling for the EDC should represent the uncertainty in the annual extreme
635 wind direction change. The wind direction profile and duration can be considered deterministic
636 along with the parameters Λ_1 , D and σ_1 (90% quantile). The extreme wind direction change can
637 be modelled by a Gumbel distribution based on the return periods defined in Table 3.

638 **Table 3 – EDC parameters for different return periods.**

Return Period	Extreme Direction Change (θ_e)	Duration (T)
IEC 61400-1 Ed. 4	$\beta = 4.0$	$T = 6s$
1 year	$\beta = 4.8$	$T = 6s$
50 year	$\beta = 6.4$	$T = 6s$

639 The ECD represents the 50 year extreme coherent gust with direction change occurring during
640 normal operating conditions. The ECD is in IEC 61400-1 defined by a gust and wind direction
641 variation, expressed over the event duration, which is described by the coherent gust magnitude
642 V_{cg} , wind direction change magnitude θ_{cg} and duration T .

$$V(z, t) = \begin{cases} V(z) & \text{for } t < 0 \\ V(z) \pm 0.5 V_{cg} (1 - \cos(\pi t/T)) & \text{for } 0 \leq t \leq T \\ V(z) + V_{cg} & \text{for } t > T \end{cases} \quad (12)$$

$$\theta_{cg} = \begin{cases} 180^\circ & \text{for } V_{hub} < 4m/s \\ 720^\circ & \text{for } 4m/s < V_{hub} < V_{ref} \\ \frac{720^\circ}{V_{hub}} & \end{cases} \quad (13)$$

$$\theta(t) = \begin{cases} 0^\circ & \text{for } t < 0 \\ \pm 0.5 \theta_{cg} (1 - \cos(\pi t/T)) & \text{for } 0 \leq t \leq T \\ \pm \theta_{cg} & \text{for } t > T \end{cases} \quad (14)$$

643 The uncertainty modelling for the ECD should represent the uncertainty in the annual extreme
644 coherent gust and wind direction change. The gust profile, wind direction profile and duration
645 ($T=10s$) can be considered deterministic. The annual extreme coherent gust magnitude and
646 wind direction change can be assumed fully correlated and can be modelled by a Gumbel
647 distribution with a coefficient of variation of 10%.

648 The EWS represents the 50 year extreme transient events with horizontal and vertical wind
649 shear. The EWS is in IEC 61400-1 defined by a wind speed profile for the event duration, which
650 is described by the wind shear magnitude parameter β and duration T .

651 Transient (positive and negative) vertical shear:

$$V(z, t) = \begin{cases} V_{hub} \left(\frac{z}{z_{hub}} \right)^\alpha \pm \left(\frac{z - z_{hub}}{D} \right) \left(2.5 \left[\frac{m}{s} \right] + 0.2 \beta \sigma_1 \left(\frac{D}{\Lambda_1} \right)^{1/4} \right) (1 - \cos(2\pi t/T)) & \text{for } 0 \leq t \leq T \\ V_{hub} \left(\frac{z}{z_{hub}} \right)^\alpha & \text{otherwise} \end{cases} \quad (15)$$

652 Transient horizontal shear:

$$V(y, z, t) = \begin{cases} V_{hub} \left(\frac{z}{z_{hub}} \right)^\alpha \pm \left(\frac{y}{D} \right) \left(2.5 \left[\frac{m}{s} \right] + 0.2 \beta \sigma_1 \left(\frac{D}{\Lambda_1} \right)^{1/4} \right) (1 - \cos(2\pi t/T)) & \text{for } 0 \leq t \leq T \\ V_{hub} \left(\frac{z}{z_{hub}} \right)^\alpha & \text{otherwise} \end{cases} \quad (16)$$

653 The uncertainty modelling for the EWS should represent the uncertainty in the annual extreme
 654 horizontal and vertical wind shear magnitude. The wind speed profile and duration can be
 655 considered deterministic along with the parameters Λ_1 , D and σ_1 (90% quantile). The annual
 656 extreme horizontal and vertical wind shear magnitude parameter β can be modelled by a
 657 Gumbel distribution based on the return periods defined in Table 4.

658 **Table 4 – EWS parameters for different return periods.**

Return Period	Extreme Wind shear magnitude	Duration (T)
IEC 61400-1 Ed. 4	$\beta = 6.4$	$T = 12s$
1 year	$\beta = 4.8$	$T = 12s$
50 year	$\beta = 6.4$	$T = 12s$

659 6.2.3 Other conditions

660 Other atmospheric conditions include e.g. wake conditions, tropical cyclones, ice formation and
 661 extreme temperatures are listed in IEC 61400-1 and IEC 61400-3-1.

662 Wake conditions may be modelled according to IEC 61400-1 Annex E. The model uncertainty
 663 related to the wake modelling should represent the fidelity and validation of the model, see 6.3.
 664 Additionally, the physical and statistical uncertainty in the wake conditions and the frequency
 665 of their occurrence should be considered.

666 Tropical cyclone conditions may be represented by the Extreme Wind Model (EWM), but the
 667 coefficient of variation (COV) for the annual extreme wind speed / pressure is normally higher
 668 than for other extreme wind conditions and should therefore be representative for these events.

669 Ice formation may be modelled according to IEC 61400-1 Annex L. The physical and model
 670 uncertainty in the accretion of ice or snow on the structure should be considered along with the
 671 frequency of occurrence.

672 The additional environmental conditions listed in IEC 61400-1 and IEC 61400-3-1 (with the
 673 exception of earthquakes and tsunamis) can in most probabilistic analysis be represented by a
 674 deterministic value corresponding to the expected value or a low / high quantile. In case the
 675 additional environmental conditions have a significant impact on the probabilistic analysis,
 676 stochastic models should be established.

677 6.2.3.1 Earthquakes

678 Earthquakes generate loads in terms of ground acceleration acting at the foundation of a wind
 679 turbine, which is specified by a spectrum at a given return period. IEC 61400-1 specifies the
 680 load level for design with a return period of 475 years and defines superposition with other

loads and associated safety factors. The widely used return period of 475 years corresponds to a 10% probability of exceedance in 50 years.

Seismic loading is highly dependent on local conditions and is defined in seismic codes, which often demand, besides prescription of the load spectrum the use of certain models for assessment of structural earthquake resistance.

Typically, probabilistic seismic hazard analyses (PSHA) are carried out in order to define relevant seismic loading for a specific wind turbine site. By use of PSHA, the probability of exceedance of a specified level of ground motion can be calculated.

6.2.4 Electrical network conditions

The external electrical conditions at the wind turbine terminals influence the reliability of both electrical and mechanical components dependent on the design of the energy conversion system.

IEC 61400-1 provides guidance on the types of electrical network conditions. Statistics on such conditions are not commonly available and vary from country to country. National grid utilities provide some information publicly or on demand. Furthermore, measurements at wind turbine sites can provide data for defining appropriate discrete or continuous distributions.

An example for application of continuous distribution is the range of grid voltage and frequency as an occurrence probability distribution.

Discrete distributions are more suited for less frequent conditions, such as, for example, power ramps, temporary derating, grid loss and fault ride through (FRT) events.

The latter two, grid loss and FRT, are part of the standard load case definitions in IEC 61400-1. While grid loss is fully defined by its occurrence rate, FRT events have a number of other attributes that needs to be considered such as magnitude and length of the voltage drop or peak, level of symmetry and number of consecutive events. These attributes can have a significant load effect on both, the mechanical and the electrical system. Modelling these attributes requires appropriate information on the occurrence distribution as well as on suitable binning of the event types.

6.3 Load uncertainty modelling

6.3.1 General

The load uncertainty modelling refers to the uncertainties in the assessment of the load on the individual wind turbine components and subcomponents. Typically, the following steps are followed in load assessments, see also Figure 2:

- a) Input to the aeroelastic model (such as external conditions, structural design, aerodynamics and wind turbine controller) is defined.
- b) The direct outcome of the aeroelastic simulations are time series of section forces in components (modelled as finite elements in the aeroelastic simulations), for combinations of the input variables.
- c) Relevant loads are extracted from the timeseries for each considered load case using appropriate methods (e.g. extreme values, rainflow cycle counting and Markov matrix).
- d) Extracted loads are combined with their probability of occurrence to obtain the long-term distributions.

- e) Load effects in critical locations of components are estimated using transfer functions based on FEM or analytical/empirical formulations.

As part of the probabilistic load assessment, uncertainties in all steps should be considered and included. The assessment of uncertainties should be performed in relation to relevant limit state equations for selected components, failure modes and design load cases.

6.3.2 Aeroelastic Model

Uncertainty on the input to the aeroelastic model (see Figure 6.2) cause uncertainties on the output. Therefore, uncertainties related to the input should be quantified on the base level and propagated through the computational models used in the load assessment. This includes uncertainties in the assessment of section forces using an aeroelastic model and if relevant assessment of load effects based on section forces using FEM models or analytical models. The formulation of the uncertainty model should consider the influence of nonlinearities in the relation between section forces and load effects.

The uncertainty propagation can be performed by simulation-based methods (Monte-Carlo, Importance Sampling) or local expansion methods (Taylor series) to determine the resulting model uncertainty for the considered component, failure mode and design load case. The uncertainty propagation should take any potential correlation between uncertainties in the input parameters into account. The convergence of the uncertainty propagation should be assessed. The uncertainty propagation can be performed with simplified simulations models like e.g. surrogate models.

For some input to the aeroelastic model, it is not possible to propagate the uncertainties (e.g. model choices) through the aeroelastic model. The uncertainty in these inputs should therefore be quantified based on measurements, model variations or subjective information and represented by model uncertainties, see equation (17), Figure 1 and Annex A.

$$Y = X_{Model} \cdot M(X, \theta) \quad (17)$$

A typical split between the uncertainties which should be propagated through the aeroelastic model (shaded) and those which should be represented by model uncertainty (dotted) is shown in Figure 3.

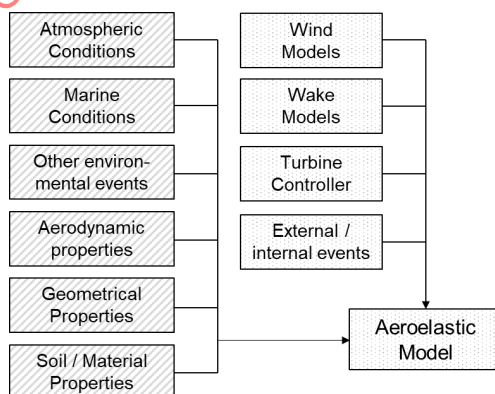


Figure 3 – Typical split between uncertainties which should be propagated through the aeroelastic model (shaded) and those which should be represented by model uncertainty (dotted), see also the typical flow chart in Figure 2.

Other contributors to the aeroelastic model uncertainty are uncertainties related to the methods used for wind turbine modelling and simulation (e.g. BEM theory, multibody, FEM), the discretization in finite elements (degrees of freedom) and time domain (simulation time steps).

The model uncertainty related to the aeroelastic model will in general be dependent on the fidelity and validation of the model applied. The model uncertainty may be determined based on load measurements and validation campaigns from e.g. proto-type turbines according to IEC 61400-13, where measurement load cases corresponding to the design load cases are defined.

The model uncertainty for the aeroelastic model with respect to extreme loads may be determined based on 10-minute statistics (min, max, mean, std) from the measurement load cases defined in IEC 61400-13³. The model uncertainty with respect to fatigue loads may be determined based on 10-minute damage equivalent loads (DEL). The model uncertainty may be determined based on Annex A.3, but measurement uncertainty will typically be included in the assessment, potentially together with other model uncertainties listed in Figure 2 and Figure 3.

The assessment of the model uncertainty should focus on the considered design situation, components, and environmental conditions of interest. Statistical uncertainty due to the limited amount of measurement / validation data available should be considered if the data requirements in IEC 61400-13 are not fulfilled.

If the uncertainty propagation or assessment of model uncertainties have been performed for a specific component, failure mode or design load case, the resulting model uncertainty may be re-used for similar wind turbine types and design situations when appropriately justified.

6.3.3 Extreme loads

The estimated extreme loads are dependent on the number of simulations and consideration should be given to the convergence criteria and the statistical uncertainty related to the assessment. The extreme loads are normally assessed using one of the following methods:

- Extrapolation methods typically involving peak extraction or Inverse First-Order Reliability Methods (IFORM). The independence of the peaks and goodness of fit for the distribution function used to determine the exceedance probability of e.g. 50 years should be evaluated.
- Averaging methods where the extreme load is determined using a specific averaging scheme (e.g. mean value of the largest half) of the peak values from each time series. The statistical uncertainty related to the number of simulations should be evaluated.
- (Prototype / field measurements where the uncertainty related to the aeroelastic model is omitted, but measurement uncertainties are introduced. The statistical uncertainty related to the number of measurements should be evaluated.)

6.3.4 Fatigue loads

Fatigue damage occurs from an accumulation of cycles due to the fluctuating loads. The fatigue loads are for structural components normally represented by the number of load cycles with different ranges and mean load levels extracted by e.g. the rainflow cycle counting method, whereas the fatigue loads for mechanical components normally are represented by the time different load levels occur represented by duration loads.

The model and statistical uncertainty related to the fatigue load assessment should be evaluated. The model uncertainty related to the fatigue load assessment (e.g. rainflow cycle counting) is normally assessed together with the model uncertainty for the fatigue damage assessment (e.g. Miner's Rule) and represented by a single model uncertainty.

³ In addition detrending of turbulence may be considered to apply to load cases given in IEC 61400-1.

6.4 Structural resistance uncertainty modelling

6.4.1 General

The uncertainty in structural resistance is in general dependent on the variation in geometrical and material properties, resistance models along with the manufacturing methods and quality.

The structural resistance shall according to IEC 61400-1 be analysed for the following limit states where relevant:

- Analysis of ultimate strength
- Analysis of fatigue failure
- Stability analysis
- Critical deflection analysis

Each type of analysis requires a different formulation of the limit state function and deals with different sources of uncertainties, see 6.1.1. The limit state function can in general be formulated based on the design requirements for the individual component specified in e.g. IEC 61400-1, IEC 61400-6 or IEC 61400-8.

Further guidance on the assessment of uncertainties, characteristic values and partial safety factors for structural resistance is given IEC 61400-1 Annex K.

6.4.2 Geometrical properties

The uncertainty in geometrical properties can either be estimated based on observations / measurements or the manufacturing tolerance specification defined for the considered component along with the applied quality control.

The uncertainty in geometrical properties is for most wind turbine components small and has therefore normally minor effect on the structural resistance. If this is justified the geometrical properties can be modelled deterministic in the limit state function.

6.4.3 Material properties

The uncertainty and potential bias in the material properties can either be estimated based on measurements or the manufacturing / supplier specifications for the considered material along with the applied quality control.

The uncertainty modelling for the material properties and the associated structural resistance should consider the failure mode (brittle vs. ductile), scale effects and degradation during the design lifetime.

6.4.4 Resistance models

The resistance model can either represent the structural resistance as a mathematical model which is dependent of e.g. geometrical and material properties (Model 1 and 2 in IEC 61400-1 Annex K.3) or alternatively specify the structural resistance directly based on e.g. tests (Model 3 in IEC 61400-1 Annex K.3).

