

CRANFIELD UNIVERSITY

ABDULHAKIM ADEOYE SHITTU

STRUCTURAL RELIABILITY ASSESSMENT OF COMPLEX
OFFSHORE STRUCTURES BASED ON NON-INTRUSIVE
STOCHASTIC METHODS

SCHOOL OF WATER, ENERGY, AND ENVIRONMENT
Energy and Power

PhD

Academic Year: 2020 - 2021

Supervisor: Dr Ali Mehmanparast
Associate Supervisor: Prof. Athanasios Kolios
November 2020

CRANFIELD UNIVERSITY

SCHOOL OF WATER, ENERGY, AND ENVIRONMENT
Energy and Power

PhD

Academic Year 2020 - 2021

ABDULHAKIM ADEOYE SHITTU

STRUCTURAL RELIABILITY OF COMPLEX OFFSHORE
STRUCTURES BASED ON NON-INTRUSIVE STOCHASTIC
METHODS

Supervisor: Dr Ali Mehmanparast
Associate Supervisor: Prof. Athanasios Kolios
November 2020

This thesis is submitted in partial fulfilment of the requirements for
the degree of PhD

© Cranfield University 2020. All rights reserved. No part of this
publication may be reproduced without the written permission of the
copyright owner.

ABSTRACT

Offshore Wind Turbines (OWTs) are deployed in harsh environments often characterised by stochastic loads and resistance properties. It becomes necessary to propose an accurate and efficient approach for the assessment of uncertainties in material properties and operating environments. Structural Reliability Assessment (SRA) as a form of uncertainty analysis is a useful tool in the design of structures because it can directly quantify how uncertainty about input parameters can affect structural performance. First, this thesis developed a novel non-intrusive SRA method for an OWT jacket structure which maps the response of the structure through a finite number of simulations to develop a response surface and then employ First Order Reliability Methods (FORM) to evaluate the reliability index. This method was validated against a commercial FEA package (DesignXplorer© from ANSYS) which employs direct simulations to predict the probability of failure. The method developed was used in performing stochastic sensitivity analysis of the variables imposed on the OWT support structure. The results from this study, reveals that the uncertainties in the design wind speed is a design driving factor and the hydrodynamic load effects are secondary to this, for the ultimate (ULS), and fatigue limit states (FLS), among others. Second, the SRA of the same structure subjected to pitting corrosion-fatigue was assessed using a damage tolerance modelling approach. The non-intrusive formulation in this study used an Artificial Neural Network (ANN) response surface modelling technique instead of the Multivariate (Quadratic) Polynomial Regression (MPR) method used previously apart from the FEA to represent the crack propagation regimes. The results reveal that for the inherent stochastic conditions, the structure becomes unsafe after the 18th year, before the attainment of the design life of 20 years, among others. The benefit of this approach is that it allows for high fidelity computational tools to be employed for the analysis, hence extending its applicability to various specialist engineering problems through the advanced modelling techniques.

Keywords:

First order reliability method, finite element analysis, surrogate/ meta-modelling, multivariate polynomial regression, artificial neural networks, time-variant phenomena

ACKNOWLEDGEMENTS

First of all, all praise be to Allah the lord of the worlds, the most beneficent, the most merciful, for His guidance throughout and also for His grace on me to insha Allah complete this PhD programme successfully. I would like to express my profound gratitude to my supervisors, Dr Ali Mehmanparast, and Prof Athanasios Kolios, for their confident supervision and generous support throughout the three years of this PhD and ensuring this thesis is of the highest standards. Their advice, brilliant ideas, and timely corrections proved to be very effective, and would not be forgotten. To Prof Athanasios Kolios, special thanks for accepting me as your PhD student at Cranfield University and painstakingly guiding the first few steps of my research career.

I also wish to acknowledge the Petroleum Technology Development Fund (PTDF) Nigeria for supporting my PhD in the UK at Cranfield University for three years, as well as Federal University Wukari, Taraba State, for granting my study fellowship request. In addition, I would like to acknowledge the UK Engineering and Physical Sciences Research Council (EPSCR) for funding. Also, I would like to express my sincere gratitude to my other supervisors Prof Phil Hart, Prof Feargal Brennan and Dr Mahmood Shafiee for our fruitful discussions, your critical analysis, and valuable feedback to my work. To Dr Lin Wang, Dr Peyman Amirafshari, Prof Konstantinos Salonitis, and Dr Karl Pilario thank you for your counsel and for the opportunity to work with you.

Special thanks also to Dr Clare Humphries, the IT staff, and Sam Skears for all your help concerning important matters about the PhD and other requirements. I would like to thank my friends Ahmed Aliyu, Kehinde Oyetunde, Abdulhadi Shittu, Mukhtar Adamu, Aminu Bukar, Dr Fatima Shittu, Dr Jibril Shittu, Nana Hauwa Shittu, Dr Victor Igwemezie, Dr Waseem Khodabux, Engr. Godwin Lazhi Yisa, Segun Osundare, Dr Ebuwa Osagie, Arc Ibrahim Shittu, Osas Ehigiator, Maren Dangut, Richard Oribi Ivanhoe, Dr Stephen Okonji, Dr Hakuri Joshua and others too numerous to mention I have had a chance to interact with. Your company has made my PhD journey in Cranfield memorable.

My deepest gratitude also goes to my family in the UK, the Cranfield Islamic Society (CIS) and the Nigerian Society especially Dr Abdulkabir Aliyu, Kamal Abudu, Kabiru Ayuba, Hussein Zahradeen and others too numerous to mention. I couldn't have made it without your help. Thank you for the times we spent in the masjid, for welcoming me into your homes and allowing me to celebrate with you on many occasions and so much more. I will truly miss you all.

Most of all, I am thankful to Olawumi Yusuf for generously giving me her constant support and the motivation that I needed and for being there for me throughout the whole PhD adventure. To my parents, Alh. R.A.A. Shittu and Haj. S.L. Shittu, my siblings, my relatives, and my son Abdulrahman Ayantola Oluwatodimu Shittu back home, I am grateful to have you all in my life. Thank you all for supporting me to pursue a PhD, right from the start. I dedicate this work to you.

DECLARATION

I declare that no part of this work referred to in this PhD thesis has been submitted for any other degree or qualification of any university or institute of learning. The two journal papers contained in this thesis were published by MDPI and Wiley which allow reusing and reproducing the entire published material in an unchanged form in the PhD thesis.

MDPI “All articles published by MDPI are made immediately available worldwide under an open access license. This means the published material can be used in this thesis as long as proper accreditation/ citation of the original publication is given”. Available online: <https://www.mdpi.com/about/openaccess>.

Wiley “Author may share any version of their articles for the purpose of submission of thesis, or doctorate”. Available online: <https://authorservices.wiley.com/author-resources/Journal-Authors/Promotion/article-sharing-policy.html>

TABLE OF CONTENTS

ABSTRACT	i
ACKNOWLEDGEMENTS.....	iii
DECLARATION.....	v
LIST OF FIGURES.....	xi
LIST OF TABLES	xv
LIST OF ABBREVIATIONS	xix
1 INTRODUCTION.....	1
1.1 Background.....	1
1.2 Aim and Objectives	6
1.3 List of Publications.....	7
1.4 Structure of the Thesis.....	7
References	8
2 A SYSTEMATIC REVIEW OF STRUCTURAL RELIABILITY METHODS FOR DEFORMATION AND FATIGUE ANALYSIS OF OFFSHORE JACKET STRUCTURES.....	11
2.1 Introduction	12
2.2 Level III Analytical Structural Reliability Analysis Methods	15
2.2.1 First Order Reliability Method (FORM)	16
2.2.2 Second-Order Reliability Method (SORM)	20
2.3 Level III (Direct) Reliability Methods.....	21
2.4 Advanced Approximation Modelling Methods	23
2.4.1 Response Surface Method	24
2.4.2 Surrogate Models (SMs)	26
2.5 Probabilistic Fatigue and Fracture Mechanics Approaches	30
2.6 Other Methods and Applications.....	31
2.6.1 Stochastic Finite Element Method (SFEM).....	31
2.6.2 Reliability Analysis of Systems.....	32
2.6.3 Time-Variant Reliability of Systems.....	33
2.7 Critical Discussion.....	34
2.8 Conclusion	45
References	46
3 COMPARATIVE STUDY OF STRUCTURAL RELIABILITY ASSESSMENT METHODS FOR OFFSHORE WIND TURBINE JACKET SUPPORT STRUCTURES.....	51
3.1 Introduction	52
3.2 Theoretical Background on the ANSYS DesignXplorer© Probabilistic Methods.....	56
3.2.1 Monte Carlo Simulation.....	56
3.2.2 Direct Sampling (“Crude” Monte Carlo).....	57
3.2.3 Six Sigma Analysis (SSA) Theory	60

3.2.4 ANSYS DesignXplorer© for Structural Reliability Analysis.....	61
3.3 Development of a Non-Intrusive, Modular Formulation for Structural Reliability Assessment.....	62
3.3.1 A Modular Structural Reliability Assessment Algorithm.....	62
3.3.2 Multivariate Regression.....	63
3.3.3 FORM (First-Order Reliability Method).....	64
3.4 Design Load Analysis	65
3.4.1 Sources of Loads	65
3.4.2 Site Specifications and Design Load Cases.....	70
3.5 Baseline 10 MW OWT	71
3.5.1 Parametric FEA.....	72
3.5.2 Validation of the FEA.....	77
3.6 Implementation of Structural Reliability Assessment on the OWT Support Structure.....	79
3.6.1 Constraints and Design Criteria	80
3.6.2 Stochastic Variables and FEA.....	83
3.7 Results and Discussion.....	84
3.8 Conclusions	92
References	93
4 SENSITIVITY ANALYSIS OF DESIGN PARAMETERS FOR RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE JACKET SUPPORT STRUCTURES.....	99
4.1 Introduction	100
4.2 Design load analysis	104
4.2.1 Sources of loads	104
4.2.2 Design load cases (DLCs) and site specifications.....	108
4.3 OWT case study	109
4.3.1 Parametric FEA.....	110
4.3.2 Validation of the FEA model.....	114
4.4 Implementation of the stochastic sensitivity analysis (SSA) on the OWT support structure.....	116
4.4.1 Limit state design criteria.....	116
4.4.2 A non-intrusive formulation.....	120
4.4.3 SSA.....	121
4.4.4 Stochastic variables	125
4.4.5 FORM (First Order Reliability Method)	125
4.5 Results and discussion	127
4.6 Conclusion	140
References	141
5 STRUCTURAL RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE SUPPORT STRUCTURES SUBJECTED TO PITTING	