When the resistance model is a mathematical model the model uncertainty and potential bias should be estimated based on component tests using the statistical method described in Annex A and IEC 61400-1 Annex K.12. In situations where component tests are not available

and/or not practical possible to obtain, higher fidelity models can be used to assess the model uncertainty and potential bias in the resistance model, but model uncertainty related to the higher fidelity model should be considered.

When the resistance model specifies the structural resistance directly the physical uncertainty and potential bias should be estimated based measurements.

6.4.5 Fatigue strength and damage accumulation

The uncertainty in the fatigue strength can either be estimated based on measurements or the manufacturing / supplier specifications for the considered material along with the applied quality control. In IEC 61400-1 section 7.6.3.3 typical coefficient of variations are specified for different materials.

The fatigue strength is often determined based on a limited number of measurements. Bayesian statistical methods can be applied in order to incorporate the knowledge obtained from past measurements with a similar material / component.

The model uncertainty related to fatigue cycle counting and fatigue damage accumulation should be considered. A correction for the mean stress level should be applied for materials where the mean stress level significantly influences the fatigue strength.

6.5 Component reliability uncertainty modelling

The reliability of a component or the probability for different fault situations on the wind turbine is often determined from historical data and described by the time to failure distribution or failure rates.

Component reliability modelling is normally applied to electrical and mechanical components, where the time to failure often is modelled by a Weibull distribution, whose parameters are determined based on failure statistics. Model uncertainty should represent the deviations between the failure statistics and the actual component and application (component generation, environment, loading conditions, etc.). Statistical uncertainty should represent the sample size for the failure statistics.

The reliability for different fault situations can in structural reliability analysis e.g. be modelled by formulating a limit state equation conditional on the fault.

7 Performance modelling

7.1 General

For components, failure modes and DLCs selected for probabilistic design, limit state equations shall be formulated allowing for the calculation of the annual failure probability. Guidance is provided to formulate conditional limit states and in relation to different design load cases (DLC's).

Combinations of mechanical loads acting on the turbine structures shall be considered to ensure structural performance based on the load cases specified in the IEC 61400-1 and IEC 61400-3 as applicable.

7.2 Structural performance of primary structures

All relevant limit states shall be evaluated, which may also include serviceability limit states and accidental situations. Return periods of extreme events for ultimate limit state analysis may be evaluated with suitable measurements and past historical data. Load evaluation is made primarily through the results of the aeroelastic simulations. The effects of consequence classes on the conditions can also be directly included.

In the following is described the basis for deriving probabilistic models for structural performance modelling and how to adapt the probabilistic models to the semi-probabilistic models in IEC 61400-1 and IEC 61400-3 where the models may be characterized by a certain return period, typically 50 years.

7.2.1 Load Performance calibration for ultimate limit states

This subsection details the computation of the probability of failure under extreme load cases and fatigue load cases and develops a procedure for quantifying the probability of failure, given external conditions. Defining DLCs for the load effect for known specific site conditions and frequency of occurrences of faults can be designed using probabilistic methods. This allows that the inputs to load cases can be tailored to a specified annual probability of failure or joint return period. Annual failure probability obtained by limit state equations with annual extreme load effect.

For limit state equations $g(\cdot)$ formulated using the distribution for the extreme annual load effect L , the annual failure probability P_f is calculated from:

$$P_f = P(g(L, X) \leq 0) \quad (18)$$

where X is the set of stochastic variables for resistance and model uncertainties, and L is the extreme annual load effect described by the distribution function $F_L(L)$. To obtain the distribution $F_L(L)$, the following steps are generally followed: a) Run aeroelastic simulations for relevant ranges of environmental conditions and other conditions required in the DLC, b) extract extreme load effects from generated time series, and c) estimate the distribution for the extreme annual load effect by fitting and aggregation over environmental conditions (in either order).

This approach assumes that resistance and model uncertainties are time-invariant.

7.2.1.1 Annual failure probability obtained by conditional failure probabilities

For load cases with discrete events (deterministic wind field events, fault events or operational events (start-up / shutdown)) (such as DLC 1.4, 1.5, 2.1, 2.2, 2.3, 2.5, 3.3, 4.2, 5.1), the probability of failure given an event E is calculated from the limit state equation:

$$P_{f|E} = P(g(L_E, X) \leq 0) \quad (19)$$

where L_E is the extreme load effect during event E , described by the distribution $F_{L_E}(L_E)$, which is found by aggregation over the relevant environmental conditions.

Instead of combining various environmental conditions (or other conditions) in the distribution $F_{L_E}(L_E)$, the conditional probability of failure may be calculated conditioned on specific environmental conditions, c and mean wind speed V , in which case, the limit state equation is written:

$$P_{f|E,v,c} = P(g(L_E(V, c), X) \leq 0) \quad (20)$$

7.2.1.2 Description of annual failure probability conditioned on specific environmental conditions

The characteristic load exceedance probability shall be determined for environmental conditions given in 6.2, whereby the probability of failure of the structure can be directly assessed. Applying Eq. (23) with $g(L_E(V, c), X)$ substituted as $R(X) - L(X, V, c, E)$,

The probability of failure conditional on an event E occurring at specified environmental conditions is computed by:

$$P_{f|E} = \int_0^\infty \int_{-\infty}^\infty P(R(X) - L(X, V, c, E) \leq 0) p(V, c, E) dc dV \quad (21)$$

$$p(V, c, E) = p_{E|c,V}(E|c, V) \cdot p_{c|V}(c|V) \cdot p(V)$$

where X are the set of random parameters representing material and loads uncertainties, $L(X, V, c, E)$ is the extreme load effect conditional on an event, E and the environmental quantities of interest, $p(V, c, E)$ is the joint probability of the mean wind speed (V), environmental variable of interest (c), such as turbulence and an event, and R is the structural resistance given in terms of load level, such as bending moment corresponding to a failure stress. Uncertainties in the material properties and loads are to be included in the probability distributions for R and L respectively as per 6.3 and 6.4 and equation (21). can be solved, for example using Monte-Carlo simulations. The resulting failure probability can be determined thereby for a given structure using a set of extreme loads obtained from the output of aeroelastic simulations using a set of environmental conditions as input.

As a special case of Eq. (24), in some ultimate limit state cases, (Example: blade strike of a tower, stress hotspot dependent on load direction etc.), the probability of the direction of the load or deflection, θ is also required to be considered in equation (21), in which case, the probability of failure can be written as:

$$P_{f|E} = \int_{-\infty}^\infty \int_0^\infty \int_0^{2\pi} (P(R(\theta, X) - L(\theta, X, V, c, E) \leq 0) p(V, c, E) d\theta dV dc \quad (22)$$

In the absence of an event, E , $p(V, c, E)$ in equations (21) and (22) is replaced with $p(V, c)$ and the corresponding load probability distribution over the environmental conditions (V, c) is utilized.

Further details and examples on the formulation of environmental conditions and limit states with conditional events or independent events (Example: DLC 2.x from IEC 61400-1) are given in Annex D.

If fault events, internal or external to the wind turbine, are not fully dependent on specific environmental conditions, then the annual failure rate (λ_F) may be estimated based on a numerical integration (binning), by combining conditional probability of failure given an event E , while specifying the rate of events λ_E , as:

$$\lambda_F = \sum_{V,c} P_{F|E,v,c} \lambda_E(V,c) P(c|V) P(V) \quad (23)$$

where the occurrence of events E is expressed through the rate $\lambda_E(V,c)$ of the event given environmental condition c occurring with probability $P(c|V)$ and mean wind speed V occurring with probability $P(V)$. It is further noted that, for small values of annual failure rate ($\lambda_F \leq 0.02$), the annual failure probability may be approximated by the numerical value of the failure rate:

$$P_f \approx \lambda_F, \quad \lambda_F \leq 0.02$$

7.2.1.3 Load Performance calibration for Fatigue limit states

Wind turbine operational cases and situations with shutdowns, stand still, start-ups should be evaluated to determine their individual influence towards fatigue damage. Equivalent turbulence level, wind/wave misalignment can be calibrated to specific structures, where the full probability distribution of the environmental conditions is not used in the load simulations. At a minimum the distribution of wind turbulence, the distribution of significant wave height and peak spectral period for offshore structures shall be considered conditional or jointly with the probability of the mean wind speed. IEC 61400-1 or 61400-3 load cases for fatigue that consider events or turbine stand-still should consider the probability of occurrence of those events or the duration of stand-still in the assessment of fatigue damage.

The allowable material properties in the fatigue analysis should be based on standardized tests. The material behaviour under fatigue should be modelled by an appropriate distribution with the mean value and coefficient of variation obtained through standardized tests. In the absence of such data, the distribution function can be estimated based on the characteristic material values and appropriate assumptions on the standard deviation.

An appropriate fatigue limit state such as the Miners sum may be used to model the material failure under fatigue. The distribution of the Miner sum upon failure may be assumed to be lognormally distributed. The limit state analysis for fatigue shall include probability distributions for the stress amplitude and for the material resistance. Uncertainties on dependent variables such as stress concentration factors, geometric effects, surface finish etc. will also be accounted for where appropriate. The component stress cycles should be obtained through the simulation of appropriate load cases from the IEC 61400-1 using either the full distribution of wind turbulence or at the 90% turbulence value. The annual probability of failure in year t , conditional on survival until that year is estimated by:

$$\Delta P_f(t) = \frac{P(g(t) \leq 0) - P(g(t - \Delta t) \leq 0)}{1 - P(g(t - \Delta t) \leq 0)} \quad (24)$$

Where $g(t)$ is the fatigue limit state equation of the material in a given year, t and $\Delta t = 1 \text{ year}$.

7.2.2 Evaluation of Serviceability limit states

Serviceability limit states concern the response of the wind turbine structures during normal functioning of the structure under normal use, long term functioning and appearance. For reliability based design, the annual probability of failure under serviceability limit state shall be utilized based on the values stipulated in section 5, unless specific instances require another probability of failure based on historical data. For concrete structures, the serviceability limit

state can involve maximum allowable crack sizes and sliding of the concrete layers, such as for a grouted joint and care should be taken that the evaluation of this limit state includes adequate representation of the material behaviour. The serviceability analysis of fixed support structures shall follow appropriate standards such as the IEC 61400-6.

The load cases in the IEC 61400-1 towards ultimate limit state can be considered for serviceability limit states also. For serviceability analysis of response behaviour, the partial load factors and partial resistance factors shall be taken as unity in the partial factor design method.

7.3 Performance of primary mechanical and electrical components

The performance requirements of mechanical or electrical components requires additional assessments such as thermal effects, lubrication quality, hydraulic pressure, friction effects, that are not considered in the performance of primary structures. The performance of components in the primary load path such as the bedplate, generator, gearbox casing, hub etc. shall be made considering relevant design load cases in IEC 61400-1 in conjunction with the requirements in other relevant standards such as the IEC 61400-4 and IEC 61400-8. The load effect modelling may require the use of additional appropriate software on top of aeroelastic tools. Electro-mechanical modelling of the drivetrain may be necessary to evaluate its structural performance. The structural integrity of individual elements shall be verified by taking into consideration all its boundary conditions and adjacent connections. Additional fail-safe components may be evaluated without the need for added partial safety factors in loading. Control and protection systems shall be assessed according to the required mean time between failures (MTBF). The MTBF can either be a requirement from a risk assessment or a result of the application of IEC 61400-1 Table 3.

7.3.1 Requirements for mechanical components

Reference to section 9 of the IEC 61400-1 is made in terms of description of essential mechanical components and systems. Stresses in mechanical components will be adequately modelled for appropriate limit states analysis and these may involve stress components not considered in structural design, such as Hertzian contact stresses at an interface and hoop stresses in bearing rings where reference is made to IEC 61400-4. The limit state equations for mechanical components used in its design shall be based on critical failure modes of that component and include the effects of ambient conditions on its material properties. If the mechanical component is in the primary load path of the wind turbine, then a target annual probability of failure as specified in chapter 5 is to be used. Higher annual probabilities of failure may be used where the failure of the component does not result in a critical failure of the wind turbine.

7.3.2 Serviceability limit states for mechanical components

Mechanical component such as bearings, bolts, gears etc, shall be evaluated for applicable serviceability limit states, examples of which include allowable deflection of bearings, sliding of bolts and temperatures in the gearbox or generator. Such limit states shall be assessed considering all relevant load cases.

7.3.3 Requirements for electrical components and control and protection systems

A Failure Mode Effects Analysis (FMEA) shall be used to determine the type of failures and the need for further analysis of the annual probability of failure of control and protection systems in accordance with IEC 61400-1, section 8.4. Protection functions shall be designed minimizing the probability of the identified failures or their consequences sufficiently. Control and protection systems should possess sufficient redundancy so that a single failure of a component within a control and protection unit shall not result in loss of protection for the wind turbine. Load cases DLC 2.x in the IEC 61400-1 deal with loss of control and protection systems and these should be run considering the annual probability of occurrence of their respective events. Equations (19), (20) and (21) can be used to calibrate the load case parameters to a target probability of failure or to a given return period of environmental conditions, if the mean time between failures

(MTBF) of control and protection systems is known or the frequency of occurrence of a fault is known. The MTBF can also be calibrated to a given partial safety factor for loads as described in IEC 61400-1 Table 3. Beside the hardware related MTBF, software failures shall be included within the scope of the failure analysis.

Electrical components of the wind turbine such as the generator, converter, transformer, as well as batteries and motors that drive individual units shall comply with the requirements made in IEC 61400-1 section 10 on electrical systems.

7.3.3.1 Modelling of grid events

Wind farms are required to comply to grid codes as required for various regions. Specific situations such as Low Voltage Ride Through (LVRT) as per DLC 2.5 in the IEC 61400-1 can affect the design loads on the turbine structures. In these situations, equation can be used to determine the probability of failure of a specific structure or component and thereby calibrate the return period of the grid event to be within design specifications. For example, if the turbine is designed to withstand extremes with a maximum expected return period of 50-years, then equation (21) can be used to ascertain that the loads from the grid event conform to the specified return period or exceed that period.

7.4 Robustness of sub-systems

The Robustness verification of each sub-system includes the following cases:

- Accidental limit states
- Large environmental effects offshore
- Redundancy of components
- Sensor redundancy when present for the detection of faulty behaviour

In relation to robustness the following adverse (failure) events are considered

- identified accidental actions
- unforeseen adverse events

Design approaches for identified accidental actions

- design the wind turbine incl. substructure to resist the action
- prevent or reduce the action e.g. protective measures, control of events

Design for identified accidental actions shall be undertaken in accordance with a relevant standard.

Note: an example of an identified accidental action is collision of a ship with an offshore wind turbine.

A wind turbine / wind turbine farm system shall be designed and operated to prevent disproportionate consequences, as a result of unforeseen adverse events such as the failure or collapse of a structural member or part of a wind turbine including the substructure, or to provide additional structural resistance to reduce the likelihood and extent of such an event.

Note: Progressive collapse of mooring lines of a floating wind turbine is an example of a damage that is disproportionate to the original cause. Increased robustness may be obtained by a design with increased redundancy and ductility.

8 Assessment of reliability

8.1 General

The estimation of the reliability of a structure for a given failure mode is obtained based on the associated limit state equation, where all stochastic variables are well characterized.

Section 6 provides guidance on general characterization of uncertainties and stochastic variables of interest for wind turbine design and safety assessment, while Section 7 details on how to formulate limit state equations for various failure modes and design situations. The current section provides guidance on how to perform the last step of assessing reliability both for direct reliability design (where the structural design parameter is directly calculated to satisfied a given target reliability) as well as for performing calibration of safety factors.

8.1.1 Reliability measures

A standard reliability measure may be chosen to be the generalized reliability index β defined as

$$\beta = -\Phi^{-1}(P_f) \quad (25)$$

where P_f is the probability of failure and $\Phi^{-1}(\cdot)$ is the inverse normal cumulative distribution.

Another equivalent reliability measure is the complement of the probability of failure, the *Probability of Survival* P_s

$$P_s = 1 - P_f \quad (26)$$

In many cases the failure probability of a structure is time dependent either due to deterioration of the structure resistance over time or because the load is a time-varying stochastic process. Particularly in the case of fatigue limit state analysis, one is often concerned with the probability of failure during the n^{th} year of operation given survival up to the n^{th} year, which is given by (24).

Illustrations of such reliability measures are provided in Figure 4.

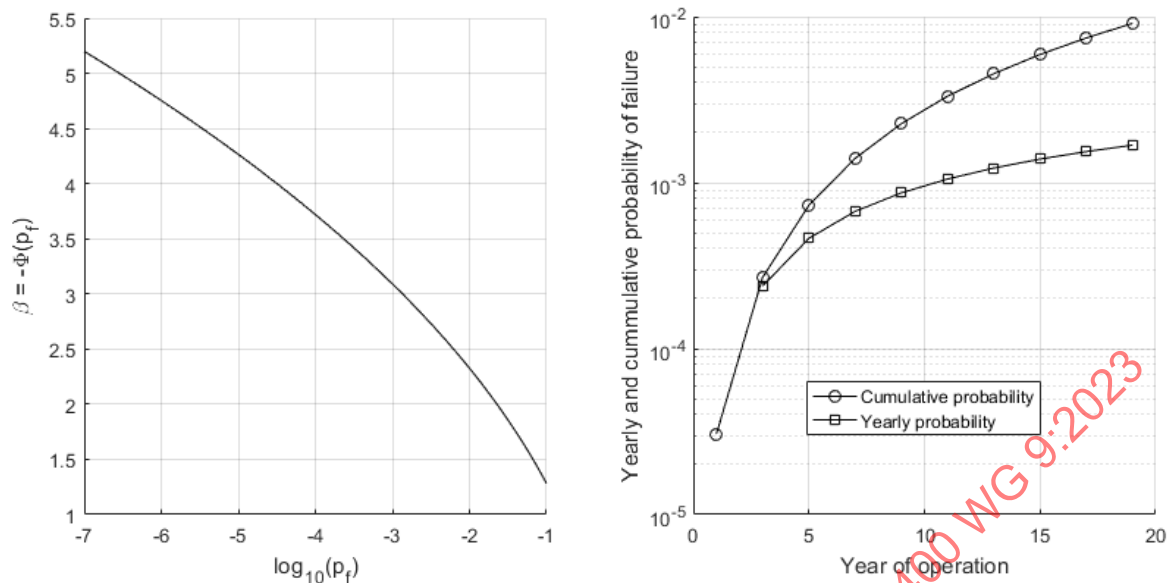


Figure 4 – Measures of reliability. (a) The reliability index as a function of the power of failure probability and (b) the cumulative probability of fatigue failure compared to the resulting yearly probability of failure

8.1.2 Computation of failure probability

The failure probability of a structural component with respect to a single failure mode is

$$P_f = \int_{g(X) \leq 0} f_X(X) dX \quad (27)$$

where:

X is the vector of basic random variables

$g(X)$ is the limit state function for the failure mode considered

$f_X(X)$ is the joint probability density function of X

An important class of limit states are those for which all the variables are treated as time independent, either by neglecting time variations in cases where this is considered acceptable or by transforming time-dependent random processes into random variables (e.g., by using extreme value distributions). Typical formulations for extreme loading ultimate limit states follow the approach of using extreme value distributions, which is what will be considered in this Section.

The designer is free to choose any calculation method capable of solving the integral in equation (27). As the direct evaluation of the probability integration is usually impractical for real engineering applications, there are a few numerical methods the designer can refer to. The structural reliability methods most used for calculating P_f are divided into *asymptotic approximate* methods, of which the first and second order reliability methods - FORM and SORM respectively – are the most common examples and *simulation methods* such as direct Monte-Carlo simulations, importance sampling, and directional simulation.

First Order Reliability Methods (FORM) can be used to estimate the probability of failure and the reliability index β and due to its common application, a brief overview of the method is presented as follows. The first step is to simplify the integrand $f_X(X)$ through a variable change

1111 from the “physical” X-space to the standard normal U-space by use of the Rosenblatt
1112 transformation (Rosenblatt 1952):

$$U_i = \Phi^{-1}[F_{X_i}(X_i)] \quad (28)$$

1113 where F_{X_i} is cumulative distribution of each random variable component X_i and $\Phi^{-1}(\cdot)$ is the
1114 inverse normal cumulative distribution function.

1115 After the transformation, the probability integration becomes:

$$P_f = \int_{g(U) < 0} \phi_U(\mathbf{u}) d\mathbf{u} \quad (29)$$

1116 This integrand is simplified since ϕ_U becomes the product of the standard normal probability
1117 density functions of u_i since in the new space the variables are independent.

1118 The second step is to approximate the integration boundary $g(U) = 0$ by linearizing it (first order
1119 Taylor expansion) around the “most probable failure point” ($\mathbf{u}^*$) which is the point that has the
1120 highest probability density at the hyper-surface defined by the limit state equation, see Figure 5
1121 for an illustration of a problem consisting of only two physical dimensions.

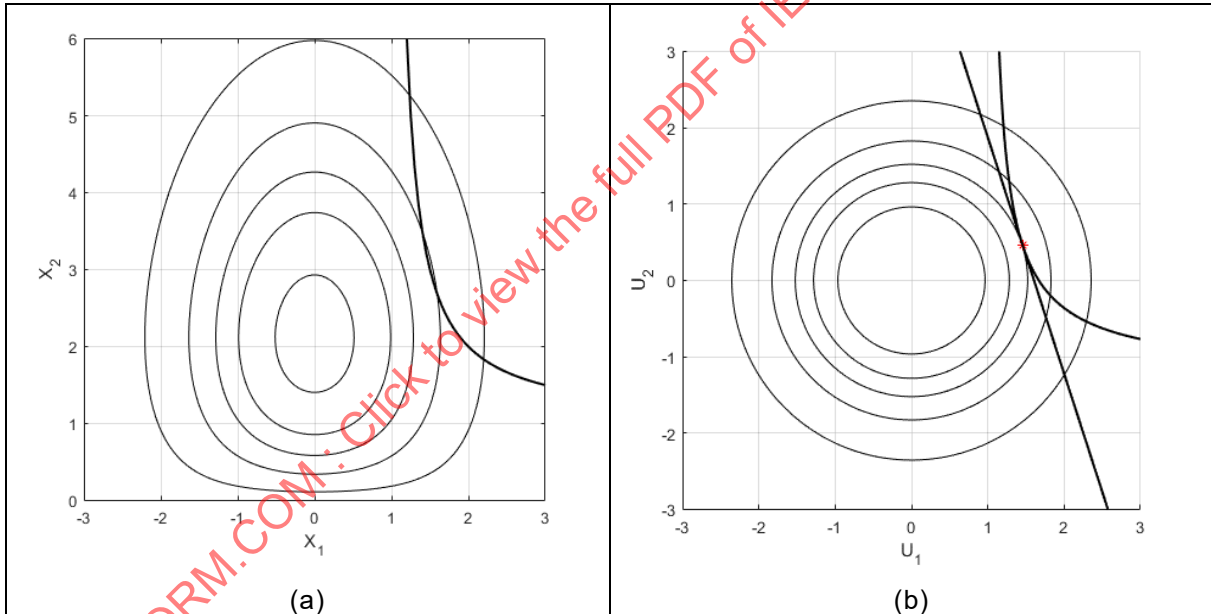


Figure 5 – Illustration of the FORM method for a simplified two-variable case: (a) Original physical space. (b) Change of variables through the Rosenblatt transformation and approximation of the integration boundary by its first order Taylor expansion at the most probable point.

1126 It can be shown that under such approximations the reliability index β is equal to the norm of
1127 vector $\mathbf{u}^*$. The probability of failure can therefore be estimated based on (30), giving $P_F \approx$
1128 $\Phi(-\beta)$.

1129 Some examples of how to apply such methods to simplified problems relevant to wind turbine
1130 design are presented in Annex C.

8.1.3 Accuracy requirements

Due to the computational complexity, the calculated failure probability is an approximation to the exact result. Two fundamental accuracy requirements are:

- Overestimation of the reliability due to use of an approximative calculation method shall be within limits generally accepted for the specific type of structure as stated on structural safety standards and relevant national codes.
- The overestimation of the reliability index due to the calculation method applied should not exceed 5 % with respect to the target level.

The accuracy of the reliability calculation method is linked to the sensitivity with respect to structural dimensions and material properties in the resulting design. When using approximate methods, this accuracy may be estimated by comparing the results with ones obtained with use of simulations methods for a similar case. When using a simulation method, the accuracy of the solution may be estimated on some conditions by computing the sensitivity of the result with the number of simulations performed.

8.1.4 Sensitivity analysis

A sensitivity analysis shall be performed in the context of any probabilistic design exercise with the objective of identifying which uncertainty considerations are contributing most to the computed reliability.

To perform such a study, the reliability method used should be capable of producing a sensitivity analysis including importance factors for uncertain parameters.

An example of how to perform a sensitivity analysis is given in C.1.6.

8.2 Reliability-based method

In a full reliability-based design the design parameters (i.e. geometric properties of a given component) are themselves determined based on a reliability analysis. This means that loads (actions), resistances (strength parameters) and models are modelled by probabilistic models and design parameters of the component are determined to achieve the target failure probability.

8.2.1 Probability of failure for extreme design situations

Annex C.1 illustrates the reliability assessment/design for extreme design situation based on a simple modelling of the ultimate limit state. In some analysis it is not possible to develop an analytical model such as the one represented in equation (72) in which case numerical models may be used to build a mapping between load effect and stress/resistance. In such cases, it should be ensured that any additional numerical uncertainty is captured in the factor X_{str} . More complex cases where even such a mapping is not possible, direct use of numerical models for evaluation of (72) can be used and the probability of failure computed through direct Monte-Carlo simulations. It is noted that the computation complexity of setting up different models covering the desired uncertainty space and running such models the required number of times may prove to be prohibitive.

8.2.2 Probability of failure for fatigue design situations

Annex C.2 illustrates the reliability assessment for fatigue design situations based on a simple damage accumulation model (Palmgren-Miner) with mean stress level. The example should be considered just as an illustration of reliability-based fatigue analysis, not a recognized baseline for general fatigue design.

1174 Modelling of fatigue resistance of materials can be generally divided in two main approaches:
1175 damage summation and fracture mechanics (crack growth models).

1176 **Damage based approaches**

1177 These can be further sub-divided corrected/normalized S-N diagrams and lifetime diagrams,
1178 depending on the type of material and component failure mode under consideration. References
1179 to recognized standards for the material/component type justifying the application of a particular
1180 model should be provided (e.g. ISO 2394 or EN 1993-1-9) as long as also in accordance with
1181 IEC 61400-1.

1182 **Fracture mechanics approaches**

1183 Due to a general dependence of fatigue loads with atmospheric turbulence levels, the load cycle
1184 history for wind turbines cannot be predicted in advance. Therefore, the use of fracture
1185 mechanics approaches in the design phase are typically subject to a calibration of the method
1186 against simpler damage accumulation models (such as the Palmgren-Miner model). On the
1187 other hand, it may be possible or even necessary to use it as a verification of safe life and in
1188 the planning of inspection intervals, see 8.2.3. Further guidance is provided in component
1189 design standards such as IEC61400-8.

1190 **8.2.3 Updating probability of failure using test or inspection data**

1191 Two distinct types of updating are considered here:

- 1192 • When knowledge of new information due to test, operational data or access to new
1193 measurement or modelling databases allows one to update some of the probability
1194 distributions composing the overall probabilistic model used in a particular investigation
- 1195 • When knowledge of a particular event (i.e. crack detection) is gained by realization of
1196 inspections on an operating turbine

1197 For the first type of updating, Bayesian updating methods as described in Annex A.1 can be
1198 used to combine new knowledge with the initial assumptions of the probabilistic model and
1199 generate updated probability distribution for a particular variable of interest. Examples of such
1200 application is updating structural properties of a particular material given tests of specific
1201 batches (i.e. sampling of concrete) or updating uncertainties through use of site specific data
1202 as discussed in Annex E.

1203 In the second case, both Bayesian methods (i.e. Bayesian updating, Bayesian networks) and
1204 reliability-based inspection (RBI) methods can be used. RBI is based on Bayesian decision
1205 theory, and it aims at minimizing the total expected cost of an inspection plan while considering
1206 the expected costs of failure, inspection, and repair.

1207 When using methods such as RBI, it should be considered that inspections are error prone and
1208 therefore have themselves a probability of correctly detecting a defect or event (i.e. crack of a
1209 given size – for crack detections in particular, note that crack identification procedures are
1210 limited in their accuracy due to coating, method of measurement, etc.). For updating failure
1211 probabilities based on crack detection and propagation, the use of fracture mechanics is
1212 necessary (see also (BS 7910 and IEC 61400-8).

1213 Note that the methods highlighted above are not exhaustive, and many probabilistic or statistical
1214 methods are available to address a particular problem.

8.3 Semi-probabilistic method

As described in ISO2394, semi-probabilistic methods may be applied as an alternative to risk and reliability-based decision making. Consequence class categorizations, design situations and design equations are defined following the design basis requirements put forward in IEC 61400-1 and in accordance with clause 5 of this standard.

8.3.1 Representative and characteristic values

Actions

Characteristic values for actions shall be defined according to the principles in ISO2394. In particular, the characteristic value of variable actions for normal design situations is chosen to be the 98% quantile of the annual maximum action effect, as intended by the calculations indicated in IEC 61400-1.

Resistance

Characteristic values for properties of materials shall be defined according to the principles in ISO 2394. Typically, and according to IEC 61400-1, the characteristic value of the resistance parameter is defined by the 5% quantile

Uncertainties

The representative uncertainty levels indicated in Annex A are used and form an acceptable baseline if one follows state-of-the-art industry practices and recognized practices established by the related governing safety standards for structural design.

8.3.2 Partial factor method for extreme and fatigue design situations

When using partial factors, the designer may either use the load and material factors present in other standards in the IEC 61400 series or calibrate the factors to be used following the principles in this technical specification. When calibrating partial factors, the designer shall ensure that failure probabilities for the relevant failure modes are close to the target reliability level defined in 5.

8.3.3 Reliability-based calibration of partial safety factors

Re-calibration of safety factors may be based on justified revision of the representative uncertainty levels or assumptions on the load effects or related event probabilities which define a particular design case.

In the case of re-calibration, first an updating of the probabilistic model governing the limit state under study shall be made based on a suitable method such as the ones suggested in 8.2.3 or Annex A. The new probabilistic model can then be used to estimate the partial safety factor according to the method described in Annex C.