CORROSION-FATIGUE: A DAMAGE TOLERANCE MODELLING APPROACH	145
5.1 Introduction	146
5.2 Research background.....	150
5.2.1 SMART® crack growth analysis.....	150
5.2.2 Fracture mechanics analysis of planar flaws.....	151
5.2.3 Modelling of corrosion fatigue	153
5.3 Methodology	158
5.3.1 Design considerations for OWT support structures.....	158
5.3.2 OWT support structure subjected to pitting corrosion-fatigue.....	164
5.3.3 Structural Reliability Assessment (SRA) of the OWT support structure	165
5.4 Results and discussion	172
5.4.1 Mesh sensitivity analysis	172
5.4.2 Validation of the FEA tool against experimental data.....	172
5.4.3 Validation of the FEA model.....	173
5.4.4 Validation of the FORM	174
5.4.5 Corrosion-fatigue SRA results.....	175
5.4.6 Global sensitivity analysis	176
5.5 Conclusions	178
References	179
6 COMPARATIVE STUDY BETWEEN SN AND FRACTURE MECHANICS APPROACH ON RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE JACKET FOUNDATIONS.....	185
6.1 Introduction	186
6.2 A review of previous studies and existing models.....	189
6.3 Basics of fatigue and fracture reliability assessment.....	193
6.3.1 S-N curve approach	194
6.3.2 Fracture mechanics approach.....	194
6.3.3 Limit state function based on the S-N curve approach.....	197
6.3.4 Limit state function based on fracture mechanics approach.....	198
6.4 Application using a case study.....	198
6.4.1 Design considerations for OWT support structures.....	198
6.4.2 OWT support structure having flaws and subjected to corrosion-fatigue	208
6.4.3 Structural reliability assessment (SRA) of the OWT support structure	209
6.5 Results and discussion	214
6.5.1 Fatigue SRA results	215
6.5.2 Comparison between S-N curve and FM approaches.....	215
6.5.3 Sensitivity studies.....	216
6.5.4 Reassess reliability in the presence of SHM/CM data.....	222

6.6 Conclusion	224
References	225
7 OVERALL DISCUSSION.....	232
References	241
8 CONCLUSIONS AND FUTURE WORKS.....	242
8.1 Conclusions	242
8.2 Future Works	243
References	244

LIST OF FIGURES

Figure 1-1. An outline of key topics and how these are linked sequentially	8
Figure 2-1. Schematic representation of load process and degradation of resistance. See [4] for more details. Reprinted with permission from ref. [4]. Copyright 2020, Elsevier.	13
Figure 2-2. Methods for Structural Reliability Analysis [1,2,9,10].	15
Figure 2-3. Illustration of the FORM approximation. See [13] for more details. Adapted with permission from ref. [13]. Copyright 2020, Elsevier.	16
Figure 2-4. Schematic iterative procedure of FORM-based conjugate search direction. See [22] for more details. Reprinted with permission from ref. [22]. Copyright 2020, Elsevier.	20
Figure 2-5. Flowchart of a proposed non-intrusive formulation. See [15] for more details. Reprinted with permission from ref. [15]. Copyright 2020, Wiley.	26
Figure 2-6. Reliability assessment problem in the standard Gaussian space with the two stages involved in a proposed adaptive Kriging SM: (a) stage 1 for design point search and POF prediction based on FORM with the adaptive Kriging-based trust region method; (b) stage 2 for the POF prediction based on MCS-IS with the Kriging model defined iteratively around the FORM design point with the active refinement algorithm of the AK-MCS method [47]. Reprinted with permission from ref. [47]. Copyright 2020, Elsevier.	27
Figure 3-1. Flow chart of the non-intrusive formulation method [2].	63
Figure 3-2. Representation of the loads on the support structure of the offshore wind turbine (OWT) and jacket geometry embedded in layered soil.	68
Figure 3-3. Mesh convergence test.	75
Figure 3-4. Three-dimensional (3D) display of meshing performed on the structural model.	75
Figure 3-5. The 3D display of structural model with applied loads and boundary conditions.	77
Figure 3-6. Display of structural model's modal analysis results showing the first mode frequency.	78
Figure 3-7. Display of results of total deformation showing the deflection at the RNA level.	79
Figure 3-8. Cumulative density function (CDF) and histogram for the output parameter: (a) maximum von Mises stress (stress constraint case); (b)	

fatigue safety factor minimum (fatigue constraint case); (c) maximum deformation; (d) first eigen-frequency (vibration constraint case);, (e) total deformation load multiplier (buckling constraint case)-DesignXplorer©.	85
Figure 3-9. Reliability index of different design constraints (non-intrusive formulation).....	87
Figure 3-10. Fatigue reliability assessment (non-intrusive formulation)...	88
Figure 3-11. Fatigue reliability index with different coefficients of variation (COVs).	89
Figure 3-12. Global sensitivity chart: (a) stress design constraint (ULS); (b) deformation design constraint (SLS); (c) fatigue design constraint; (d) buckling constraint (ULS); (e) vibration constraint (SLS).	92
Figure 4-1. Representation of the loads on the support structure of the OWT and jacket geometry embedded in layered soil [11].	106
Figure 4-2. 3D display of meshing performed on the structural model [11].	112
Figure 4-3. A 3D structural model with applied loads and BCs on a global scale [11].	114
Figure 4-4. Display of the structural model's modal analysis results showing the first mode frequency [11].	115
Figure 4-5. Display of results of total deformation showing the deflection at RNA level [11].	116
Figure 4-6. Flow chart of non-intrusive formulation with SSA.	120
Figure 4-7: Variation of the reliability indices with CoV: (a) stress (b) buckling (c) fatigue (d) deformation (e) vibration limit state	128
Figure 4-8. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c)POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the stress limit states and their variation with CoV.	130
Figure 4-9. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c) POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the buckling limit state and their variation with CoV.	133
Figure 4-10. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c)POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard	

deviations (σ) for the fatigue limit state and their variation with CoV.	134
Figure 4-11. Sensitivities of: (a) beta index to parameter means (μ) (b) POF to parameter standard deviations (σ) (c) POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the deformation limit state and their variation with CoV.	135
Figure 4-12. Sensitivities of: (a) beta index to the parameter means (μ) (b) POF to parameter standard deviations (σ) (c) POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the vibration limit state and their variation with CoV.	136
Figure 4-13. Variation of reliability indices with change in percentage correlation for: (a) the stress (b) buckling (c) fatigue (d) deformation (e) vibration limit states.	140
Figure 5-1. The K-T diagrams for air and artificial seawater environments. Source: Li and Akid [38].	157
Figure 5-2: Mesh convergence test [6]	159
Figure 5-3. The 3D structural model: (a) with applied loads and boundary conditions on a global scale [6]; (b) half of the critical joint of the support sub-structure showing hemispherical pit; (c) curved plate with applied stress and BC in ANSYS.	161
Figure 5-4. Flow chart of non-intrusive formulation	169
Figure 5-5. Curves of fatigue life prediction obtained from different element sizes for applied stress: (a) $\sigma = 58.63\text{MPa}$; (b) $\sigma = 117.25\text{MPa}$	173
Figure 5-6. Comparison between experimental data according to [38] against the FEA tool adopting the same test set-up.	173
Figure 5-7. Fatigue crack growth rate with ΔK obtained from SMART [®] and theoretical analysis respectively for: (a) $a_0 = 223\mu\text{m}$; (b) $a_0 = 446\mu\text{m}$	175
Figure 5-8. Crack heights versus the number of cycles obtained from SMART [®] and Theoretical analysis respectively: (a) $a_0 = 223\mu\text{m}$; (b) $a_0 = 446\mu\text{m}$	176
Figure 5-9. Corrosion fatigue reliability assessment	177
Figure 5-10. Global sensitivity analysis	177
Figure 6-1. Representation of the loads on the support structure of the OWT and jacket geometry embedded in layered soil	199

Figure 6-2: The 3D structural model with applied loads and boundary conditions on a global scale (Fatigue load case)	200
Figure 6-3. 3D display of meshing performed on the structural model [41]	203
Figure 6-4. Display of structural model's modal analysis results showing the first mode frequency [41]	204
Figure 6-5. Display of results of total deformation showing the deflection at RNA level [41]	204
Figure 6-6. 3D display of structural model showing the equivalent alternating stress	209
Figure 6-7. 3D structural model of curved plate with applied stress and BC in ANSYS [20]	209
Figure 6-8. Flow chart of non-intrusive formulation for the FM approach [20].	213
Figure 6-9. Two artificial neural networks (ANNs) that relate the variables given in Table 6-7 [20].	213
Figure 6-10. Fatigue reliability assessment using the S-N curve approach	214
Figure 6-11. Fatigue reliability assessment using the FM approach	215
Figure 6-12. Comparison between the S-N curve and FM approaches ...	216
Figure 6-13. Fatigue reliability analysis assuming different levels of correlation between C1 and C2.	217
Figure 6-14. Fatigue reliability assessment using the bilinear FM model at different COV values of C1	218
Figure 6-15. Fatigue reliability assessment using the bilinear FM model at different COV values of C2	219
Figure 6-16. Fatigue reliability assessment using the bilinear FM model at different COV values of C1 and C2 (assuming the COVs of C1 and C2 are equal)	219
Figure 6-17: Variation of the sensitivity factor (α) with time at various mean values of initial crack depth (a_i).	221
Figure 6-18. Variation of the sensitivity factor (α) with time at various COVs of initial crack depth (a_i)	221
Figure 6-19. Fatigue reliability assessment using the FM approach at different values of the stress range	223

Figure 6-20. Fatigue reliability assessment at different values of initial crack size.....	223
---	------------

LIST OF TABLES

Table 1-1 Comparison between deterministic and stochastic modelling ...	4
Table 2-1. Capabilities and limitations of the most common level III approximation structural reliability methods.....	38
Table 2-2. Capabilities and limitations of the most common level III direct structural reliability methods	39
Table 2-3. Capabilities and limitations of the most common advanced approximation structural reliability methods.....	41
Table 2-4. Capabilities and limitations of the other common structural reliability methods.....	44
Table 3-1. Water levels and wave data of interest for the K-13 deep-water site [5]......	68
Table 3-2. Main properties of the baseline 10-MW OWT model [5].	72
Table 3-3. Baseline 10-MW support structure parameters [5,8,82,85]. MSL—mean sea level; OD - outer diameter; TP - transition piece; RNA—rotor-nacelle assembly; UL—ultimate limit; FL—fatigue limit.	72
Table 3-4. Mesh sensitivity.	74
Table 3-5. K-13 deep-water site’s soil profile [5].....	76
Table 3-6. Comparison of the support structure mode frequencies with reference values.	77
Table 3-7. Static deformation of the baseline 10 MW on jacket.....	78
Table 3-8. Stochastic variables.	83
Table 3-9. Characteristics of design variables.....	84
Table 3-10. Computed probability of failure and safety index values using first-order reliability method (FORM) for different limit states.	87
Table 3-11. Comparison between the reliability index values computed by the two methods.	89
Table 4-1: Water levels and wave data of interest for the K-13 deep water site.	106
Table 4-2: Main properties of the baseline 10 MW OWT model [4].	110