9 Site suitability analysis

9.1 General approach and scope

Wind turbines are subjected to site-specific environmental and electrical conditions including the influence of nearby turbines, which may affect their loading, durability and operation. It shall be shown that the site-specific conditions do not compromise the structural integrity.

This site suitability assessment can either be done using the semi-probabilistic approach presented in IEC61400-1 or the reliability-based probabilistic approach hereby presented, as defined in ISO 2394.

The IEC61400-1 is taken as basis with regards to the definition of load cases and requirements for the site suitability assessment.

The principles presented here are applicable for the site suitability structural assessment of onshore and offshore with turbines, as well as for the structural assessment of the lifetime extension of installed wind turbines.

This approach can be applied to wind turbines that had been designed using the probabilistic approach described in previous chapters of this Technical Specification; or designed using the semi-probabilistic approach based on partial safety factors in IEC 61400-1. In the latter case the design capacity in terms of the quantile of the strength distribution and the partial safety factor shall be available for the considered limit states. The quantile of the load distribution may be derived from frequency distributions of environmental parameters that are characteristic of long-term conditions on site or from time series observations acquired on site adjusted to reflect conditions prevailing over the long term.

The site suitability assessment based on a probabilistic approach focuses on assessing the relative variation of the structural reliability level respect to the design assumptions, when site specific conditions are considered, and accounting for different sources of uncertainties associated to the site assessment data and models.

The probabilistic approach can be applied to perform a complete site suitability assessment or just the assessment of some limit states, failure modes, or load cases (FLS, ULS, Accidental...). All other limit states can be assessed using the deterministic approach of IEC61400-1. If a probabilistic approach was used for the design and the site assessment is made according to the deterministic approach of IEC 61400-1 based on load calculations, then the characteristic strength for the considered limit state as defined in IEC 61400-1 should be provided from the probabilistic design. Similarly, if the site assessment is performed by reference to wind data according to IEC 61400-1 then the characteristic wind conditions for the considered limit state as defined in IEC 61400-1 should be provided from the probabilistic design.

If the site suitability assessment based on a probabilistic approach is performed by using simplified loads or resistance models, an additional uncertainty factor and/or bias shall be included in the models to account for that simplification. For instance, if a generic resistance model is used to model the load-bearing capacity of the structural component without further details about the actual strength characteristics of the component. If there is no information about the actual strength of the component, it shall be assumed that the component is designed to the limit in the design wind conditions.

The results from this analysis can be used to make decisions regarding site suitability of wind turbines, instead of a deterministic approach, as long as the resulting reliability level is kept within and acceptable target values defined in 5.

9.2 Reliability models for site suitability analysis

Different Limit State Equations can be defined for the assessment of different limit states relevant for the site assessment, in accordance with other parts of this Technical Specification. As defined in 9.1, the limit states evaluated with the probabilistic approach can cover all or part of the load cases defined in IEC61400-1.

As described in 7 the limit state function usually has two parts, one representing the resistance or load-bearing capacity (R), and other representing the load effects (L).

For the site suitability assessment special attention should be put on those parts of the limit state equations that are more dependent on site-specific conditions or site suitability data, methods and tools with respect to the design assumptions, such as:

- Wind conditions and related uncertainties.
- Computational models to estimate structural loads for site specific conditions, especially if they are different to the ones used in the design (aeroelastic simulations, metamodels, surface response, regression models...).
- Resistance models to estimate load-bearing capacity, especially if they are different to the ones used in the design (Damage models, Palmgren-Miner rule...).
- Considerations about fatigue assessment.
 - Reliability models may be time-variant or time-invariant, to consider eventual effects that may change along time.
 - Reliability models may be used to assess reliability at the end of the turbine lifetime or at any year during the total lifetime
 - The reliability models may also include the influence of defining decision rules along turbine lifetime based on inspection, monitoring and maintenance plans.
- Probability of the site-specific events. If the limit state equation is associated to an event whose recurrence period is site dependent, the total probability of failure shall account for the probability of that event.

9.2.1 Loads models for site suitability assessment

The loads model to be used for a probabilistic approach of a site-suitability assessment shall represent the dependency of the structural loads respect to the environmental conditions. Those loads models shall include stochastic variables accounting for the uncertainties in the environmental parameters (wind, marine), and the uncertainties in the methods to estimate wind turbine loads based on the site-specific conditions.

Regarding the uncertainties related to site suitability assessment see 9.3.

For the failure modes selected for the probabilistic assessment, limit state equations should be formulated based on the deterministic design equation, representing variables by their probability distributions, instead of using characteristic values and partial safety factors. Uncertainties related to external conditions, load assessment, and resistance (as described in chapter 6) should be included either directly, where the input variable is represented directly as a random variable in the limit state equation (see section a) below); or indirectly, where the effect of uncertainty on one or more variables is represented as a model uncertainty multiplied on the load effect in the limit state equation (see section b) below). A combination of both approaches is also possible.

- a) If the uncertainty related to the external conditions is included as random variables in the limit state equation

$$LOAD = X_{model} X_{..} f(W_{density}, W_{shear}, W_{turbulence}, \dots) \quad (30)$$

X are random variables accounting for uncertainties not related to external conditions (aeroelastic model, material properties, loads application, etc).

f is the loads model used to obtain the wind turbine loads based on wind or marine conditions, such as aeroelastic simulations, metamodels, surface response, regression models or others.

W are random variables representing the different environmental parameters relevant for the loads (air density, wind shear, turbulence intensity, etc). They can be defined either by analytical formulation or Monte Carlo simulation.

In this case, a hierarchical modelling (see ISO 2394) is recommended to model the uncertainty on wind or marine conditions. With this approach each of the environmental variables can be defined as a function of several variables, each one representing a specific type of variability:

$$W_{ijk} = f(W_i, W_{ij}, W_{ijk}) \quad (31)$$

The random variable may also be defined as a result of several random variables accounting for different sources of uncertainties (physical, measurement, statistical or model):

$$W = A + B W_{physical} W_{measurement} W_{statistical} W_{model} \quad (32)$$

- b) If the uncertainty related to the external conditions is included as random variables that multiply the load effect at the nominal values of the external conditions

- c)

$$LOAD = X_{\text{model}} X_{\text{meas}} X_{\text{stat}} X_{\text{model}} f(\rho_{\text{nom}}, \sigma_{1 \text{ nom}}, \alpha_{\text{nom}}, \dots) \quad (33)$$

1359 X are the stochastic variables accounting for all sources of uncertainties. Such as
 1360 general measurement uncertainty, statistical uncertainty and model uncertainty. Those
 1361 include not only uncertainty in environmental parameters, but any other uncertainty

1362 f is the loads model used to obtain the wind turbine loads based on the nominal value
 1363 of the different wind or marine parameters (air density, wind shear, turbulence intensity,
 1364 etc).

1365 If the approach b) is used, the stochastic variables X shall be properly calibrated based on the
 1366 uncertainty in environmental parameters. This can be done using approach a) or other methods.

1367 A different loads model f shall be used for different load case and load effect of interest if
 1368 required. Some of the stochastic variables accounting for other uncertainties may also depend
 1369 on the load case and load effect.

1370 The propagation of the uncertainties of environmental conditions through the loads model shall
 1371 be done applying recognized techniques as described in 6.3.2.
 1372

1373 **9.2.2 Resistance model for site suitability assessment**

1374 The resistance models for probabilistic design are generally described in 6. However, the
 1375 assessment of structural integrity for site-specific conditions may be based on different, usually
 1376 simplified, resistance models.

1377 If the resistance or loads model used for site suitability assessment is different to the one used
 1378 in the design, that should be accounted for with appropriate uncertainties. The eventual change
 1379 of resistance along turbine lifetime should also be considered if relevant using appropriate time
 1380 variant reliability analysis.

1381 Site suitability assessment can be performed either using complete detailed information of
 1382 turbine structural design or using only limited information. An absolute or a relative approach
 1383 may be followed to perform a probabilistic site suitability assessment.

1384 **9.2.2.1 Absolute approach**

1385 In an absolute approach loads can be derived either by the aero-elastic model used in design
 1386 or using alternative, simplified loads models (see clause 9.2.1), in which case the corresponding
 1387 uncertainty of the loads model should be accounted for, along with other assumptions on
 1388 uncertainties of the load side (apart from the uncertainties on wind climate, which are obviously
 1389 site specific) that were used in the design, e.g. uncertainty in aero-elastic modelling, uncertainty
 1390 in transforming loads into stresses, ...

1391 Uncertainties in the wind climate are modelled site specifically.

1392 On the resistance side uncertainty modelling from the design is used, based on the known
 1393 material and geometry properties of the components under consideration.

9.2.2.2 Relative approach

A relative approach is a simplified approach that can be applied, for instance, if the design assumptions (in particular those regarding the probabilistic design) are unknown. The following steps are undertaken.

1. A generic model will be used in the aero-elastic calculations. e.g. based on simplified turbine data or reverse-engineered to match the information/data available at this point (e.g. power curve, thrust curve, eigenfrequencies, foundation loads, ...). Since this model is deviating from the complete detailed aeroelastic model, it has some uncertainty associated that needs to be estimated / assessed. For the remaining uncertainties on the load side (other than the wind climate parameters) assumptions shall be justified (e.g. for exposure or loads-to-stress-transforms). See Clause 6 and Annex A for guidance on representative values of uncertainties
2. Define assumptions on design uncertainties (in compliance with IEC 61400-1 and this technical specification) for loads.
3. On the resistance side reasonable assumptions shall be made for uncertainties for material, damage accumulation or other failure modes (e.g. buckling).
4. Calibrate a design parameter to reach the target component reliability under design assumptions; check result for plausibility.
5. Uncertainties in the wind climate are modelled site specifically.
6. Calculate site specific reliability with assumptions and z parameter from previous steps.

Annex F includes an example of the relative approach to site suitability assessment.

9.2.3 Site-specific exposure events

The structural reliability assessment for site specific conditions may also account for the probability of exposure events whose intensity and/or probability of occurrence is site dependent, since it will affect the final probability of failure. The exposure events represent all events which can cause damage or otherwise affect the performance indicators of the wind turbine structure

Exposure events for wind turbines can be classified as fault events or wind events

9.2.3.1 Fault events

Fault events can either be internal turbine faults (e.g. turbine control system fault) or external fault events. This is of special relevance for the failure load cases defined in IEC 61400-1. Some examples of fault events are:

- External electrical events, such as loss of electrical network, voltage drops, ...
- Turbine control system faults, considering that the probability of some turbine faults may depend on site-specific conditions (e.g. a site with severe dust, corrosion or humidity conditions may increase the faults of some actuation or electrical systems)

The probabilistic analysis of fault events, as for design situation 2) and load cases DLC6.2 and DLC7.1 of IEC 61400-1, can be done based on failure rates, so that the rate of structural failure due to fault events can be obtained as:

$$\lambda_F = \lambda_E P(L > R|E) \quad (34)$$

where

λ_F Failure rate obtained as number of turbine failures per year.

λ_E Number of events per year.

1436 $P(L > R|E)$ Probability of structural failure per turbine per year conditioned on the given
 1437 event

1438 9.2.3.2 Wind conditions

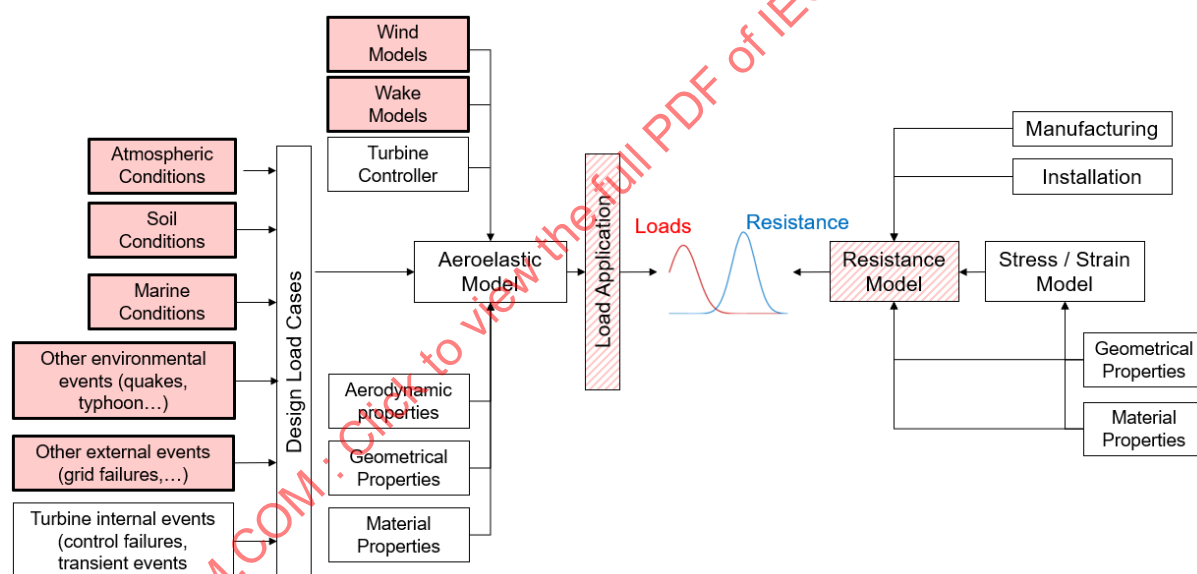
1439 Wind events are those where the turbine is not subjected to faults (internal nor external) and
 1440 the loads are driven by wind conditions

1441 The site-specific wind conditions are assessed based on the analysis of deterministic wind field
 1442 events and turbulent models, according to IEC61400-1

1443 Site-specific wind data can be used to define stochastic models for deterministic wind field or
 1444 turbulent wind conditions, including also models for wind speed, turbulence intensity, air
 1445 density, wind shear and flow inclination. If the turbine was designed using a stochastic model
 1446 for deterministic wind field event or turbulent wind conditions different to the ones described in
 1447 6.2.2.2, the assumptions for such models should be validated for the specific site where the
 1448 turbine suitability is assessed.

1449 9.3 Site specific uncertainty modelling

1450 The general description and requirements for representation and modelling of uncertainty for
 1451 probabilistic design of wind turbines are described in 6. Figure 6 highlights the more relevant
 1452 uncertainties related to site suitability assessment. Uncertainty modelling can either include the
 1453 variability, usually expressed as coefficient of variation or standard deviation, and/or a bias



1454
 1455 **Figure 6 – Highlight of relevant uncertainties related to site suitability assessment.**

- 1456 – Physical and epistemic uncertainties of atmospheric conditions (refer to IEC61400-1 for a
 1457 more detailed description of atmospheric parameters):
 - 1458 – Extreme 10min average wind speed
 - 1459 – Wind speed probability density function
 - 1460 – Wind speed standard deviation from ambient turbulence
 - 1461 – Extreme ambient wind speed standard deviation
 - 1462 – Flow inclination
 - 1463 – Wind shear
 - 1464 – Air density
- 1465 – Physical and epistemic uncertainties of marine conditions, defined in IEC61400-3, such as:

- 1466 – Wave spectrum (significant wave height, wave periods, etc.)
 - 1467 – Separation of swell and wind driven waves
 - 1468 – Wind/wave misalignment
 - 1469 – Currents
 - 1470 – Tide and storm surge
 - 1471 – Extreme wave and associated wave periods
 - 1472 – Soil conditions:
 - 1473 – Geotechnical conditions (p-y curves)
 - 1474 – Seabed variation (offshore)
 - 1475 – Scour development (offshore)
 - 1476 – Wind and wake models
 - 1477 – Models for turbulent wind simulation
 - 1478 – Models to account for the wake effect on the wind flow
 - 1479 – Uncertainty on external events (type, intensity, recurrence period...)
 - 1480 – Grid events (grid drops, network outages, ...)
 - 1481 – Other environmental events (earthquakes, icing...)
 - 1482 – Turbine operational transients (shutdowns, start-up...)
 - 1483 – Turbine failures in control system, electrical components
 - 1484 – Statistical and Model uncertainty of loads estimations
 - 1485 – Wind turbine characteristics (geometry, structural properties, aerodynamic properties)
 - 1486 – Foundation characteristics (foundation and terrain)
 - 1487 – Loads models used to estimate the site-specific loads based on wind conditions (full
 - 1488 aeroelastic simulations, surrogate models, interpolation models, response surface
 - 1489 methods, neural networks ...).
 - 1490 – Uncertainties on models for structural dynamics, aerodynamics, sensors, actuators
 - 1491 – Statistical uncertainty due to the limited amount of simulations
- 1492 Site suitability assessment is usually based on simplified loads and/or resistance models, in
- 1493 which case it should be considered the uncertainties due to consider simplified load effects
- 1494 models (e.g.- Damage equivalent Load) instead of more detailed load indicators (e.g.- complete
- 1495 Markov matrices); and the uncertainty in the resistance models used to determine structural
- 1496 stress based on load effects. See 9.3 for site specific uncertainty modelling and quantification
- 1497 The uncertainties in the site-specific atmospheric conditions used for site suitability assessment
- 1498 shall be accounted for. Main sources of such uncertainties are described below
- 1499 – Physical uncertainty of atmospheric conditions: It is the inherent uncertainty related
 - 1500 to the natural randomness of the wind characteristics, for example the uncertainty
 - 1501 in the wind speed distribution due to the year-to-year variation of climatic conditions.
 - 1502 – Measurement uncertainties of the environmental conditions derived from different
 - 1503 sources, for example:
 - 1504 – The operational characteristics of the wind sensor device, due to the
 - 1505 classification or type of instrument. This covers the sensitivity of accuracy of a
 - 1506 type of wind sensor to environmental variables and other operational conditions
 - 1507 – The calibration of the individual unit used in the specific measurement campaign
 - 1508 – Mounting effects. For anemometers mounted on meteorological masts this is due
 - 1509 to the interference of the mast or the boom on the actual flow measured by the

- 1510 anemometer. For remote sensor devices it is the uncertainty of non-ideal
1511 levelling of the device.
- 1512 – Configuration, or the proper maintenance, installation and operation of
1513 measurement devices during a specific measurement campaign.
- 1514 – The influence from the terrain.
- 1515 – Amount of measured data: It is statistical uncertainty due to the limited amount of
1516 data.
- 1517 – Long-term estimations: It is the model uncertainty of the methods used to predict the
1518 long-term characteristics of the wind distribution based on the data available. (e.g.-
1519 Measure-Correlate-Predict methods); or to predict the extreme values of the wind
1520 characteristics (e.g.- Gumbel method, Method of Independent Storms,...). It is also
1521 related to the amount of data available.
- 1522 – Vertical extrapolation uncertainty: It is the statistical uncertainty due to the limited
1523 number of heights where wind data is available, that may be especially relevant for
1524 estimation of wind shear characteristics
- 1525 – Wind modelling: It is the model uncertainty of the wind flow models used to estimate
1526 the wind conditions at different locations of the site based on the data available at
1527 the measurement position. It depends on several factors, such as:
- 1528 – Wind flow model: It is the model uncertainty of the computational fluid dynamic
1529 model itself
- 1530 – Mesoscale wind flow model: It is the uncertainty of the wind flow models based
1531 on mesoscale data, in opposition to flow models based on wind data measured
1532 directly at the site.
- 1533 – Terrain map quality: it is the statistical uncertainty due to the limited information
1534 of terrain topography, depending on the quality of the map to represent
1535 accurately such topography based on the contour lines.
- 1536 – Wind shear complexity: It is the uncertainty in the characterization of wind shear
1537 depending on how well the terrain roughness is characterized and the stability
1538 effects of atmosphere.
- 1539 – Terrain complexity: It is the uncertainty of the wind modelling due to the
1540 characteristics of terrain topography
- 1541 – Horizontal extrapolation: It is the model uncertainty to predict the wind
1542 characteristics far from the measurement point.
- 1543 – Wake models: It is the uncertainty of the models used to predict the
1544 characteristics of the wind in the wakes.
- 1545 – Turbulence models used to generate the synthetic turbulent wind field for
1546 aeroelastic simulations

1547 It may not be necessary to model all uncertainties listed above explicitly. Instead, related
1548 uncertainties can be combined into a single stochastic variable, and some uncertainties can be
1549 covered by general model uncertainties related to e.g., turbulent wind field generation and/or
1550 loads simulation.

1551 Annex G provides some qualitative examples of best- and worst-case scenarios for the different
1552 sources of uncertainties in atmospheric conditions.

1553 Sources of uncertainty in the marine conditions include:

- 1554 – Wave conditions: It is the uncertainty related to the measurement and/or numerical
1555 hindcasting techniques used to derive the joint probability distribution of mean wind
1556 speed, wind direction, wave direction, significant wave height and peak spectral period
1557 in relation to:
- 1558 – Normal sea states

- 1559 – Severe sea states
- 1560 – Extreme sea states
- 1561 – Sea currents: It is the uncertainty related to the derivation of near- and sub-surface
- 1562 currents in relation to:
- 1563 – Normal current models
- 1564 – Extreme current models
- 1565 – Water levels: It is the uncertainty related to the measurement and/or estimation of the
- 1566 Normal water level range as well as the long-term joint probability distribution of the
- 1567 extreme water level range
- 1568 – Marine growth on the substructure or mooring lines of floating turbines
- 1569 – Soil conditions: It is the uncertainty related to the interpretation of data from e.g. Cone
- 1570 Penetration Test, and borehole logs, seabed variations and scour development
- 1571 – Depth or seabed level

1572 Other possible sources of uncertainties should be considered when relevant for the site
1573 suitability assessment, such:

- 1574 – Uncertainty in the characterization of other environmental events, like typhoons,
- 1575 earthquakes, sea ice, tides, currents, icing
- 1576 – Uncertainty in the soil conditions.
- 1577 – Uncertainty in strength characteristics of the material due to site specific environmental
- 1578 conditions, like the effect of corrosion or extreme low temperatures.
- 1579 – Uncertainty in the knowledge of some other exposure events.
- 1580 – Uncertainty in the Loads application models. It is the uncertainty in aeroelastic response
- 1581 loads model used to estimate the site-specific wind turbine loads based on the wind
- 1582 conditions, especially if they are different to the loads models used for the design.

1583 If the strength characteristics of the wind turbine can be assumed to be invariant to the site
1584 conditions, only the uncertainties on the loads part need to be modified according the site-
1585 specific conditions.

1586 For offshore wind turbines, some parts of the structure are usually site-specific designs, such
1587 as the substructure in fixed turbines; or the floating platforms, mooring lines and anchoring
1588 systems in floating turbines. In those cases, it may be especially relevant to consider site-
1589 specific uncertainties also in the structural and geometrical characteristics of such parts.

1590 A sensitivity analysis of the different sources of uncertainties should be done to identify the
1591 most relevant uncertainties sources to include in the reliability model.

1592 **9.3.1 Quantification of site-specific uncertainties**

1593 The quantification of site-specific uncertainties shall be based on the methods described in 6.

1594 Different approaches are used to quantify the different types of uncertainties of a specific site:

1595 Physical uncertainties of the environmental conditions can be assessed based on sites with
1596 similar climatic characteristics.

1597 Measurement uncertainties of the environmental parameters can be defined by the uncertainty
1598 of the calibration of the measurement devices and by analysis of a similar measurement set up
1599 (same type of anemometer or wind sensing device) installed in a similar way in representative
1600 operating conditions.

1601 Statistical uncertainties of the environmental parameters can be defined by analysis of large
1602 datasets of data on sites with similar climatic characteristics.

1603 Model uncertainties of the wind flow model can be defined based on the comparison with more
1604 advanced models or flow measurements in sites with similar characteristics (terrain complexity,
1605 surface roughness, atmospheric stability, etc.).

1606 Model uncertainties in the loads and resistance models used for site suitability assessment can
1607 be defined based on the comparison with more advanced validated simulation models or with
1608 measurements in real turbines.

1609 Annex G provides some qualitative examples of uncertainty scenarios of epistemic
1610 uncertainties in the wind assessment as well as some reference values for uncertainties in
1611 relevant wind parameters in a normal scenario.
1612

1613 **9.4 Reliability assessment**

1614 The reliability assessment for the site suitability analysis can either be performed by
1615 determination of the probability of failure based on detailed load and strength models for site-
1616 specific conditions representing the aerodynamic, structural geometrical and material
1617 properties of the turbine components, or by determination of the probability of failure for the
1618 site conditions based on a simplified model relative to that for the design conditions. In the latter
1619 case the reliability model should be calibrated to match the expected target design reliability
1620 when the design assumptions are used e.g.- by means of adjustment of a design parameter z
1621 in the resistance model of the limit state function

1622 The reliability assessment shall be done using the methods described in 8, showing that the
1623 resulting reliability level meets the acceptable target values defined in 5.2.
1624

Annex A (informative)

Uncertainty quantification

Uncertainty quantification is here understood as the estimation of distribution types and distribution parameters for variables modelling uncertainties. Generally, it is necessary to include statistical uncertainties in the assessment. This annex describes the application of Bayesian methods and the Maximum likelihood method for this purpose.

A.1 Bayesian methods

Bayesian methods enable the combination of new data with existing information, and it enables hierarchical modelling of uncertainties. The theoretical description is generic and can be applied to all hierarchies and distribution types.

Bayes rule states that the posterior distribution $P(\theta|\varepsilon)$ of a variable is proportional to the product of the prior distribution $P(\theta)$ and the likelihood function $P(\varepsilon|\theta)$:

$$P(\theta|\varepsilon) \propto P(\theta) P(\varepsilon|\theta) \quad (35)$$

Here θ is a variable, and ε is the data or *evidence* available for updating/estimating the distribution for θ . For example, θ can be a parameter in a distribution for a variable X . The updated distribution for X , considering the data and prior information, is called the predictive distribution $P(X|\varepsilon)$, and it includes both the variation of X around the mean value, and the variation caused by statistical uncertainty on the parameters.

While Bayes rule holds for all distribution types, closed form solutions can only be found for specific combinations of prior and likelihood functions; the so-called conjugate distributions. An example is the normal distribution. If both the prior and likelihood distributions are normal distributions, the posterior distribution is also a normal distribution, and a closed form solution can be found. For hierarchical models with normal distributions, where other variables are described as linear combinations of normal distributions, exact solutions can be found for the posterior distributions. For discrete distributions, exact solutions can also be derived. However, for arbitrary choices of continuous distributions, exact solutions cannot be found for the posterior distributions. Instead sampling based methods can be applied, or the continuous parameters can be discretized. For hierarchical models, graphical models such as Bayesian networks are especially suitable.

When comparing Bayesian methods to other methods for estimation of parameters, Bayesian methods have the advantage, that existing information can be accounted for in the prior. However, Bayesian methods can also be used when no prior information is available, by using a non-informative prior: e.g. a normal distribution with a very high coefficient of variation.

A.1.1 Closed form solutions for parameter estimation

Closed form solutions exist for the predictive distribution of X for (among others) the following cases, where the population of X follows a normal distribution with unknown mean and known/unknown standard deviation σ .

- Known population standard deviation (Figure A.1)
 - No prior information on the mean
 - Prior information on the mean
- Unknown population standard deviation (Figure A.2)
 - No prior information on the mean and/or standard deviation
 - Prior information on the mean and/or standard deviation



Figure A.1 – Graphical representation of the structure for estimation of (a) the mean value of X when the population variance is known and (b) the mean value and the variance of X .

The predictive distribution of X is estimated using the prior information (if any) and a sample with sample size n , sample mean m , and sample standard deviation s :

$$m = \frac{1}{n} \sum_{i=1}^n x_i \quad (36)$$

$$s = \sqrt{\frac{1}{n-1} (x_i - m)^2} \quad (37)$$

Known population standard deviation, no prior information

The predictive distribution for X is a normal distribution:

$$X'' = m + Z \cdot \sigma \sqrt{1 + \frac{1}{n}} \quad (38)$$

where Z follows a standard normal distribution. Note that for a large sample size n , $\sqrt{1 + \frac{1}{n}} \approx 1$, whereby X asymptotically approaches a normal distribution with mean and standard deviation equal to the sample values m and s .

Known population standard deviation, prior information

Prior information on the mean of X : normal distribution with sample mean m' and size n' . The predictive distribution for X becomes a normal distribution:

$$X'' = m'' + Z \cdot \sigma \sqrt{1 + \frac{1}{n''}} \quad (39)$$

where

- Z follows a standard normal distribution.
- $n'' = n' + n$
- $m'' = \frac{m'n' + mn}{n''}$

Unknown population standard deviation, no prior information

The predictive distribution for X is a Student's t distribution:

$$X'' = m + T_{n-1} s \sqrt{1 + \frac{1}{n}} \quad (40)$$

where T_{n-1} follows a Student's t distribution with $n-1$ degrees of freedom. Note that for a large sample size n , the Student's t distribution approximates a normal distribution and $\sqrt{1 + \frac{1}{n}} \approx 1$, whereby X asymptotically approaches a normal distribution with mean and standard deviation equal to the sample values m and s .

Unknown population standard deviation, prior information

The prior information on the mean and standard deviation of X is given by parameters m', ν', s', n' . The prior for the mean is a normal distribution with mean $E[\mu] = m'$ and standard deviation $\sigma/\sqrt{n'}$ (corresponding to prior information originating from a sample with size n'). To obtain a conjugate prior for the standard deviation, the inverse of the squared standard deviation has a gamma distribution as prior, defined by the prior expected value of the standard deviation $E[\sigma] = s'$ and the prior degrees of freedom ν' . The prior degrees of freedom is related to the coefficient of variation of the standard deviation as follows: $COV[\sigma] = 1/\sqrt{2\nu'}$

The predictive distribution for X is a Student's t distribution:

$$X'' = m'' + T_{\nu''} s'' \sqrt{1 + \frac{1}{n''}} \quad (41)$$

where

- $T_{\nu''}$ follows a Student's t distribution with ν'' degrees of freedom
- $\nu = n - 1$
- $\nu'' = \nu' + \nu + 1$ for $n' \geq 1$ and $\nu'' = \nu' + \nu$ for $n' = 0$
- $n'' = n' + n$
- $m'' = \frac{m'n' + mn}{n''}$
- $s''^2 = (\nu' s'^2 + n' m'^2 + \nu s^2 + nm^2 - n'' m''^2)/\nu''$

Lognormal variable

If a variable X follows a lognormal distribution, $Y = \ln X$ follows a normal distribution. Therefore, the same approaches as above can be used for lognormal distributions, by making the inference on the logarithm of the variable.