Table 4-3: Baseline 10 MW support structure parameters [4,10,49,52]. MSL – mean sea level; OD – outer diameter; WL – wall thickness; TP – transition piece; RNA – rotor-nacelle assembly; UL – ultimate limit; FL – fatigue limit.	110
Table 4-4: Mesh sensitivity.	112
Table 4-5: K-13 Deep-water site’s soil profile [4].	113
Table 4-6: Comparison of the support structure mode frequencies with reference values.	115
Table 4-7: Static deformation of the baseline 10 MW on the jacket.	115
Table 4-8: Stochastic variables.	125
Table 4-9: Percentage (%) influence of design parameters on reliability corresponding to the stress limit state.	137
Table 4-10: Percentage (%) influence of design parameters on reliability corresponding to the buckling limit state.	137
Table 4-11: Percentage (%) influence of design parameters on reliability corresponding to the fatigue limits state.	138
Table 4-12: Percentage (%) influence of design parameters on reliability corresponding to the deformation limit state.	138
Table 4-13: Percentage (%) influence of design parameters on reliability corresponding to the vibration limit state.	139
Table 5-1. Baseline 10 MW support structure parameters [6, 9, 10, 48, 49]	158
Table 5-2. K-13 deep-water site’s soil profile [6,10].	159
Table 5-3. Mesh sensitivity [6]	160
Table 5-4. Comparison of the support structure mode frequencies with reference values [6]	161
Table 5-5. Static deformation of the baseline 10 MW wind turbine jacket [6]	162
Table 5-6. Water levels and wave data of interest for the K-13 deepwater site [6]	163
Table 5-7. Stochastic variables for the pit growth regime.	167
Table 5-8. Stochastic variables for the crack propagation regimes for the SMART® crack growth analysis case.	167
Table 5-9. Stochastic variables for the crack propagation regimes for the theoretical analysis case.	168

Table 5-10. Training results for the ANNs used in the study.....	170
Table 5-11. Probability of failure results as predicted by the FORM and MCS	176
Table 6-1: Baseline 10 MW support structure parameters [6, 9, 10, 48, 49]	200
Table 6-2: K-13 Deepwater site's soil profile [6,41].....	202
Table 6-3: Mesh sensitivity [41]	202
Table 6-4: Comparison of the support structure mode frequencies with reference values [41]	205
Table 6-5: Static deformation of the baseline 10 MW wind turbine jacket [41]	205
Table 6-6: Water levels and wave data of interest for the K-13 Deepwater site [41]	206
Table 6-7: Stochastic variables.....	210
Table 7-1. Research contribution presented by means of novelty, scientific soundness and value for each objectives.....	233

LIST OF ABBREVIATIONS

AI	Analytical Integration;
AK-IS	Active Learning Kriging with Importance Sampling;
AK-MCS	Active learning Kriging with Monte-Carlo Simulation;
ALM	Active Learning Methods;
ANN	Artificial Neural Networks;
ASCE	American Society of Civil Engineers;
ASME	American Society of Mechanical Engineers;
ASVM	Adaptive Support Vector Machine;
BM	Bending Moment;
CDF	Cumulative Density Function;
CGF	Cumulant Generating Function;
CM	Computational Models;
CSRSM	Collocation Based Stochastic Response Surface Method;
DNV	Det Norske Veritas;
DoE	Design of Experiment;
EGRA	Efficient Global Reliability Analysis;
EMRM	Elastic modulus reduction method;
FAL	Finite-based Armijo line search direction;
FCG	Fatigue Crack Growth;
FEA	Finite Element Analysis;
FEM	Finite Element Method;
FLS	Fatigue Limit State;
FM	Fracture Mechanics;
FORM	First Order Reliability Method;
FR	Fletcher and Reeves method;
FRA	Fatigue Reliability Analysis;
GA	Genetic Algorithm;
HL	Hasofer and Lind method;
HL-RF	Hasofer Lind - Rackwitz Fiessler method;
HRHL-RF	hybrid relaxed Hasofer Lind - Rackwitz Fiessler method;
HSAC	hybrid Self-Adaptive Conjugate;
ICE	Institution of Civil Engineers;
IFEM	Interval finite element method;

IMC	Interval Monte Carlo simulation;
IS	Importance Sampling;
ISKRA	Improved Sequential Kriging Reliability Analysis;
ISO	International Standards Organisation;
IT	Information Technology;
KIM	Kriging Interpolation Model;
KL	Karhunen-leove expansion;
LEFM	Linear-elastic Fracture Mechanics;
LHS	Latin Hypercube Sampling;
LIF	Least Improvement Function;
LS	Limit State(s);
LSF	Limit State Function;
LSS	Limit State Surface;
MC	Monte Carlo;
MCMC	Markov Chain Monte-Carlo;
MCS	Monte-Carlo Simulation;
MEM	Maximum Entropy Fitting Method;
MFEM	Multi-scale finite element method;
MLS	Moving Least Square;
MM	Meta-Model(s);
MPP	Most Probable failure Point;
MPR	Multivariate (Quadratic) Polynomial Regression;
MVFOSM	Mean Value First Order Second Moment Method;
NF	Number of Fitting points;
NI	Numerical Integration;
OWT	Offshore Wind Turbine;
PCE	Polynomial Chaos Expansion;
PC-Kriging	Polynomial Chaos-Kriging;
PDF	Probability Density Function;
PF	Performance Function;
PLS	Partial Least Squares;
PMA	Performance Measure Approach;
POF	Probability of Failure;
PSMFEM	Perturbation-based stochastic multi-scale finite element method;
PSO	Particles Swarms Optimization;

RA	Reliability Analysis;
RBF	Radial Basis Function;
RBO	Reliability-Based Optimization;
RHL-RF	Relaxed Hasofer Lind - Rackwitz Fiessler method;
RI	Reliability Index;
RS	Response surface;
RSM	Response Surface Model;
SAC	Self-Adaptive Conjugate;
SDPSO	Spar Drilling Production Storage Offloading;
SFEM	Stochastic Finite Element Method;
SGA	Shredding Genetic Algorithm;
SGFEM	Stochastic Galerkin FEM;
SHM	Structural Health Monitoring;
SKRA	Sequential Kriging Reliability Analysis;
SLS	Serviceability Limit State;
SM	Surrogate Modelling;
SORA	Sequential Optimization and Reliability Assessment;
SORM	Second-Order Reliability Method;
SPA	Saddle Point Approximation;
SR	Structural Reliability;
SRA	Structural Reliability Assessment;
SRBDO	System Reliability-Based Design Optimization;
SRE	Structural Reliability Evaluation;
SRSM	Stochastic Response Surface Method;
SS	Subset Simulation;
SSFEM	Spectral Stochastic Finite Element Method;
STM	Stability Transformation Method;
SVM	Support Vector Machines;
SVR	Support Vector Regression;
T-D	Time-dependent;
T-I	Time-independent/ Time-invariant;
T-V	Time-variant;
UBC	Ultimate Bearing Capacity;
ULS	Ultimate Limit State.

1 INTRODUCTION

1.1 Background

Renewable energy technologies are now widely deployed in many parts of the world, including Europe, China, USA, etc. [1]. Wind energy is a technically and economically feasible option to partially address the global issues related to the energy crisis and climate change. The majority of wind energy is harnessed by onshore wind farms [2], despite regular local opposition due to visual and sound impacts. A solution is to deploy wind turbines at sea thus minimising sound and visual impact, with additional capacity factor benefits obtained from the improved wind domain due to unobstructed fetch. This has led to the increasing development of the offshore wind industry, especially in Europe, where the offshore wind energy capacity is expected to reach 64.8 GW by 2030 [3].

Most of the existing offshore wind turbines use monopile foundations and are installed in water depths less than 50 m. However, for larger turbines in deeper waters, monopiles become very large and increasingly uneconomical due to the difficulty of fabricating and installing such systems, as well as the consideration of modal requirements. More information on monopile foundations can be found in [4,5]. To address these issues, space frame structures such as jackets are used which have lighter weight and are stiffer than monopiles. Space frames can be cheaper in deep-water circumstances, and hence they can contribute to the offshore wind industry's goal on the reduction of Levelized Cost of Energy (LCoE). However, designing these structures effectively is resource-intensive, especially when designing to withstand the wide set of dynamic loading mechanisms. Thus, research is still required to improve the design and analysis of jacket type support structures [6,7], with due consideration of the requirement for manufacturing optimisation if ever these structures are to be mass-produced.

In conventional structural analysis, the environmental loads, geometric dimensions, material properties, and parameters are treated as deterministic quantities, which are often expressed in the design through characteristic values incorporating partial safety factors for consideration of uncertainties. This type of analysis is adequate in cases where randomness is relatively small. However, structures used for offshore deployment are generally complex and subjected to high uncertainties introduced by the environment, manufacturing, and operational processes. Randomness in design parameters for such systems should be systematically accounted for via stochastic modelling, allowing for a better informed and potentially optimised design that would take

into consideration the life cycle of the structure and associated time-variant mechanisms of damage. Reliability analysis enables an efficient approach to better understand the response of the system to variation of an input parameter, enabling the systematic modelling of uncertainties occurring from highly complex models, loading conditions, etc. [8]. In particular, for offshore jacket foundations, soil-structure interactions and particularities of marine environments introduce considerable uncertainties (e.g., soil properties, wind, wave, and current loads, etc.), leading to the requirement of employing proper reliability analysis methods. A structural reliability model of OWT support structures requires two key components, i.e., (1) a structural model describing the structural behaviour of OWT support structures, and (2) a suitable reliability assessment method which finds the reliability index β (or the probability of failure P_f) of critical members with respect to the constraints [9].

Structural models for OWT support structures can be roughly classified into two groups, i.e., one-dimensional (1D) beam models and three-dimensional (3D) finite element analysis (FEA) models. In the 1D beam model, the support structure is discretised into a sequence of elastic Euler or Timoshenko beam elements. It is computationally efficient and capable of accurately modelling global structural behaviour, such as deflections and modal frequencies [10]. However, it is incapable of accurately representing the structural responses at a local scale, such as stress concentration effects [11]. In the 3D FEA model, the jacket foundations are usually defined by applying brick or shell elements. In comparison to the one-dimensional beam model, the three-dimensional finite element model has the capability of examining detailed stress distributions and accurately capturing structural responses within the structure. The three-dimensional finite element analysis model was extensively applied to structural modelling of wind turbine structures due to its high fidelity [12]. Thus, the 3D FEA model is adopted in this thesis to determine the structural responses of OWT jacket foundations.

Since OWT jacket foundations are anchored via piles to the soil system, it is crucial to account for soil-structure interaction to adequately capture the response of the structure. A straightforward method to perform soil modelling is to assume equivalent springs to represent soil-based stiffness, which is known as the p-y method [13]. However, in this method, the deflection, as well as the modal frequency, are underestimated. A more reliable way of carrying out soil modelling is to define 3-D FEA brick elements to achieve precision and reliability in the results [14,15]. Considering its efficacy, 3-D finite element analysis with brick elements is adopted to model the soil in this study.

Several studies [13,16,25–29,17–24] showed that structural reliability assessment is commonly applied to assess the safety level of OWT structures. Most reliability methods are established as time-invariant; however, in numerous instances, owing to the continuous degradation of the resistance of the structure through corrosion, fatigue, etc., or due to fluctuating loads in time, reliability models should be accounted for as time-variant [30,31]. At first, the structural reliability assessment focuses on the evaluation of the reliability of each component, assuming a series system formulation where a single point failure illustrates a global failure of the structure [12]. In a second level, however, the embedded redundancy in the system is evaluated through methods such as push-over analysis, which is again based on the calculation of component reliability. Level I methods are deterministic reliability methods that only use one characteristic value to describe each uncertain variable. Common design standard formats, such as load resistance and allowable stress, belong to this category. These methods correspond to standard deterministic design methods. They can be combined with more advanced, higher-order methods in the case of partial safety factors calibration, which can optimise their application [32]. The conventional structural reliability methods include level II (approximate) reliability methods or analytical techniques which consist of the first-order reliability method (FORM) [33] and the second-order reliability method (SORM) [34], as well as level III reliability methods which include Monte Carlo Simulations (MCS). In FORM, the limit state function is approached through Taylor's expansion, and the problem of evaluating the reliability of a complex system is translated into a problem of mathematical optimisation. SORM generally performs better in cases of highly nonlinear systems than FORM, while, in other cases, the two methods give similar results. MCS involves direct simulations and, hence, reduces the uncertainty in the results due to approximations in the solution algorithm. However, its application is constrained in the calculation of high probabilities for relatively non-complex engineering systems. MCS can be incorporated with variance reduction techniques, e.g., Latin hypercube sampling (LHS), weighted Latin hypercube sampling (WLHS), importance sampling, subset simulation, etc. [12].

The stochastic expansion consists of intrusive and non-intrusive formulations. An intrusive formulation is one whereby the representation of uncertainty is expressed explicitly within the analysis of the system. Practically, this refers to methods that use Karhunen-Leove expansion (K-L) and polynomial chaos expansion (PCE) to directly modify the stiffness matrix of a finite element analysis procedure, such as SSFEM (spectral stochastic FEM) and stochastic Galerkin FEM. On the other hand, non-intrusive

formulations, such as stochastic response surface methods [3,12,32], represent uncertainties in a non-explicit way and treat the analysis code as a “black box” without requiring access to the source code.

Ditlevsen and Madsen, [35] envisaged engineering judgment as the art of being able to decide whether results obtained from a structural analysis or design model are sufficiently realistic that the engineer dares to base his or her practical decisions on these results. They added that the formulation of a mathematical model is not only guided by the wish of getting a realistic description, but it is also necessary that the model becomes operational in the sense that it is suited for solution, i.e., that it can deliver answers to posed questions, and that important aspects of the model formulation process is, therefore, the art of balancing realism against operability. Hence, probabilistic structural analysis which can be seen as an extension of the deterministic structural analysis is the art of formulating a mathematical model within which one can ask and get answers to questions such as:

- (1) What is the probability that a structure behaves in a specified way when given that one or more of its material properties or geometric dimensions and properties are of a random or incompletely known nature, and/or that the actions on the structure in some respects have random or incompletely known properties?
- (2) How is a structure behaving when its material properties, geometric properties and actions all are uniquely given?
- (3) What dimensions should be assigned to the structure in order that it has optimal properties in a given well-defined sense within the possibilities of the probabilistic model?
- (4) What value should the probability of occurrence of a specified behaviour be in order that the structure in a well-defined sense is optimally designed with respect to this behaviour?

Table 1-1 briefly compares deterministic with stochastic modelling [31].

Table 1-1 Comparison between deterministic and stochastic modelling

Deterministic modelling	Stochastic modelling
Most complex systems are still designed using this approach which adopts	Developed to quantify uncertainties for complex systems which can develop initial

<p>simplified rules and schemes, such as safety factor design, however, these conventional methods do not directly account for the random nature of most input parameters</p>	<p>guidance for safe design and identify where further inspections and investigations could increase the safety and efficiency of the structure. These methods are rapidly finding application in the multidisciplinary design environment due to the engineering system's stringent performance requirements, narrow margins of safety, liability, and market competition.</p>
---	---

<p>In structural design problems involving uncertainties, a structure designed using deterministic approach may have a greater probability of failure than a structure of the same cost designed using a stochastic approach that accounts for uncertainties</p>	<p>Design requirements are precisely satisfied in the deterministic approach, and any variation of the parameters could potentially violate the system constraints. The stochastic modelling approach accounts for possible variation in magnitude of parameters.</p>
--	---

<p>When unconventional structures are designed, there is little relevant data or sufficient prior knowledge. Appropriate perceptions of uncertainty are essential for safe and efficient decisions. The deterministic modelling approach cannot be employed in such cases.</p>	<p>Stochastic modelling approaches are convenient tools to describe or model physical phenomena that are too complex to treat with the present level of scientific knowledge.</p>
--	---

<p>Uncertainties are accounted for in the design through characteristic values incorporating partial safety factors based on engineering judgement and previous experience with similar structures. This approach discards statistical data. Unlike the stochastic modelling approach, probabilistic-based information about mechanical performance (usually adopted for developing rational policies</p>	<p>Randomness is accounted for accurately through stochastic modelling where probabilistic distribution/ statistical data such as mean value, variance and confidence interval of variables which can provide a broader perspective and a complete description of the given structural system are incorporated explicitly into the design algorithm.</p>
---	--

towards pricing, warranties, component life, spare parts requirements, etc.) cannot be used.

Adequate in cases where randomness is very small	Ideal for complex structures where high uncertainties are involved
Randomness in environmental loads, geometric dimensions, material properties, etc. is usually overestimated, leading to too much conservatism, overdesign and hence, wastage.	Usually leads to optimized design through systematic design which can accommodate a sensitivity analysis of the system, allowing engineers to find critical parameters of uncertainty models.
Often leads to expensive overall costs	Often leads to a balance between safety and total expected costs

1.2 Aim and Objectives

The overall aim is to develop surrogate modelling methods for the advanced structural reliability assessment/ evaluation of a complex offshore wind turbine jacket type support structure in the presence of highly stochastic variables. In order to achieve this aim, the following objectives have been set out for this thesis:

- (1) Carry out an extensive literature review on structural reliability methods, including limit state design approaches and on models for predicting pitting corrosion fatigue.
- (2) Develop a Stochastic Parametric Finite Element Analysis (FEA) model of a complex frame type structure, using sequential steps of a high capability tool such as ANSYS.
- (3) Develop a corrosion fatigue model based on the pit and crack growth whereby the nucleation/ development and growth to critical size of the corrosion pits are predicted using existing data whereas a pit to crack transition prediction model at the critical joint will be formulated using the SMART© fracture.
- (4) Develop novel SRA meta-model frameworks for the consideration of stochastic loads and time-dependent phenomena such as fatigue and corrosion on structures.
- (5) To perform stochastic sensitivity analysis (SSA) for the structure using an algorithm coded in MATLAB based on similar SRA framework developed in step 4.

- (6) To perform a comparative study between the SN-curve to the FM approaches to fatigue assessment from a structural reliability perspective for a typical welded OWT jacket support structure using a combination of SRA frameworks similar to that developed in steps 2-4.

1.3 List of Publications

- (1) Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Applied Sciences*. MDPI AG; 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860 (Accessed: 15 June 2020)
- (2) Shittu AA., Mehmanparast A., Shafiee M., Kolios A., Hart P., Pilario KE. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting Corrosion-Fatigue: A Damage Tolerance Modelling Approach. *Wind Energy*. John Wiley & Sons, Ltd; 1 November 2020; 23(11). Available at: DOI:10.1002/we.2542 (Accessed: 21 November 2020)
- (3) Shittu AA., Mehmanparast A., Amirafshari P., Hart P., Kolios A. Sensitivity analysis of design parameters for reliability assessment of offshore wind turbine jacket support structures. Article submitted for publication: Under review. 2020.
- (4) Shittu AA., Kolios A., Hart P., Amirafshari P., Mehmanparast A. A systematic review of structural reliability analysis methods with applicability to the design of complex offshore structures. Article submitted for publication: Under review. 2020.
- (5) Shittu AA., Mehmanparast A., Pilario KE., Hart P., Kolios AJ. Comparative study between SN and fracture mechanics approach on reliability assessment of offshore wind turbine jacket foundations. Article submitted for publication: Under review. 2020.

1.4 Structure of the Thesis

This thesis is by paper publication, and the structure of the rest of the thesis is given as follows. The background of this work that led to establishing the research aim and objectives were presented in Chapter 1. A literature review paper on SRA methods identifying key applications of each method, their proposed variations, qualifying characteristics, advantages and limitations is presented in Chapter 2. A paper on a comparative analysis on the structural reliability of an OWT support structure between a commercial package and the purpose-developed, non-intrusive stochastic formulation

was presented in Chapter 3. In Chapter 4, a paper on the SRA of an OWT jacket foundation subjected to pitting corrosion-fatigue performed by employing the damage tolerance model approach by applying the FEA based linear-elastic fracture mechanics (LEFM) method was presented. A paper which includes a comprehensive stochastic sensitivity analysis was presented in Chapter 5 in order to ascertain the most critical variables that can radically impact on the reliability performance of the OWT support structure. A paper on the safety level evaluation of an imperfect welded OWT jacket foundation joint performed to test its reliability in the presence of corrosion-fatigue using the FM, and SN-curve approaches were presented in Chapter 6. All the Chapters are linked together in a logical way in a discussion so as to demonstrate the coherence of the overall work done towards achieving the overall aim in Chapter 7. Finally, in Chapter 9, the conclusion and recommendations for future work are presented. **Figure 1-1** shows an outline of the content of each Chapter and how they are linked with the objectives of this thesis.