For example, for the case with unknown population standard deviation and no prior information:

$$\ln X = m_{\ln X} + T_{n-1} s_{\ln X} \sqrt{1 + \frac{1}{n}} \quad (42)$$

where

- T_{n-1} follows a Student's t distribution with $n-1$ degrees of freedom
- $m_{\ln X}$ is the sample mean of $\ln(X)$
- $s_{\ln X}$ is the sample standard deviation of $\ln(X)$

The predictive distribution for X is then given by:

$$X = \exp \left(m_{\ln X} + T_{n-1} s_{\ln X} \sqrt{1 + \frac{1}{n}} \right) = \exp(m_{\ln X}) \exp \left(T_{n-1} s_{\ln X} \sqrt{1 + \frac{1}{n}} \right) \quad (43)$$

A.1.2 Exact inference for continuous parameters

Exact inference can be performed for hierarchical models of normal distributions, where the top nodes follow normal distributions (prior distributions with given mean and variance), and the conditional probability distribution of the other nodes are normal distributions with mean values written as a linear combination of other normal distributed variables, and with known standard deviation. For variables that can be written as a product of lognormal distributed variables, the logarithmic transformation can be used, whereby the same approach can be used.

A.1.3 Sampling-based inference

For models with arbitrary continuous distribution types and relationships between parameters, sampling based methods such as Markov Chain Monte Carlo (MCMC) methods can be used. Top nodes are described by their prior probability distributions, and other nodes can be represented by deterministic functional relationships or by density functions, where other nodes can enter as distribution parameters. Nodes described by functional relationships are referred to as logic nodes, whereas the other nodes are stochastic nodes. In a Markov Chain, the joint distribution of the simulated sample approximates the true joint distribution, when samples from the run-in period are discarded, and a sufficient number of samples is obtained, see (Gilks et al. (1996).

A.1.4 Exact inference for discretized parameters

For hierarchical models with discrete distributions, where all distributions are given as (conditional) probability distributions, efficient algorithms exist for exact inference. The same method can be used for continuous distributions, by first discretizing the variables. Functional relationships can be approximated by conditional probability distributions.

A.2 Maximum likelihood

An often used method for parameter estimation is the Maximum Likelihood method. Here, distribution parameters are estimated such that the probability of receiving the sample is maximized. For some distribution types, analytical closed form solutions exist for the maximum likelihood estimate of the parameters. For other distributions, optimization algorithms can be used to estimate the parameters, based on a sample. The statistical uncertainty (standard deviations and correlation coefficients) related to the estimated parameters can be estimated based on the hessian matrix (consisting of the second derivatives of the loglikelihood function in the point of the maximum likelihood estimate).

The likelihood function is the product of the probability density function $f_X(x; \theta)$ evaluated in the n sample points, as function of distribution parameters θ :

$$L(\theta) = \prod_{i=1}^n f_X(x_i; \theta) \quad (44)$$

To ease the computations for analytical solutions and to avoid numerical underflow for numerical calculations, the loglikelihood function is used. When taking the natural logarithm of the likelihood function, the loglikelihood function is obtained:

$$LL(\theta) = \sum_{i=1}^n \ln(f_X(x_i; \theta)) \quad (45)$$

The maximum likelihood estimate is found as the parameters maximizing $LL(\theta)$ (and thereby also $L(\theta)$). This can be done using numerical optimization algorithms or analytically from j equations:

$$\frac{\partial LL(\theta)}{\partial \theta_j} = 0 \quad (46)$$

1755 The hessian matrix for three parameters $\theta_1, \theta_2, \theta_3$ is given by:

$$H = \begin{bmatrix} \frac{\partial^2 LL(\theta)}{\partial \theta_1^2} & \frac{\partial^2 LL(\theta)}{\partial \theta_1 \partial \theta_2} & \frac{\partial^2 LL(\theta)}{\partial \theta_1 \partial \theta_3} \\ \frac{\partial^2 LL(\theta)}{\partial \theta_1 \partial \theta_2} & \frac{\partial^2 LL(\theta)}{\partial \theta_2^2} & \frac{\partial^2 LL(\theta)}{\partial \theta_2 \partial \theta_3} \\ \frac{\partial^2 LL(\theta)}{\partial \theta_1 \partial \theta_3} & \frac{\partial^2 LL(\theta)}{\partial \theta_2 \partial \theta_3} & \frac{\partial^2 LL(\theta)}{\partial \theta_3^2} \end{bmatrix} \quad (47)$$

1756 The covariance matrix is then given by:

$$C = [-H]^{-1} = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \rho_{13}\sigma_1\sigma_3 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 & \rho_{23}\sigma_2\sigma_3 \\ \rho_{13}\sigma_1\sigma_3 & \rho_{23}\sigma_2\sigma_3 & \sigma_3^2 \end{bmatrix} \quad (48)$$

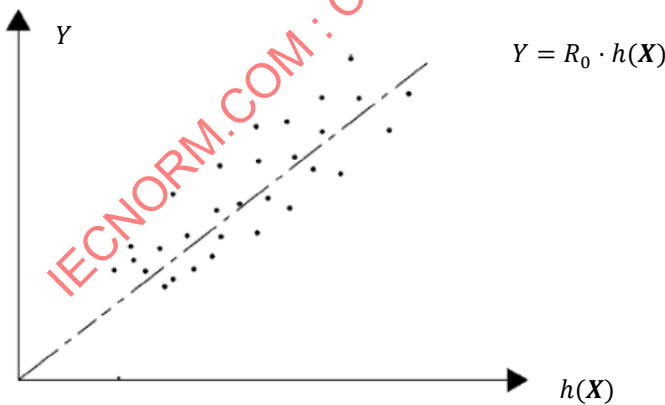
1757 where σ_j is the standard deviation of parameter θ_j and ρ_{jk} is the correlation coefficient between
1758 parameter θ_j and θ_k .

1759 The distributions for the parameters become asymptotically (more than 25-30 datapoints) normal
1760 distributed according to (Lindley 1976).

1761 A.3 Model Uncertainties

1762 Model uncertainties should be included in probabilistic models to account for the uncertainty introduced
1763 by the use of computational models for e.g. resistances and load effects. That is, the differences
1764 between the measured outcome of an experiment and the prediction based on the mathematical model.
1765 Ideally, to isolate the model uncertainty, all input parameters to the computational model should be
1766 measured in relation to the experiment.

1767 To estimate the model uncertainty, the experiment values Y are plotted as function of model values
1768 $h(X)$, as shown in Figure A.2.



1770 **Figure A.2 – Plot for estimation of model uncertainty.**

1771 Often, a lognormal multiplicative model uncertainty is assumed:

$$Y \cong R_0 \cdot h(X) \quad (49)$$

where

- Y is the test results
- R_0 is a lognormal variable for the model uncertainty with mean μ_0 and standard deviation σ_0
- $h()$ is the computational model
- X is the vector of input parameters (stochastic variables modelling physical uncertainties measured in relation to the experiment)

Several approaches can be applied to quantify the model uncertainty, when a sample with values of Y and associated input X are available. The Bayesian approach presented in A.1.1 provides an exact solution, when the relation in (6.16) is assumed and the model uncertainty is lognormal. Realizations of the model uncertainty can be evaluated as $R_{0,i} = Y_i/h(X_i)$, and the logarithmic transformation can be applied.

The model with lognormal multiplicative model uncertainty implies that the standard deviation of the error is proportional to the outcome of the computational model, thus for higher values, the error is generally larger, as the coefficient of variation is constant. If the error has constant standard deviation, regardless of the outcome of the computational model, an additive model uncertainty is more appropriate. Here, a normal distribution is often used, as this has a closed form analytical solution.

For distribution types other than normal and lognormal, closed form solutions cannot always be found, but other uncertainty quantification methods, e.g. sampling-based methods, can be used. Sampling-based methods can also be used when measurement uncertainties are to be considered on the measured input and results of the experiments.

IEC 61400-1 ed.4 Annex K uses an alternative method, which has some issues: The use of the “Least Squares” best-fit to estimate the slope b is inconsistent with the assumption of a lognormal distribution for the error term δ , as implicitly assumed. Also, with the applied method, the error term δ will generally not have a mean value equal to one, but this is also implicitly assumed.

It should be evaluated whether the assumed model with lognormal distributed multiplicative model uncertainty appropriately describes the data. The following points should be evaluated:

- Does R_0 follow a lognormal distribution (does $\ln(R_0)$ follow a normal distribution)
 - This can e.g. be evaluated using a qq-plot, a Kolmogorov Smirnov, Shapiro-Wilk, or Anderson-Darling test.
- Is the model uncertainty invariant w.r.t. $h(X)$
 - This can be evaluated by plotting the sample values of the logarithmic error $(\ln R_0)_i$ as function of $h(x_i)$.

A closed form solution can also be found when prior information on the mean and standard deviation is available. Also if the model uncertainty is a normal distributed additive error $Y \cong R_0 + h(X)$, an exact closed form solution can be obtained with the methods presented in A.1.1.

A.3.1.1 Example: Model uncertainty quantification

This example demonstrates methods for model uncertainty quantification. For the example, theoretical and experimental values of the buckling reduction factor is used for 10 experiments.

Bayesian analytical

The Bayesian approach presented in section A.1.1 provides an exact solution, when the following relation is assumed:

$$Y \cong R_0 h(X) \quad (50)$$

Table A.1 shows the theoretical and experimental values and the realizations of the model uncertainty calculated as $R_{0,i} = Y_i/h(X_i)$.

1816

Table A.1 – Theoretical and experimental values

Experiment number	Theoretical value	Experiment value	Model uncertainty realization
i	$h(X_i)$	Y_i	$R_{0,i}$
1	1.00	0.750	0.7500
2	2.00	1.599	0.7995
3	3.00	3.053	1.0173
4	4.00	4.153	1.0382
5	5.00	7.468	1.4936
6	6.00	8.066	1.3443
7	7.00	7.093	1.0133
8	8.00	7.828	0.9785
9	9.00	13.285	1.4761
10	10.00	8.760	0.8760

1817

1818 When R_0 follows a lognormal distribution, $\ln R_0$ follows a normal distribution. The mean and standard
1819 deviation of $\ln R_0$ is found by:

$$m_{\ln R_0} = \frac{1}{n} \sum_{i=1}^n (\ln(R_{0,i})) = 0.0489 \quad (51)$$

$$s_{\ln R_0} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\ln(R_{0,i}) - m_{\ln R_0})^2} = 0.2424 \quad (52)$$

1820 These are the parameters of the estimated lognormal distribution, and the mean and standard deviation
1821 are calculated from standard relations:

$$1822 \quad m_{R_0} = \exp\left(m_{\ln R_0} + \frac{1}{2} s_{\ln R_0}^2\right) = 1.0814$$

$$1823 \quad s_{R_0} = \sqrt{m_{R_0}^2 (\exp(s_{\ln R_0}^2) - 1)} = 0.2661$$

1824 These are the best estimates for the model uncertainty, but they do not account for statistical uncertainty.

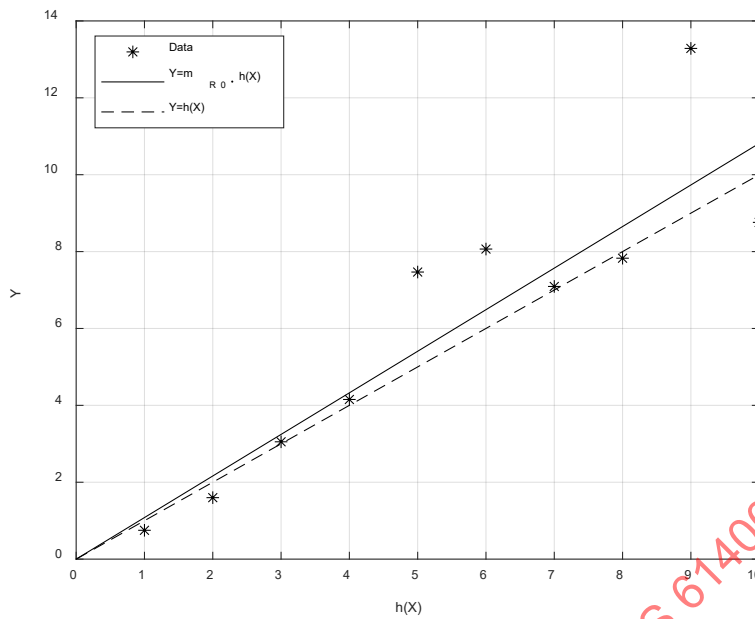


Figure A.3 – Experiment value Y as function of theoretical value h(x)

For a sample drawn from R_0 , where both mean and standard deviation are uncertain without any prior information, the predictive distribution for $\ln R_0$ can be found based on the sample size n , sample mean $m_{\ln R_0}$ and sample standard deviation $s_{\ln R_0}$:

$$\ln R_0 = m_{\ln R_0} + T_{n-1} s_{\ln R_0} \sqrt{1 + \frac{1}{n}}$$

where T_{n-1} follows a Student's t distribution with $n-1$ degrees of freedom.

For the model uncertainty R_0 , the predictive distribution accounting for statistical uncertainty is given by:

$$R_0 = \exp(m_{\ln R_0}) \exp\left(T_{n-1} s_{\ln R_0} \sqrt{1 + \frac{1}{n}}\right) \quad (53)$$

Realizations corresponding to non-exceedance probability p is found from:

$$r_0(p) = \exp(m_{\ln R_0}) \exp\left(t_{p,n-1} s_{\ln R_0} \sqrt{1 + \frac{1}{n}}\right) \quad (54)$$

For example, for $p = 0.05$, and $n = 10$, the Student's t distribution gives $t_{p,n-1} = -1.8331$, and thus the equation gives $r_0(0.05) = 0.6589$.

Figure A.4 – Cumulative distribution and probability density functions for the predictive distribution, the estimated lognormal distribution and the predictive distribution shows the cumulative distribution and probability density functions for the predictive distribution, The estimated lognormal distribution and the predictive distribution show the obtained cumulative distribution function and probability density function for the predictive distribution, the estimated lognormal distribution (not accounting for statistical uncertainty), and the predictive distribution

1842 if the sample size was instead $n = 5$. It is observed that the lower tail is significantly affected by
1843 the statistical uncertainty for low sample sizes.