Figure 1-1. An outline of key topics and how these are linked sequentially

References

1. Kolios A., Wang L. Advanced reliability assessment of offshore wind turbine monopiles by combining reliability analysis method and SHM / CM technology. 2018; : 1412–1419.
2. IRENA. Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects. (A Global Energy Transformation paper) International Renewable Energy Agency. Abu Dhabi; 2019.
3. Shittu AA., Mehmanparast A., Shafiee M., Kolios A., Hart P., Pilario KE. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting

- Corrosion-Fatigue: A Damage Tolerance Modelling Approach. Wind Energy. John Wiley & Sons, Ltd; 12 July 2020; Early view. Available at: DOI:10.1002/we.2542 (Accessed: 17 July 2020)
4. Wang X., Zeng X., Yang X., Li J. Feasibility study of offshore wind turbines with hybrid monopile foundation based on centrifuge modeling. *Applied Energy*. January 2018; 209: 127–139. Available at: DOI:10.1016/j.apenergy.2017.10.107
 5. Wang X., Zeng X., Yang X., Li J. Seismic response of offshore wind turbine with hybrid monopile foundation based on centrifuge modelling. *Applied Energy*. February 2019; 235: 1335–1350. Available at: DOI:10.1016/j.apenergy.2018.11.057
 6. Damiani R., Song H. A Jacket Sizing Tool for Offshore Wind Turbines within the Systems Engineering Initiative. Offshore Technology Conference, OTC 24140. Houston, Texas, USA; 2013. Available at: DOI:10.4043/24140-MS
 7. Damiani RR., Song H., Robertson AN., Jonkman JM. Assessing the Importance of Nonlinearities in the Development of a Substructure Model for the Wind Turbine CAE Tool FAST. Volume 8: Ocean Renewable Energy. 2013; 8(March): V008T09A093. Available at: DOI:10.1115/OMAE2013-11434
 8. Kolios A., Di Maio LF., Wang L., Cui L., Sheng Q. Reliability assessment of point-absorber wave energy converters. *Ocean Engineering*. Elsevier Ltd; 2018; 163(October 2017): 40–50. Available at: DOI:10.1016/j.oceaneng.2018.05.048
 9. Leimeister M., Kolios A. A review of reliability-based methods for risk analysis and their application in the offshore wind industry. *Renewable and Sustainable Energy Reviews*. Elsevier Ltd; 2018; 91(July 2017): 1065–1076. Available at: DOI:10.1016/j.rser.2018.04.004
 10. Wang L., Liu X., Renevier N., Stables M., Hall GM. Nonlinear aeroelastic modelling for wind turbine blades based on blade element momentum theory and geometrically exact beam theory. *Energy*. Elsevier Ltd; 2014; 76: 487–501. Available at: DOI:10.1016/j.energy.2014.08.046
 11. Petrini F., Manenti S., Gkoumas K., Bontempi F. Structural Design and Analysis of Offshore Wind Turbines from a System Point of View. *Wind Engineering*. 2010; 34(1): 85–107. Available at: DOI:10.1260/0309-524X.34.1.85
 12. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Applied Sciences*. MDPI AG; 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860 (Accessed: 15 June 2020)
 13. Yeter B., Garbatov Y., Guedes Soares C. Uncertainty analysis of soil-pile interactions of monopile offshore wind turbine support structures. *Applied Ocean Research*. Elsevier; 2019; 82(November 2018): 74–88. Available at: DOI:10.1016/j.apor.2018.10.014
 14. Jung S., Kim SR., Patil A., Hung LC. Effect of monopile foundation modeling on the structural response of a 5-MW offshore wind turbine tower. *Ocean Engineering*. Elsevier; 2015; 109: 479–488. Available at: DOI:10.1016/j.oceaneng.2015.09.033
 15. DNV GL AS. DNVGL-ST-0126 : Support structures for wind turbines. DNV GL - Standard Høvik, Norway: Det Norske Veritas; 2016 p. 182 pp. Available at: DOI:10.1016/j.jbiomech.2014.11.025
 16. Sørensen JD. Reliability-based calibration of fatigue safety factors for offshore wind turbines. Proceedings of the Twenty-First International Offshore and Polar Engineering Conference. Maui, HI, USA; 2011.
 17. Márquez-Domínguez S., Sørensen JD. Fatigue Reliability and Calibration of Fatigue Design Factors for Offshore Wind Turbines. *energies*. 2012; 5: 1816–1834. Available at: DOI:10.3390/en5061816 (Accessed: 6 December 2019)
 18. Vahdatirad MJ., Griffiths D., Andersen LV., Sørensen JD., Fenton G. Reliability analysis of a gravity-based foundation for wind turbines: a code-based design assessment. *Géotechnique*. 2014; 64: 635–645.
 19. Yeter B., Garbatov Y., Soares CG. Fatigue reliability of an offshore wind turbine supporting structure accounting for inspection and repair. In: Soares G, Shenoi E (eds.) Analysis and

- Design of Marine Structures. London, UK: Taylor & Francis Group; 2015. pp. 737–747.
20. Yeter B., Garbatov Y., Soares CG. Reliability of offshore wind turbine support structures subjected to extreme wave-induced loads and defects. Proceedings of the ASME 2016 35th international conference on ocean, offshore and arctic engineering OMAE2016-54240. Busan, South Korea; 2016. pp. 1–8.
 21. Yeter B., Garbatov Y., Guedes Soares C. System reliability of a jacket offshore wind turbine subjected to fatigue. Proceedings of the 5th International Conference on Marine Structures, MARSTRUCT. Lisbon; 2017. pp. 939–950.
 22. Dong W., Moan T., Gao Z. Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection. Reliability Engineering and System Safety. Elsevier; 2012; 106: 11–27. Available at: DOI:10.1016/j.ress.2012.06.011
 23. Muskulus M., Schaffhirt S. Reliability-based design of wind turbine support structures. Proceedings of the Symposium on Reliability of Engineering System. Hangzhou, China; 2015.
 24. Ciampoli M., Petrini F. Performance-based design of offshore wind turbines. Earth and Space 2010: Engineering, Science, Construction, and Operations in Challenging Environments. Reston, VA, USA: American Society of Civil Engineers; 2010.
 25. Morató A., Sriramula S., Krishnan N. Reliability Analysis of Offshore Wind Turbine Support Structures Using Kriging Models. In: Walls L, Revie M, Bedford B (eds.) Risk, Reliability and Safety: Innovating Theory and Practice. Didcot, London, UK: Taylor & Francis Group; 2017.
 26. Wei K., Arwade SR., Myers AT. Incremental wind-wave analysis of the structural capacity of offshore wind turbine support structures under extreme loading. Engineering Structures. Elsevier Ltd; 15 November 2014; 79: 58–69. Available at: DOI:10.1016/j.engstruct.2014.08.010
 27. Kim DH., Lee SG. Reliability analysis of offshore wind turbine support structures under extreme ocean environmental loads. Renewable Energy. Elsevier Ltd; 2015; 79(1): 161–166. Available at: DOI:10.1016/j.renene.2014.11.052
 28. Mardfekri M., Gardoni P. Probabilistic demand models and fragility estimates for offshore wind turbine support structures. Engineering Structures. July 2013; 52: 478–487. Available at: DOI:10.1016/j.engstruct.2013.03.016
 29. Mardfekri M., Gardoni P. Multi-hazard reliability assessment of offshore wind turbines. Wind Energy. August 2015; 18(8): 1433–1450. Available at: DOI:10.1002/we.1768 (Accessed: 6 December 2019)
 30. Karadeniz H. Review of Structural Reliability Methods with Applicability in Practice. Civil Engineering. 2006; 4: 880653–880653.
 31. Choi S-K., Grandhi R., Canfield R. Reliability-based Structural Design. USA: Springer; 2006.
 32. Kolios A. A multi-configuration approach to reliability based structural integrity assessment for ultimate strength. Cranfield University; 2010.
 33. Hohenbichler M., Rackwitz R. First-order concepts in structural reliability. 1983; 177(1): 188.
 34. Der Kiureghian A., Lin H-Z., Hwang S-J. Second Order Reliability Approximations. J. Engrg. Mech. Div ASCE. 1987; 113(2): 1208–1225.
 35. Ditlevsen O., Madsen HO. Structural Reliability Methods. _Book. 2007; (January 1996): 375.

2 A SYSTEMATIC REVIEW OF STRUCTURAL RELIABILITY METHODS FOR DEFORMATION AND FATIGUE ANALYSIS OF OFFSHORE JACKET STRUCTURES

Abdulahakim Adeoye Shittu, Athanasios Kolios, Ali Mehmanparast

Statement of contributions:

Abdulahakim A. Shittu conducted the literature review, drafted and critically revised the manuscript. A. Kolios, and A. Mehmanparast provided supervision, reviewed and critically commented on the manuscript before submission.

ABSTRACT

This paper presents the state-of-the-art in Structural Reliability Analysis (SRA) methods with a view of identifying key applications of each method and its proposed variations, qualifying characteristics, advantages and limitations. Due to the increasing complexity and scale of modern offshore jacket structures, it becomes increasingly necessary to propose an accurate and efficient approach for the assessment of uncertainties in their material properties, geometric dimensions and operating environments. SRA, as a form of uncertainty analysis, has been demonstrated to be a useful tool in the design of structures because it can directly quantify how uncertainty about input parameters can affect structural performance. Herein, attention was focused specifically on the probabilistic fracture mechanics approach because this accounts accurately for fatigue reliability mostly encountered as being dominant in the design of such structures. The well-established analytical/approximate methods such as the First and Second-Order Reliability Methods (FORM/SORM) are widely used as they offer a good balance between accuracy and efficiency for realistic problems, they are however inaccurate in cases of highly non-linear systems. As a result, they have been modified using methods such as conjugate search direction approach, saddle point approximation, subset simulation, evidence theory, etc. in order to improve accuracy. Initially, direct simulations methods such as the Monte Carlo Simulation Method (MCS) with its various variance reduction techniques such as the Importance Sampling (IS), Latin Hypercube Sampling (LHS), etc. are ideal for structures having non-linear limit states but performs poorly for problems that calculate very low probabilities of failure. Overall, each method has its own merits and limitation with

FORM/SORM being the most commonly used, but recently, simulation methods have increasingly been used due to continuous advances in computation powers. Other relevant methods include the Response Surface Methods (RSM) and the Surrogate Models/Meta-models (SM/MM) which are advanced approximation methods and are ideal for structures with implicit limit state functions and high-reliability indices. Combinations of advanced approximation methods and reliability analysis methods are also found in literature as they can be suitable for complex, highly non-linear problems.

Keywords: Probabilistic fracture mechanics; SRA; FORM; SORM; MCS; RSM

2.1 Introduction

Structural reliability (SR) can be defined as ‘the ability that a structure complies with given requirements under specific conditions during its intended design life’ [1]. Suitable SR levels will, therefore, avoid intolerable damage to a structure over a specified period of time [2]. Use of probabilistic methods in structural design is increasing, and many standards have made allowance for reliability analysis (RA) either in the calibration of partial safety factors or in design and analysis [3]. ISO 2394 gives information on the principles of reliability methods. Safety margins and factors in design are determined considering T-D deterioration mechanisms [4], see **Figure 2-1**. RA allows for methods that analyse the service life variation of Failure Probability for specified modes of failure, treating uncertainties systematically. Structural reliability analysis (SRA) revolves around modelling uncertainties emanating from poor knowledge of design quantities, such as likelihood of events, variability, lack of knowledge, degree of belief, inaccuracy, etc. [5]. These terms are considered basic variables that consist of quantities of material properties and structural dimensions, yield stress and other limitations in ultimate response, operational conditions and degradation, loading and environmental factors, etc. Uncertainties for SRA can be mainly grouped into two categories: aleatory and epistemic [6]. Aleatory uncertainties are the unavoidable natural randomness associated with an uncertain quantity [5]. Epistemic uncertainties result from inadequate knowledge or information about a quantity. Since epistemic uncertainties stem from inadequate knowledge, they can be minimized by gathering data for a longer period, taking more measurements or carrying out further tests, among others. The present methodologies available for characterization of uncertainties can be classified into three groups, namely: the non-probabilistic approach, the precise probability approach, and the imprecise probability approach. Further information on these can be found in [7].

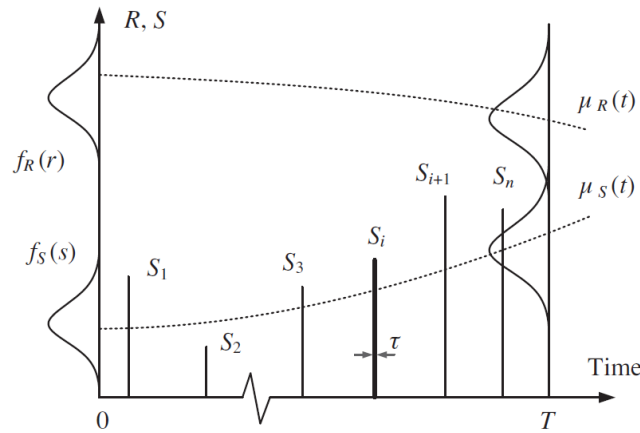


Figure 2-1. Schematic representation of load process and degradation of resistance. See [4] for more details. Reprinted with permission from ref. [4]. Copyright 2020, Elsevier.

Reliability methods have four levels (levels I to IV) of classification, according to the way that uncertainty is considered in the analysis [8]. Level I are deterministic reliability methods, which only apply one characteristic value to define each uncertain variable. Popular design standard formats, allowable stress and load-resistance belong to this category. They can be applied in combination with more advanced, higher-order methods in the case of calibration of partial safety factors, which can lead to their optimization [1]. Level II applies two values for the description of each random variable (eg. the mean and the variance) and a supplementary measure of the correlation between the variables (eg. covariance). Reliability can be interpreted geometrically as a relative distance from the mean values of loads and their effects. In Level III, the joint probability distribution of the sum of the uncertain variables is introduced, directly computing the POF for a performance function (PF). This category consists of the approximate analytical methods, including the First and Second-Order Reliability Methods, advanced mathematical techniques such as numerical integration (NI), and simulation methods, such as the Monte-Carlo Simulation (MCS) and the Directional Sampling methods. Level IV reliability methods introduces elements of target cost to the engineering principles, so as to derive a technically feasible and as such an economically optimized solution. These methods are the most advanced and can set a target reliability level, which is acceptable such that Level III methods can be applied.

This paper aims to present a state-of-the-art review of Level II and III reliability methods, identifying key applications of each method, qualifying characteristics, advantages and limitations. To the best of the authors' knowledge, the work performed herein is the first study to review research works conducted on the reliability/ probabilistic assessment/ evaluation of structures focusing specifically on applicability to design of modern offshore jacket structures against deformation and fatigue. The findings of this research can provide invaluable insights to researchers about the method used for such analyses. In order to identify relevant sources, a systematic review approach has been followed, focusing the search mainly on works published from 2005 to 2020, using predefined words and combinations of words which included 'first-order reliability method' or 'FORM' or 'second-order reliability method' or 'SORM' or 'Monte Carlo' or 'probability of failure (POF)' or 'reliability index (RI)' or 'safety' or 'probabilistic safety' or 'safety level' or 'reliability safety' or 'stochastic' or 'probabilistic', or 'structural reliability' or 'reliability', and 'analysis' or 'assessment' or 'evaluation', etc. on Scopus, science direct, web of science, ASME digital collection, ASCE library, ICE virtual library, one petro, etc. **Figure 2-2** illustrates a classification of the various SRA methods that are presented in a structured form.

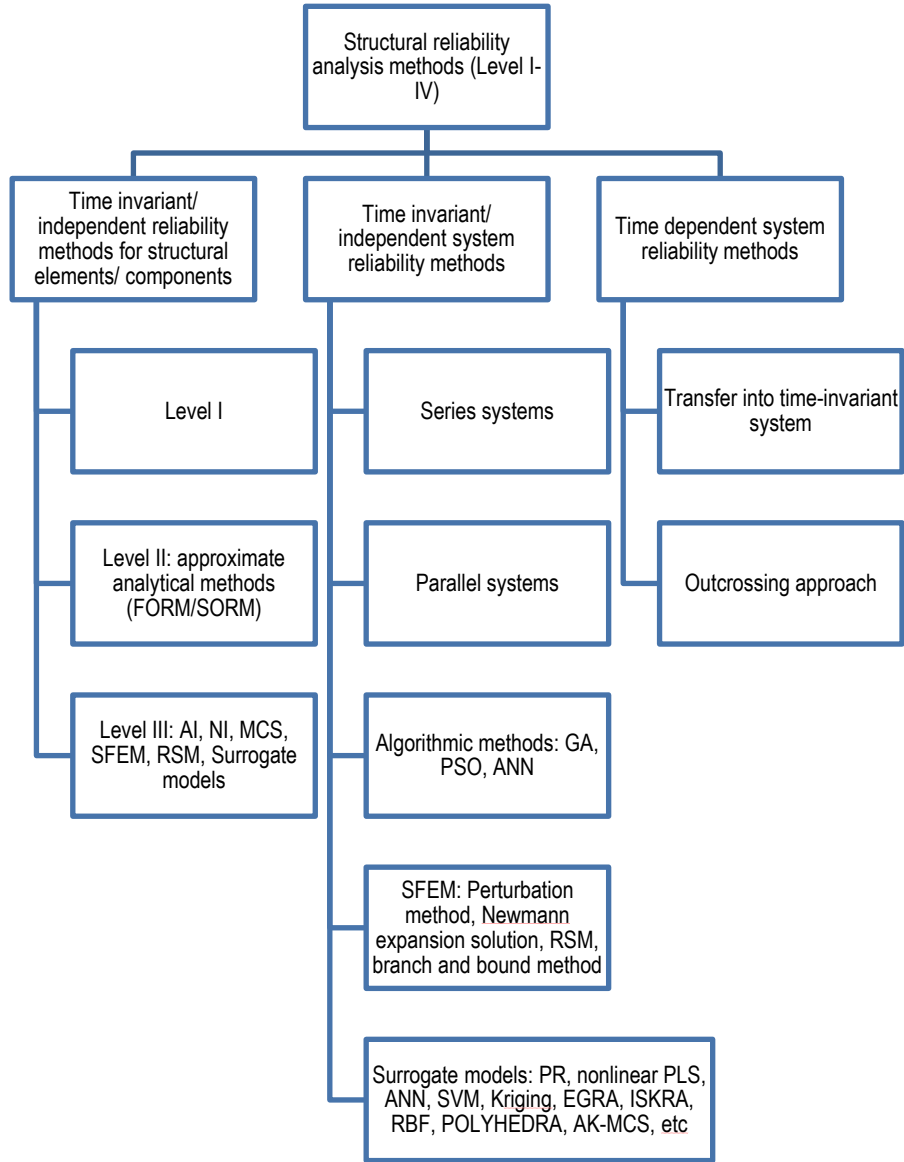


Figure 2-2. Methods for Structural Reliability Analysis [1,2,9,10].

2.2 Level III Analytical Structural Reliability Analysis Methods

The probability of failure (POF) of a structural element with regards to a single mode of failure can be formally expressed as [11]:

$$P_f = \int_{g(x) \leq 0} f_X(x) dx \quad (2-1)$$

The complexity in directly calculating the failure probability P_f from the integral expressed in Eq. (2-1) resulted in the establishment of approximate reliability methods. Such

methods involve approximating the failure surface to some simple forms, eg. hyperplane or quadratic surfaces at certain locations, referred to as design points.

This procedure is known as forward SRA. The method used for this computation algorithm is a level II technique, whereby the multidimensional integral expressed in Eq. (2-1) is estimated after the operations: (a) the basic uncertain variables are transferred onto a set of independent Gaussian random variables represented by the U vector. The transformation-operation is denoted by T such that $U = T(X)$ (b) the LSF in the U space $Z = g(u)$ is approximated to a linear or second-order (quadratic) functions at the limit state surface which forms a hyperplane or a quadratic failure surface. Methods based on linear approximation are referred to as the “First Order Reliability Methods (FORM)” and those based on quadratic approximation are known as the “Second-Order Reliability Methods (SORM)”[8].

2.2.1 First Order Reliability Method (FORM)

Theoretical background about FORM can be found in [8,12]. In the FORM, the random variables are represented by means and variances and assume normal distributions. The reliability levels are measured based on the RI. Iterative correlation procedures are used to predict the POF of a structural system or structure. In general, this involves an idealization of the failure domain, and it is usually assumed to be a basic representation of the joint probability distribution of a variable. This method of RA is computationally efficient and produces results with desired degree of accuracy, see **Figure 2-3**.

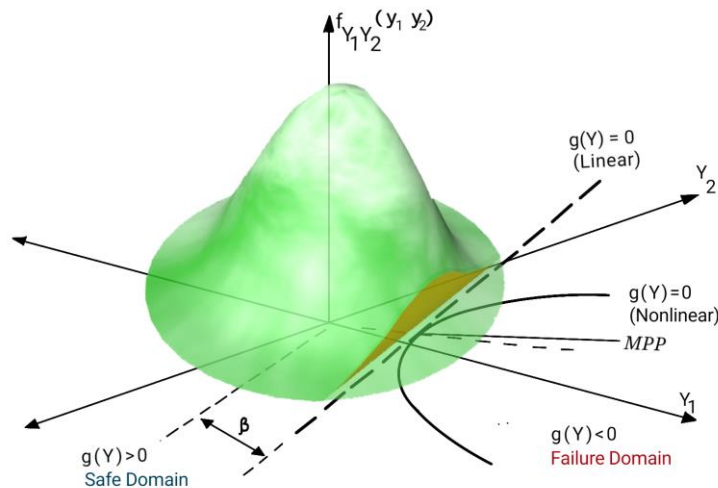


Figure 2-3. Illustration of the FORM approximation. See [13] for more details. Adapted with permission from ref. [13]. Copyright 2020, Elsevier.

The Mean Value FOSM (MVFOSM) simplifies the process of calculating the POF of an LSF. Following this method, the LSF is estimated by the first-order Taylor series expansion at the mean value point. In the Hasofer and Lind (HL) method, the RI is expressed as the minimum geometrical distance of Most Probable failure Point (MPP) on the limit state surface from the origin of a u -dimensional space. The HL RI method changes the expansion point from the point of mean value to the MPP, thereby optimizing the approach. For instance, once the PF is ascertained, the HL algorithm is employed in calculating the RI, β . This recursive algorithm is summarised below [11,14–16].