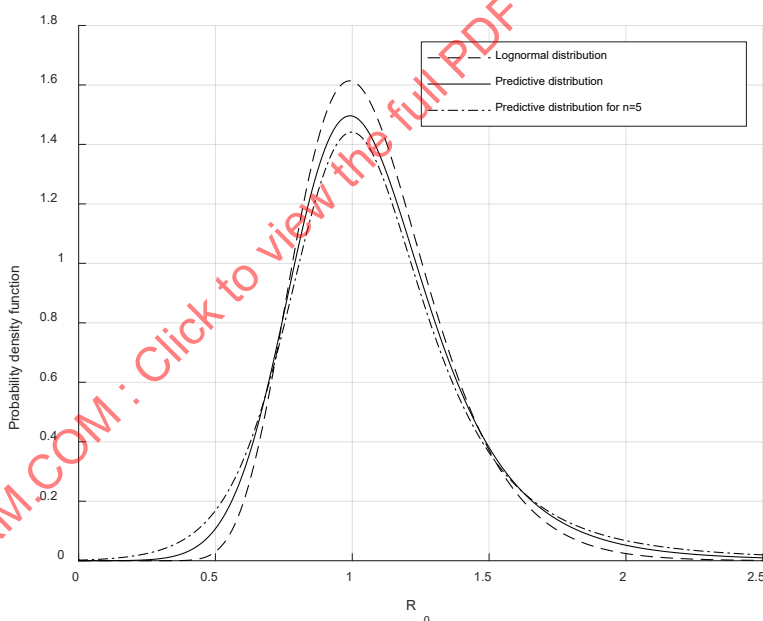
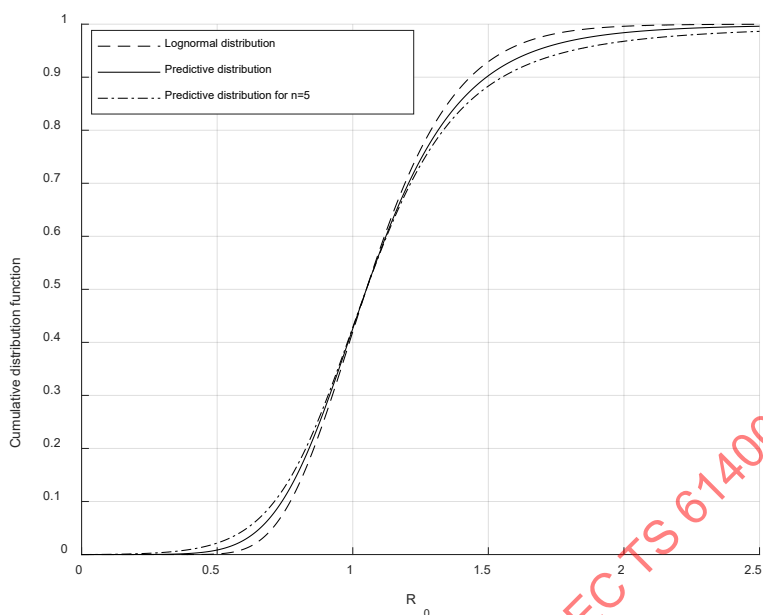


Figure A.4 – Cumulative distribution and probability density functions for the predictive distribution, the estimated lognormal distribution and the predictive distribution

MCMC methods

MCMC methods allow working with various distribution types, and there are several ways to construct the model for uncertainty quantification. Two models are shown in Figure A.5 a and Figure A.5 b for a model without and with measurement uncertainty, respectively. For the model without measurement uncertainty, realizations of the model uncertainty are calculated from the experiment values and model values: $R_0 = Y/h(X)$. If the experiment is subject to measurement uncertainty, the model value $h(X)_i$ and the measured values of the experiment outcome $Y_{meas,i}$ are used directly.

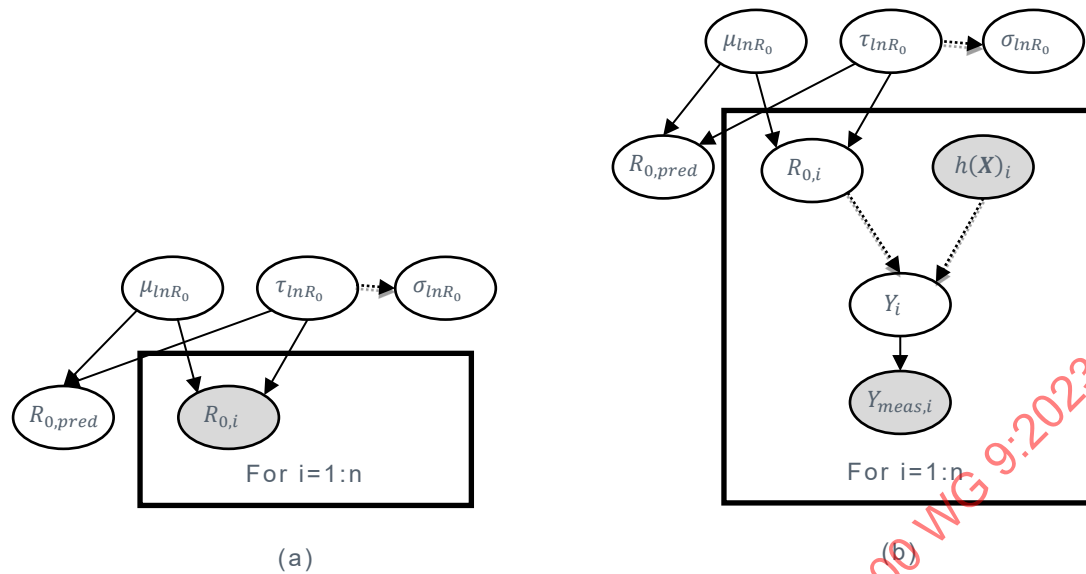


Figure A.5 – Various approaches for MCMC models for model uncertainty quantification. Full lines represent stochastic relationships, dotted lines represent logic relationship, and shaded nodes are observed nodes. (a) without measurement uncertainty, (b) with measurement uncertainty.

Full lines represent stochastic relationships, dotted lines represent logic relationship, and shaded nodes are observed nodes. The nodes $R_{0,i}$, $h(X)_i$, Y_i and $Y_{meas,i}$ each have n instantiations; one for each set of values in the sample. The nodes μ_{R_0} and τ_{R_0} are the nodes for the parameters in the distribution for the model uncertainty, in this case the mean and precision of $\ln R_0$. In relation to MCMC, the normal and lognormal distributions are often formulated with the precision ($\tau_{R_0} = 1/\sigma_{R_0}^2$) as second parameter instead of the standard deviation σ_{R_0} . The node $R_{0,pred}$ is the node for the predictive distribution of the model uncertainty, and it will follow the same distribution as $R_{0,i}$, but unlike $R_{0,i}$, it is not observed.

If no prior information is available on the parameters $\mu_{\ln R_0}$ and $\tau_{\ln R_0}$, they should be given non-informative priors. For the mean value, an appropriate non-informative prior is a normal distribution, and for the precision, a gamma distribution. Both should have parameters resulting in mean values in the right order of magnitude and sufficiently large standard deviation.

The distributions for model 1 are formulated as follows in the example.

Table A.2 – Stochastic model

Variable	Distribution	Parameter 1	Parameter 2
$\mu_{\ln R_0}$	Normal	Mean: $\mu = 0$	Precision: $\tau = 10^{-6}$
$\tau_{\ln R_0}$	Gamma	Shape: $\alpha = 0.001$	Rate: $\beta = 0.001$
$R_{0,i}$	Lognormal	Mean of $\ln R_0$: $\mu_{\ln R_0}$	Precision of $\ln R_0$: $\tau_{\ln R_0}$
$R_{0,pred}$	Lognormal	Mean of $\ln R_0$: $\mu_{\ln R_0}$	Precision of $\ln R_0$: $\tau_{\ln R_0}$

Maximum likelihood

The maximum likelihood method can also be used to estimate the parameters for the model uncertainty variable.

As R_0 is assumed to follow a lognormal distribution with parameters $\mu_{\ln R_0}, \sigma_{\ln R_0}$, it follows that $\ln R_0$ follows a normal distribution with parameters $\mu_{\ln R_0}, \sigma_{\ln R_0}$, and can be written based on the standard normal density function ϕ :

$$\ln R_0 \sim f_{\ln R_0}(\ln R_0 | \mu_{\ln R_0}, \sigma_{\ln R_0}) = \frac{1}{\sigma_{\ln R_0}} \cdot \phi\left(\frac{\ln R_0 - \mu_{\ln R_0}}{\sigma_{\ln R_0}}\right) \quad (55)$$

The likelihood and loglikelihood function are written as:

$$L(\mu_{\ln R_0}, \sigma_{\ln R_0}) = \prod_{i=1}^n \frac{1}{\sigma_{\ln R_0}} \cdot \phi\left(\frac{\ln R_{0,i} - \mu_{\ln R_0}}{\sigma_{\ln R_0}}\right) \quad (56)$$

$$LL(\mu_{\ln R_0}, \sigma_{\ln R_0}) = \sum_{i=1}^n \ln\left(\frac{1}{\sigma_{\ln R_0}} \cdot \phi\left(\frac{\ln R_{0,i} - \mu_{\ln R_0}}{\sigma_{\ln R_0}}\right)\right) \quad (57)$$

The maximum likelihood estimates of the parameters are found by maximizing $LL(\mu_{\ln R_0}, \sigma_{\ln R_0})$ with respect to the parameters $\mu_{\ln R_0}, \sigma_{\ln R_0}$ using an optimization algorithm that also provides the hessian matrix from which the covariance matrix can be estimated. The parameters are estimated to $(\mu_{\ln R_0}, \sigma_{\ln R_0}) = (0.0489, 0.2300)$ and the covariance matrix is estimated to:

$$C = \begin{bmatrix} 0.0053 & 0.0000 \\ 0.0000 & 0.0026 \end{bmatrix}$$

Assuming a multivariate normal distribution for the parameters, samples from the predictive distribution can be drawn by first drawing from the multivariate distribution for $\mu_{\ln R_0}, \sigma_{\ln R_0}$, and then from $R_0 \sim \text{logn}(\mu_{\ln R_0}, \sigma_{\ln R_0})$.

Comparison

Results from the three methods are shown in Table A.3 and Table A.4 and in Figure A.6, Figure A.7, Figure A.8 and Figure A.9. The estimated parameters are similar for the three methods, the parameter σ_Y is smaller for the maximum likelihood method. The reason is that the maximum likelihood method finds the mode values of the parameters, and as the standard deviation does not have a symmetric distribution, the mode value does not equal the expected value. The quantiles for the maximum likelihood method deviates even more, as the distributions for the mean and standard deviation are assumed normal distributed, which are not the correct sampling distributions. (The inverse of the squared standard deviation follows a gamma distribution, and for a sample size approaching infinity, this gamma distribution approaches a normal distribution.)

Table A.3 – Parameters and moments estimated using each method

	Parameters		Moments	
	$\mu_{\ln R_0}$	σ_0	μ	σ
Analytical	0.0489	0.2424	1.0814	0.2661
MCMC	0.0489	0.2428	1.0815	0.2665
ML	0.0489	0.2300	1.0782	0.2513

Table A.4 – Selected quantiles for the predictive distribution (including statistical/parameter uncertainty) and the fitted lognormal distribution (not including statistical/parameter uncertainty) using each method

Quantile	Predictive			Lognormal		
	Analytical	MCMC	ML	Analytical	MCMC	ML
0.001	0.3522	0.3428	0.4547	0.4964	0.4958	0.5159
0.01	0.5125	0.5090	0.5772	0.5974	0.5969	0.6150
0.05	0.6589	0.6567	0.7011	0.7048	0.7043	0.7193
0.1	0.7388	0.7376	0.7717	0.7697	0.7693	0.7820

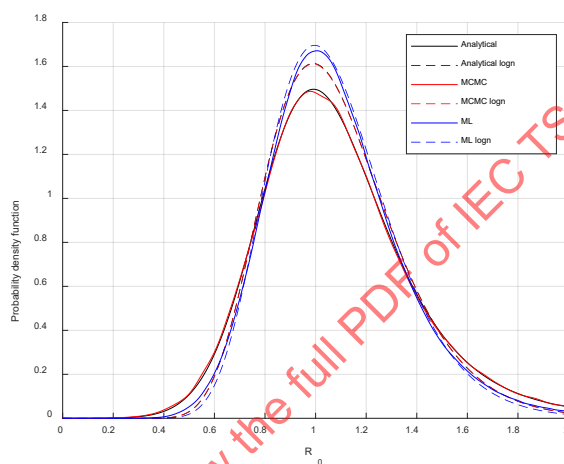


Figure A.6 – Probability density function for each method

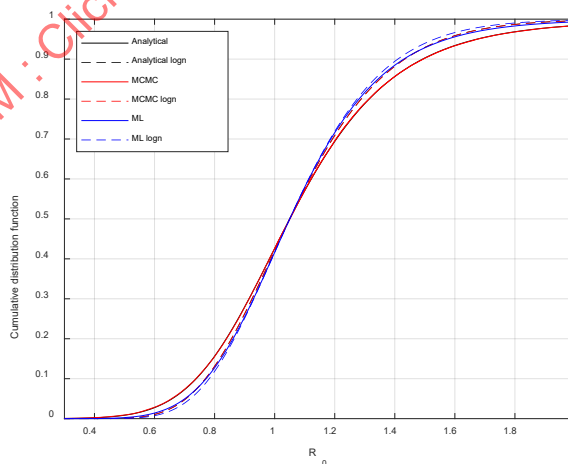


Figure A.7 – Cumulative distribution function for each method

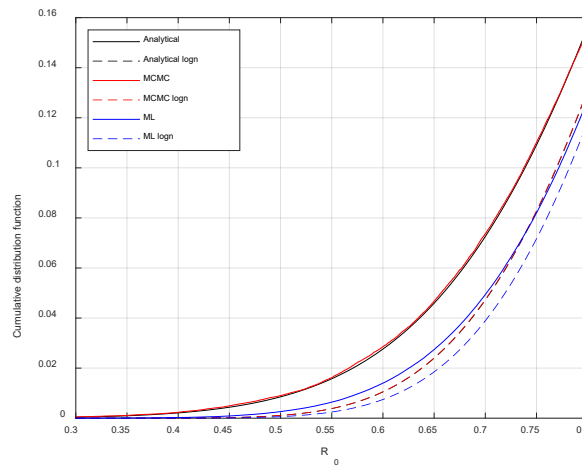


Figure A.8 – Lower tail of the cumulative distribution function for each method

If the sample size is increased to $n=50$, the difference between the methods is much less, and the significance of the statistical uncertainty disappears, as seen in Figure A.9. For a lower COV, the uncertainty will generally be reduced, and the difference between the methods will be lower.

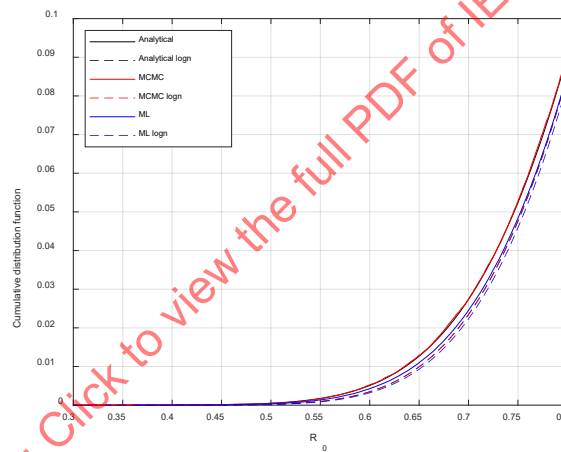


Figure A.9 – Lower tail of the cumulative distribution function for each method for a sample size $n=50$

Annex B (informative)

Inverse FORM

Inverse FORM (IFORM), Winterstein et al. (1993), can be applied to find contours for environmental conditions with a given probability of exceedance in the long-term joint distribution of e.g. mean wind speed and turbulence standard deviation or mean wind speed, significant wave height and peak spectral period. IFORM has been applied to derive formulations for the turbulence standard deviation conditional on the 10-minute mean wind speed for NTM and ETM in IEC 61400-1.

In IFORM, the stochastic variables x are transformed to the independent standard normal space (u -space) using e.g. the Rosenblatt transformation (Rosenblatt, 1952). A given exceedance probability, P , is associated with any point in u -space with a distance β to the origin through the relation:

$$\beta = -\Phi^{-1}(P) \quad (58)$$

For specific events (such as the number of grid outages, start-ups or shutdowns per year) which can be assumed to follow a Poisson process and is independent of the environmental conditions the conditional event probability can be introduced directly in the IFORM analysis. Assuming that the annual event frequency λ_E is known, the associated conditional distance to the origin β_E is obtained through the relation:

$$\beta_E = -\Phi^{-1}\left(\frac{1}{\lambda_E} P\right) \quad (59)$$

In n dimensions, the coordinates of the u -vector $\mathbf{u}$ should therefore fulfil:

$$\beta = \|\mathbf{u}\| = \sqrt{u_1^2 + \dots + u_n^2} \quad (60)$$

In two dimensions, the points are located on circle with radius β , and pairs of u -values can be found from the following (for all θ from 0 to 2π):

$$\begin{aligned} u_1 &= \beta \cos \theta \\ u_2 &= \beta \sin \theta \end{aligned} \quad (61)$$

Corresponding values for each of the variables x , are found by equating their respective distribution functions with the standard normal distribution function, and solving for the variable, x :

$$\begin{aligned} F(x) &= \Phi(u) \\ x &= F^{-1}(\Phi(u)) \end{aligned} \quad (62)$$

For example, for the Rayleigh distribution, the distribution function can be written:

$$F(x) = 1 - \exp\left(-\left(\frac{x}{\alpha}\right)^2\right) \quad (63)$$

Solving for x then yields:

$$x = \alpha \sqrt{-\ln(1 - \Phi(u))} \quad (64)$$

1950 **Example: NTM and ETM model**

1951 This example shows how to use IFORM to calculate environmental contours for the NTM and
1952 ETM model. The 10 minute mean wind speed, V , is assumed to follow a Rayleigh distribution,
1953 and the turbulence standard deviation σ follows a Weibull distribution.

1954 a) Select exceedance probability:

1955 The turbulence in NTM corresponds to the 90% quantile in the annual distribution, i.e.
1956 it is exceeded 10% of the time:

$$P_{NTM} = 0.1 \quad (65)$$

1957 The turbulence in ETM has an occurrence probability corresponding to 10 minutes out
1958 of 50 years.

$$P_{ETM} = \frac{10}{60 \cdot 24 \cdot 365 \cdot 50} = 3.805 \cdot 10^{-7} \quad (66)$$

1959 b) Calculate corresponding distance to the origin, β , in standard normal space:

$$\begin{aligned} \beta_{NTM} &= -\Phi^{-1}(P_{NTM}) = 1.282 \\ \beta_{ETM} &= -\Phi^{-1}(P_{ETM}) = 4.9 \end{aligned} \quad (67)$$

1960 c) Generate points in u-space with distance β to origin, covering the area of interest:

1961 Using equations (60) and (61) with values of θ in the range from 0 to 2π , Figure B.1 is
1962 generated:

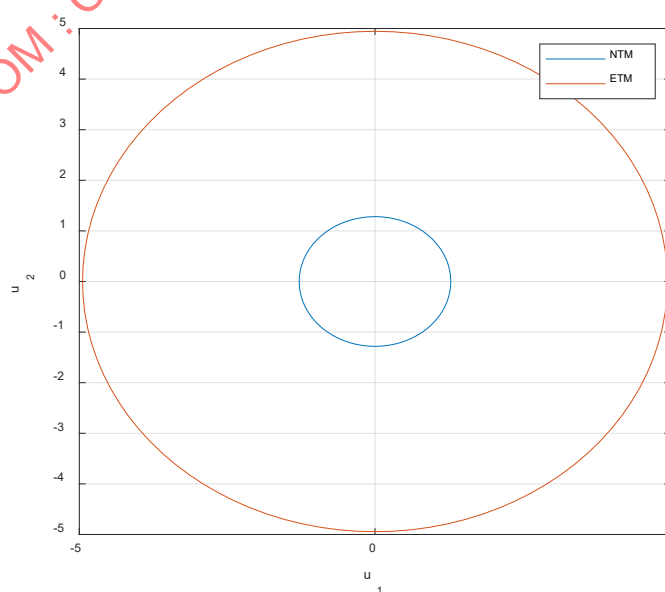


Figure B.1 – Contour lines for NTM and ETM in the u-space

- 1965 d) Calculate x-vectors corresponding to the points in u-space using the inverse cumulative
1966 distribution functions.

1967 Here $x_1 = V$ and $x_2 = \sigma$.

1968 For the 10 minute mean wind speed, a Rayleigh distributed variable with mean μ_V , the
1969 transformation is:

$$V(u_1) = \frac{2\mu_V}{\sqrt{\pi}} \sqrt{-\ln(1 - \Phi(u_1))} \quad (68)$$

1970 The turbulence standard deviation σ is assumed to follow a Weibull distribution with shape
1971 parameter k and scale parameter C , both conditioned on the wind speed:

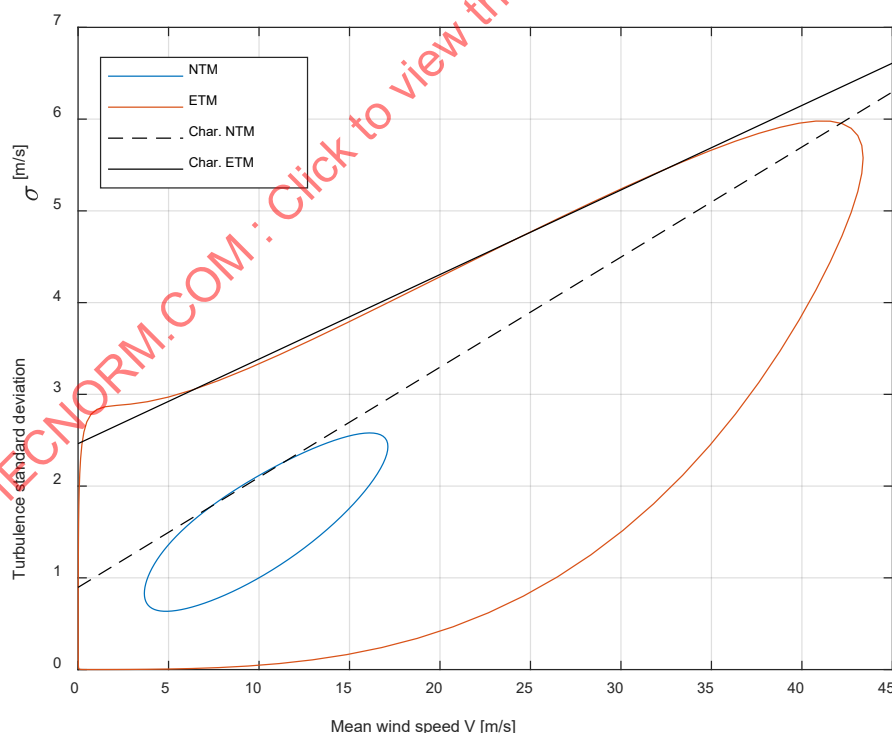
$$k(u_1) = 0.27 V(u_1) + 1.4 \quad (69)$$

$$C(u_1) = I_{ref}(0.75 V(u_1) + 3.3)$$

1972 Values of the turbulence standard deviation are then calculated from:

$$\sigma(u_1, u_2) = C(u_1) \cdot (-\ln(1 - \Phi(u_2)))^{\frac{1}{k(u_1)}} \quad (70)$$

1973 For IEC class IA, the mean μ_V is 10 m/s, and the turbulence intensity I_{ref} is 0.16. Figure B.2
1974 shows the contours for NTM and ETM together with the characteristic values defined in IEC
1975 61400-1 ed. 4.



1976

1977 **Figure B.2 – Contour lines for NTM and ETM, and the characteristic values defined in**
1978 **IEC61400-1**

1979
1980

Annex C (informative)

Example Calculations for Reliability Assessment

The purpose of this information annex is to provide some representative probabilistic models for the main wind turbine components (Tower) and design situations (DLC 1.2, 1.3 & 6.1) in order to describe the background for the partial safety factors in the IEC 61400-1 standard.

The representative probabilistic models can either be tailored directly to a specific wind turbine design or used as a baseline to define probabilistic models for other main wind turbine components or design situations.

C.1 Ultimate Limit State

C.1.1 Design Equation

The design equation is defined according to IEC 61400-1 4th edition equation (29) and (30):

$$G = z \frac{1}{\gamma_M} R_k - \gamma_f L_k \geq 0 \quad (71)$$

where z is a design parameter (which may be used to scaled the design equation to the limit $G=0$), γ_M is the partial safety factor for material parameters and resistance models, R_k is the characteristic value for the resistance, γ_f is the partial safety factor for loads and L_k is the characteristic value for the loads. The partial safety factor for consequences of failure γ_n is implicitly assumed to 1.0 corresponding to component class 2.

C.1.2 Limit State Equation

The limit state function is defined as:

$$g = z \delta R X_{Str} - X_{Site} X_{Aero} X_{Dyn} X_{Mat} X_{Wind} X_{Sim} L \quad (72)$$

where δ is the model uncertainty for the resistance model, R is the physical, model and statistical uncertainty in the dominating strength parameter and X_{Str} is the model uncertainty in the stress / strain model.

X_{Site} is the physical, model, statistical and measurement uncertainty in the site / atmospheric conditions, see Annex G, X_{Aero} is the physical and model uncertainty in the aerodynamic properties, X_{Dyn} is the model uncertainty in the aeroelastic model, X_{Mat} is the physical uncertainty in the material and geometrical properties, X_{Wind} is the model uncertainty in the wind model e.g. turbulence box and wake modelling, X_{Sim} is the statistical uncertainty in the simulation setup and L is the physical uncertainty in the load effect.

The uncertainties in the loading conditions are (when relevant) assumed propagated through the aeroelastic model to the load parameter of interest, see section 6.3.2. The stochastic variable F is normally determined by fitting a distribution function to the load parameter evaluated for different quantiles of dominating environmental conditions e.g. extreme turbulence in DLC 1.3 and extreme mean wind speeds in DLC 6.1.

The baseline stochastic variables are listed in Table C.1 – for wind loading (normal operation / idling) and gravity loading along with the resistance (Steel).

2017

Table C.1 – Baseline stochastic variables for load and resistance model.

Variable	Distribution	Mean	Char.	COV		
				Wind Loading Normal Operation	Wind Loading Idling	Gravity Loading
X_{Site}	LN	1.00	μ	10%	10%	0%
X_{Aero}	LN	1.00	μ	10%	10%	0%
X_{Dyn}	LN	1.00	μ	5%	5%	0%
X_{Mat}	LN	1.00	μ	5%	5%	5%
X_{Wind}	LN	1.00	μ	10%	10%	0%
X_{Sim}	LN	1.00	μ	5%	5%	0%
L	G / G / N	-	98% / 98% / μ	5%	23%	5%
δ	LN	1.00	μ	5%		
R (Steel)	LN	-	5%	5%		
X_{Str}	LN	1.00	μ	5%		

2018

C.1.3 Reliability Assessment

2020 The annual reliability index for the different wind turbine components and design situation are
 2021 estimated using the First Order Reliability Method (FORM) and listed in Table C.2 – . The
 2022 estimate reliability index is for DLC 1.3, DLC 6.1 and Gravity loading close to the target reliability
 2023 index of 3.3 according to 5.

Table C.2 – Annual reliability index for different main wind turbine components (Tower) and design situations (DLC 1.3 & 6.1).

Material	γ_M	Wind Loading Normal Operation DLC 1.3	Wind Loading Idling DLC 6.1	Gravity Loading
γ_f		1.35	1.35	1.10
Steel	1.20	$\beta = 3.26$	$\beta = 3.29$	$\beta = 3.22$

2026

C.1.4 Direct reliability-based design

2028 In the case of direct reliability design, one can solve for the probability of failure for various
 2029 values z of the design parameter. This method obviates the use of the design equation and its
 2030 associated safety factors, as the required safety is obtained directly through the calculation of
 2031 the design parameter z required to achieve the target reliability level.

2032 An example is provided for the probabilistic model in Table C.1 – above and focusing on the
 2033 case of an analysis of a steel component under normal operation conditions. For the direct
 2034 reliability calculation, distributions for load and resistance need to be fully characterized, and
 2035 in this example we choose (arbitrarily) reference values of 1.0 for both the characteristic levels
 2036 of load (F_K , or the 98% quantile of the load distribution) and resistance (R_K , or the 5% quantile
 2037 of the material strength distribution), we use FORM to obtain the results shown in Table C.3 –
 2038 for reliability index as a function of design parameter z .

Table C.3 – Resulting reliability index for different values of design parameter for simplified example

z	1.45	1.55	1.65	1.75
β	2.76	3.06	3.34	3.61

Alternatively, one can also iteratively calculate the value of design parameter that will meet a desired, pre-assigned, reliability level.

C.1.5 Reliability-based calibration of partial safety factors

In a different application case – going back to the use of the design equation and partial safety factors – suppose new information collected substantiates the argumentation that, for a given site where a more accurate combination of models and measurements is used, the coefficient of variation of X_{Site} is reduced to 0.05. In such cases, one could calibrate a new safety factor for loads following the same procedure outlined above.

Again, starting from the baseline probabilistic model assumed for steel components and normal operating conditions stated in Table C.1 – above, Table C.4 – shows the results for the reliability index for several different values of the safety factor choice γ_f given $\gamma_M = 1.20$ (the only applicable choices would be the ones resulting in a reliability index higher than 3.3):

Table C.4 – Resulting reliability for different partial safety factor for loads (given $\gamma_M = 1.2$)

γ_f	1.20	1.25	1.30	1.35
β	2.95	3.15	3.34	3.53

C.1.6 Assess the accuracy of the computation and perform sensitivity studies

Assume a designer has chosen the design parameter $z = 1.65$ from the calculation outlined in

C.1.1 to meet a target reliability of $\beta = 3.34$. One may estimate and justify the accuracy of this solution by applying a direct simulation method such as a crude Monte Carlo.

In a crude Monte Carlo, all the random variables composing the limit state equation are randomly drawn from their respective distributions defined in Table C.1 a sufficiently large number of times and the probability of failure is estimated as the relative number of times the resulting limit state equation is lower than 0. Table C.5 shows the estimated probability of failure as the number of Monte Carlo runs increases in magnitude.

Table C.5 – Assessment of reliability index convergence with number of draws in Monte Carlo simulations

N	10^4	10^5	10^6	10^7
β	3.23	3.27	3.27	3.27

From Table C.5 one concludes that the reliability index is converging to $\beta = 3.27$ which is within 2.5% of the value obtained by FORM. For more complex cases and limit states, one notes that the accuracy of FORM might not be guaranteed to be of this magnitude. Alternatives are the use of Second Order Reliability Method (SORM) and other direct simulation techniques such as adaptive importance sampling.

There are several ways that one can access the sensitivity of the results from a reliability analysis with respect to input variables of interest. Here two of such ways are listed.