1. Define the PF for the corresponding LS, eg. ultimate limit state (ULS), serviceability limit state (SLS), fatigue limits state (FLS), etc.
2. Let the mean value point be the initial design point, i.e. $x_{i,k} = \mu_{x_i}$ $i = 1, 2, \dots, n$, and evaluate the gradients $\nabla g(X_k)$ of the LSF at this design point. Where, $x_{i,k}$ represents the i^{th} element in the vector X_k of the k^{th} iteration, and μ_{x_i} is the mean value of the i^{th} element;
3. Compute the initial RI, β adopting the mean-value approach, i.e. $\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}}$ and its direction cosine α .

$$\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}} = \frac{g(\mu_X)}{\left[\sum_{i=1}^n \left(\frac{\partial g(\mu_X)}{\partial x_i} \right)^2 \cdot \sigma_{x_i}^2 \right]^{\frac{1}{2}}} \quad (2-2)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (2-3)$$

4. Calculate a new design point X_k and U_k , function value, as well as gradients at this new design point.

$$x_{i,k} = \mu_{x_i} + \beta \sigma_{x_i} \alpha_i \quad (2-4)$$

$$u_{i,k} = \frac{x_{i,k} - \mu_{x_i}}{\sigma_{x_i}} \quad (2-5)$$

5. Compute the RI β and direction cosine α_i using Eqs. (2-4) and (2-5), respectively.

$$\beta = \frac{g(U^*) - \sum_{i=1}^n \frac{\partial g(U)}{\partial x_i} \sigma_{x_i} u_i^*}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(U^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (2-6)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (2-7)$$

Iterate steps (4) to (5) until the values of the RI β converge. The failure probability P_f can then be calculated from the following:

$$P_f = \Phi(-\beta) = 1 - \Phi(\beta) \quad (2-8)$$

Where

$$\Phi(\beta) = \int_{-\infty}^{\beta} \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{1}{2}\right)z^2} dz \quad (2-9)$$

The Hasofer Lind - Rackwitz Fiessler (HL-RF) method is an improvement to the HL method such that its accuracy is close to level III method. This method is ideal for cases of non-Gaussian variables, and it further enables information on the distribution of the random variables to be incorporated (ie. Apart from the mean and standard deviation included in the HL algorithm, information on distributions such as Weibull, Lognormal, Normal, etc. of the random variables are also incorporated in the HL-RF algorithm). This method involves transformation to the normalized space, and an example is the application of the Rosenblatt transformation, a transformation method for dependent non-normal design variables [8]. An alternative matrix procedure for the HL-RF algorithm is presented in [11]. For the case of correlated random variables, the HL-RF algorithm is modified by introducing a correlation matrix $[\rho]$. The correlation matrix $[\rho]$ is the matrix of correlation coefficients for the uncertain variables involved in the LSF. Further information on this can be found in [8,17].

To enhance the precision of the original HL-RF method, specific modifications were suggested in several sources. Keshtegar and Chakraborty [18], presented a conjugate search direction approach which overcomes the unstable solutions resulting from periodic nature and chaos for RA problems which involve highly non-linear PFs. In the study, two

recursive FORM schemes were examined based on the conjugate descent direction applying hybrid self-adaptive conjugate (HSAC) and the self-adaptive conjugate (SAC) search directions for the estimation of RI. Keshtegar and Meng [19], developed a relaxed HL-RF (RHL-RF) based on a relaxed factor, which is calculated dynamically by the second-order interpolation between zero and one. They proposed a hybrid relaxed HL-RF (HRHL-RF) method whereby the HL-RF and RHL-RF are implemented adaptively by using an angle criterion to enhance the efficiency and robustness of the FORM formula. In [20], an efficient and robust iterative algorithm referred to as finite-based Armijo search direction (FAL) method was proposed for FORM-based SRA. To achieve the stabilization of the FORM algorithm, a finite step size was developed applying the Armijo rule and sufficient descent condition. The FAL is adjusted adaptively based on the information acquired from the recursive algorithm at each iteration and Armijo rule.

According to [21], the HL-RF algorithm of the FORM has a drawback of the phenomena of convergence failure, for example, chaos, periodic oscillation, and bifurcation for some non-linear problems. The essential reasons for numerical instabilities due to chaotic dynamics which includes chaos and periodic oscillation common to recursive FORM solutions were revealed. According to Keshtegar [22], the STM with chaos feedback control is inefficient for both concave and convex reliability issues. The author proposed the STM with chaotic conjugate search direction to enhance both the efficiency and robustness of the FORM algorithm, by developing a chaos control factor based on a logistic map, and following a recursive procedure involving the RI and the logistic map to adaptively define a transformation matrix. See **Figure 2-4** for an illustration. Pedroso [23], presented a solution to reliability problems using a parallel evolutionary algorithm with accuracy and repeatability of results. The stochastic nature of evolutionary algorithms prevents it from generating identical results. Consideration was given to an optimization problem resulting from the FORM with an implicit LSF that can include a call to Finite Element Analysis (FEA). A detailed explanation was given on a strategy to handle failure from the transformation of random variables or from the finite element call during the evolution process.

derived directly from the fitted quadratic polynomial surface because parabolic approximation consideration is removed, and the accompanying errors are eliminated [26]. In the new SORM approach, first, a Nataf transformation to a standard normal u-space is carried out. Then the design point is located, and a quadratic fit at the design point is carried out, after which, the cumulant generating function (CGF) of the fitted quadratic polynomial surface is analytically derived. Finally, the Probability Density Function (PDF), Cumulative Density Function (CDF) and failure probability of the LS are established by applying SPA.

2.3 Level III (Direct) Reliability Methods

The POF of a structural element in relation to a single failure mode is derived from the probability integration expression in Eq. (2-1). Calculating this integration expects that the LSS, $g(x) = 0$, and the joint PDF of X , $f_x(x)$, are known. The methods which calculate the POF directly from this integration are known as Level III reliability methods, which are perceived to be most accurate. The most common relevant level III methods are: (a) Monte-Carlo Methods (MC) (b) NI (c) Analytical Integration (AI) (d) Surrogate Models (SMs) (e) Stochastic Finite Element Method (SFEM) [2,27]. Theoretical background on AI, NI, and MCS can be found in [28].

Computation of the exact failure probability from Eq. (2-1) by using analytical and NIs involves approximations in the solution process and may become inefficient for certain problems. This drawback can be overcome by applying the MCS technique which avoids the extra layer of approximation; however, it becomes inefficient when the LS needs a continuous calculation procedure such as FEA [8,28] in which case it will be impractical. The concept behind MCS is that the number of samples falling into the failure domain (N_f) is determined by sampling the basic random variables/ vector X , each possessing different probability distributions.

An effective sampling method is the Latin Hypercube sampling (LHS). LHS is a method whereby multiple variables can be represented such that over-lapping data sets is avoided. First, the application divides each stochastic variable distribution in n , non-overlapping intervals with equal probability. This involves associating the analysis point derived from each data-sets by randomly selecting one value of each variable from each interval. In comparison with the crude Monte Carlo (MC) sampling, this method yields small variance in the response because of the homogeneous allocation of intervals on the PDF [8].

Besides the LHS, other available variance reduction techniques include, (a) Adaptive Sampling which updates sampling density dynamically as the simulation proceeds [8] and

(b) Conditional Expectation techniques which consist of Axis-orthogonal Simulation techniques for convex failure sets, and Directional Simulation for convex safe sets. The IS method is a derivation from the MCS whereby to achieve greater efficiency the simulation is biased; the sampling is basically carried out in the tail of the distribution to ensure the occurrence of adequate simulation failures. An alternative variance reduction technique is the subset sampling, where the failure event is expressed as a sequence of partial failure events (subsets). In the Design-point Simulation method, the MC sampling is applied around the design point. Initially, having approximate the MPP in the u -dimensional space, MCS is used here instead of performing simulations in the wider range of each distribution. In [29], it was reported that MCS is a powerful tool, straightforward in implementation and capable of solving a wide range of SRA problems. In the same study, neural networks were combined with MCS to address the issues of low POF for highly reliable structures at low computational cost, and the validity of the methodology was demonstrated.

Zhang et al. [30], considered SR when statistical parameters of distribution functions could not be ascertained accurately as a result of epistemic uncertainties. Interval bounds were used to model uncertainties in estimates constructed from confidence intervals. They developed an interval MC method which combines the simulation process with the interval analysis. Naess et al. [31], proposed a new MC based method for approximating system reliabilities, which aims to reduce the computational burden involved in the brute force MCS methods for complicated systems. It harnesses the regularity of tail probabilities to establish an approximation procedure for the calculation of far tail POFs based on the POFs estimated from MCS at more moderate levels. Gaspar et al. [32], claimed the reliability of complex structural systems could be predicted accurately by MCS. They proposed an MCS method for evaluating system reliabilities, which aims to reduce the computational cost associated with highly reliable structural systems. This method applied non-linear FEA combined with response surface (RS) modelling.

Jahani et al. [33], presented SRA such that stochastic variables are modelled as fuzzy random variables, and Interval MCS (IMC) combined with Interval Finite Element Method (IFEM) was applied in approximating the POF. IMC-IFEM and Genetic Algorithm (GA) were compared to ascertain the most efficient. It was concluded that the IMC-IFEM provided higher efficiency compared to the GA method. Dai et al. [34], developed an IS method based on support vector density estimation and adaptive Markov chain simulation. According to the methodology, samples that can adaptively populate the importance region by the

adaptive metropolis algorithm were generated and IS density by support vector density was constructed. In [35] directional simulation was merged with IS. This involves defining a sampling function on the unit hyper-sphere, which samples random directions aiming towards the MPP. Random directions are generated from the sampling function (made adaptive by a closed-form rule to renew the sampling parameters) using spherical coordinates. Zhang [36], developed a new interval IS method by applying the IS technique to an imprecise probability. This methodology has the advantage that an expensive interval analysis is not necessary. Recently, [14] reports the use of direct simulations applying the LHS to predict POF of a complex frame type structure in the presence of stochastic loads based on studies previously conducted in [37].

According to [38], Subset Simulation (SS) is an adaptive simulation method, which solves SRA problems having numerous random variables efficiently. In the study, a novel approach for Markov Chain MC (MCMC) sampling was introduced in the standard normal space. This developed two algorithm variants: a basic variant that is simpler than existing formulations with equal efficiency and accuracy, and a superior variant with adaptive scaling. The accuracy of the SS method was reportedly improved. In [39], an approach to SRA of deteriorating systems which accounts for stochastic dependence among element deterioration was presented. Bayesian updating of the system deterioration model was applied. The updated system reliability is then derived via coupling a probabilistic structural model with the updated deterioration model. SS was reported as a robust and efficient sampling-based scheme ideal for such analyses as solving the underlying high-dimensional SR problems.

2.4 Advanced Approximation Modelling Methods

RS method modelling is applied in deriving equation(s) to express one or more independent variables in terms of a dependent variable. The fundamental idea is to replace the true LSF by an approximation whose function values can be computed more easily [40]. RSM and SM methods are classifications of approximation methods usually applied in modelling complex engineering systems. RSM derives an analytical expression of the system (defined as polynomial equations) while the latter enters the system data-sets normally in a matrix closed-form for post-processing. The expression derived from either category of methods can further be incorporated with RA methods such as FORM/SORM and MCS, and applied in multi-disciplinary optimisation problems [27].

2.4.1 Response Surface Method

RSMs revolve around creating a polynomial closed-form approximation, $\hat{g}(x)$, for the exact LSF $g(x)$, which is usually recognised through an algorithmic procedure, via (a) a few select deterministic analyses and (b) regression analysis of these results. Quadratic functions are commonly employed in practice, as:

$$g(x) \approx \hat{g}(x) = a_0 + \sum_{i=1}^N a_i x_i + \sum_{i=1}^N a_{ii} x_i^2 + \sum_{i=1}^N \sum_{j=1, j \neq i}^N a_{ij} x_i x_j \quad (2-10)$$

$$= V^T(x)a$$

Where the coefficients, $a^T = \{a_0, a_i, a_{ii}, a_{ij}\}$, are to be determined, and the vector $V(x)$ is described as $V^T(x) = \{1, x_i, x_i^2, x_i x_j\}$. To develop the RS, a finite number of evaluations of the LSF, for instance, by applying finite element runs, are needed. Then the RA can be carried out analytically by means of the expression given by Eq. (2-10). This approach is especially desirable when simulation methods are used to determine reliability. The unknown coefficients, $a^T = \{a_0, a_i, a_{ii}, a_{ij}\}$, are determined via the least-square method. Having identified a set of fitting points, $\{x^k, k = 1, \dots, NF\}$ where NF denotes the number of fitting points, referred to as the experimental design, the exact values $y^k = g(x^k)$, are calculated, the error is calculated as:

$$error(a) = \sum_{k=1}^{NF} (y^k - V^T(x^k).a)^2 \quad (2-11)$$

The error expression is minimized with respect to the vector a to calculate the unknown coefficients. After determining a response-surface failure-function from Eq. (2-10), a standard reliability technique is used to compute the POF [2].

According to [1], the response of a structure subjected to certain loading conditions can be evaluated through FEA modelling. The work used a methodology, based on a generalized SRSM for the SRA of an offshore jacket, selected as a reference application. According to the methodology, FEA simulation results were incorporated with numerical reliability techniques through multivariate (quadratic) polynomial regression (MPR), so as to predict the reliability levels of components. This approach is particularly useful as it enabled enhanced analysis of elements under a stochastic perspective, accounting for design uncertainties efficiently [41]. In [14,15], the efficiency of the SRSM for advanced RA of Offshore Wind Turbine (OWT) jacket support structures was demonstrated. According to the

authors, a parametric FEA model was developed, and then stochastic FEA simulations were performed. The results obtained from the FEA were post-processed through MPR in order to obtain the PFs expressed in terms of the stochastic variables, and the RI then computed through FORM. In the presence of Structural Health Monitoring/Condition Monitoring (SHM/CM) data, the structure may be reassessed and updated. The updated safety index gives vital information for decision making for the inspection and maintenance of OWT support structures. According to [42], the SRSM is a technique employed for RA of complex structural systems with time-consuming, implicit or computationally costly LSFs. The collection of sample points, the approximation of RS and the estimation of the POF are the main aspects of the SRSM. Sample points were selected close to the MPP and the actual LS surface (LSS). They used the weighted regression technique to fit the RS, which enables the fitting points to be weighted based on their distance from the failure surface. They analytically derived the cumulant generating function (CGF) of the RS. The POF of the structural system was computed by utilizing the Saddlepoint Approximation (SPA) Method.

RSM is a popular method for RA, especially when the LSF is meant to be highly non-linear or closed-form mechanical models to define complex structural systems are not available [5]. According to [43] the SRSM is used for RA of complex systems with low POF, for which approximate methods are inaccurate, and MCS is too computationally intensive. The SRSM approximates by fitting the polynomial to a number of sampling points from the LSF with a multidimensional quadratic polynomial. To address the problem related to ill-conditioned systems and an approximated LS (which is very imprecise outside the domain of the stochastic parameters) an algorithm using orthogonal polynomials was proposed.

According to [44], RA of a jacket type OWT support structure under extreme ocean environment loads was performed. The use of the RSM methodology was demonstrated to express the LSF and RI was calculated using the FORM. Rücker and Faber [45], presented the RA of an OWT support structure building upon structural, loading, LS and uncertainty models comprising design, production and erection data by applying the SFEM. An algorithm which accounts for complexity in the individual models dictates an efficient solution scheme for reliability. This consists of an adaptive RS and an IS-MC algorithm. The RS algorithm is based on predetermined DoE, which facilitates the adjustment of design parameters for an optimized prediction variance in the domain of the design points.

2.4.2 Surrogate Models (SMs)

Theoretical background on SMs can be found in [46–48]. According to [47], SMs, or meta-models (MM) or RSM [47,48], are used for time-consuming implicit LSFs in the context of SRA. To reduce the computational burden of the direct MCS approach, the SMs can be applied to estimate implicitly the LSFs involving FEA. Artificial neural network (ANN), Kriging, adaptive Kriging, support vector regression (SVR), etc. are applied to estimate the failure probability based on the prediction of the probabilistic model with uncertainties [18].

According to [15], the SRA of a complex OWT support structure subjected to pitting corrosion-fatigue was assessed based on the damage tolerance modelling approach. A non-intrusive formulation incorporating ANN-SM and FORM was proposed to perform the SRA of the crack propagation regime following a sequence of steps. **Figure 2-5** depicts a flowchart of a non-intrusive formulation for probabilistic fracture mechanics in the presence of pitting corrosion-fatigue employing the stochastic parametric FEA.

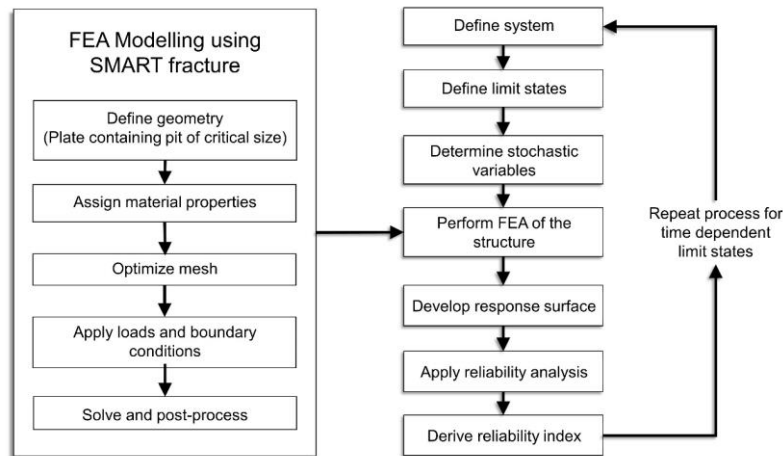


Figure 2-5. Flowchart of a proposed non-intrusive formulation. See [15] for more details. Reprinted with permission from ref. [15]. Copyright 2020, Wiley.

2.4.2.1 Kriging incorporated with FORM

Gaspar et al. [47], proposed an adaptive kriging SM which applies a moderate number of input basic random variables with active refinement, to overcome component RA problems associated with non-linear computationally intensive implicit LSFs. The presented model applies an adaptive kriging-based trust-region approach to search for the design point in the standard normal space and calculates an initial POF based on the FORM, and sensitivity factors for the input stochastic variables. In the second stage, the initial estimate is then verified or enhanced using MCS with IS based on Kriging SM defined recursively

around the MPP by employing an active refinement algorithm. In addition, they developed a convergence criterion, which detects the stabilization of the POF approximation during the active refinement process, per **Figure 2-6**.

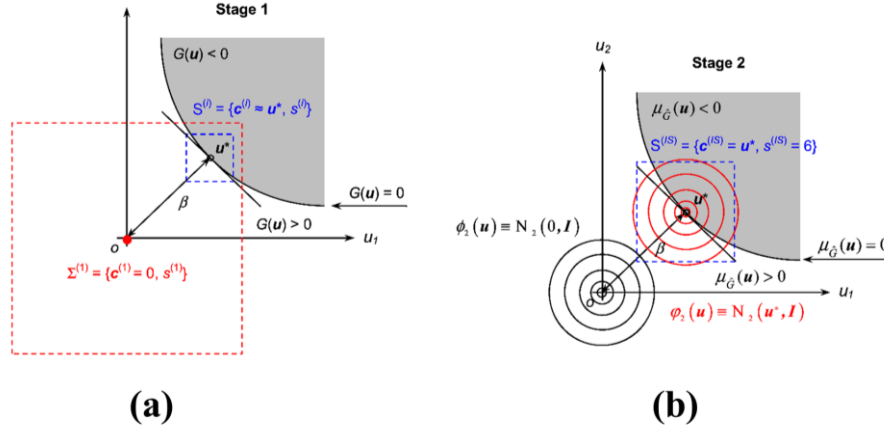


Figure 2-6. Reliability assessment problem in the standard Gaussian space with the two stages involved in a proposed adaptive Kriging SM: (a) stage 1 for design point search and POF prediction based on FORM with the adaptive Kriging-based trust region method; (b) stage 2 for the POF prediction based on MCS-IS with the Kriging model defined iteratively around the FORM design point with the active refinement algorithm of the AK-MCS method [47]. Reprinted with permission from ref. [47]. Copyright 2020, Elsevier.

2.4.2.2 Kriging incorporated with IS/SS

In [49], an efficient reliability method combining adaptive IS and KIM based on active learning mechanism was presented. It was claimed that the Kriging MM, adaptive IS, and active learning mechanism superiorities are inherited and only enables evaluating the interested samples in actual PF. In [50], a modification to an algorithm for the efficient estimation of small probabilities, combining FORM and an adaptive Kriging-based IS strategy (AK-IS) was proposed. It was reported that the modification overcomes an important limitation of the original AK-IS, providing the algorithm with the flexibility to deal with multiple failure regions characterized by complex, non-linear LS. In [51], the time-consuming task inherent in the SS and SM method when the PF needs to be numerically evaluated was addressed by an active learning method combining KIM and SS (AK-SS). It was asserted that the efficiency of the new method relies upon the advantages of SS in evaluating small POFs and the KIM with active learning for approximating the true PF.

2.4.2.3 Efficient Global Reliability Analysis (EGRA)

Bichon et al. [52], developed an efficient RA method known as the Efficient Global RA (EGRA) that characterizes the LS across the domain of random variables accurately. The technique begins by building a KIM from a small number of samples, and then selecting adaptively were to generate subsequent samples to enhance the accuracy of the model near the LS. The KIM produced is then sampled by applying multimodal adaptive IS to compute the reliability level of interest. Highly non-linear complex LS can be modelled, by locating multiple points on or around the LS, resulting in a more accurate probability integration. Few numbers of true function evaluations are required to generate a quality SM by concentrating the samples in the region where accuracy is essential.

2.4.2.4 Sequential Kriging Reliability Analysis (SKRA)

According to [46], the sequential Kriging reliability analysis (SKRA) method was proposed for non-linear implicit PFs, which were computationally unaffordable and included EGRA and AK-MCS. An adaptive sampling regions strategy was developed to avoid selecting samples in the areas where the probability density is so low, thereby having an insignificant impact on the results. The size of the sampling space was adapted based on the POF approximated by the last recursion.

2.4.2.5 Support Vector Approach

According to [53], metamodeling has been widely adopted for RA to enhance computational efficiency. They developed an efficient reliability method which harnesses Adaptive Support Vector Machine (ASVM) and the MCS. This applied a pool-based ASVM for the construction of MM with the minimum number of training samples, whereby a learning function was proposed to sequentially select informative training samples. Then the MCS was used to calculate the POF based on the SVM classifier obtained. Dai et al. [54], presented a multiwavelet linear programming SVR method for RA that mitigates the difficulties inherent in the standard quadratic programming SVR, such as being computationally expensive and possessing the inability to guarantee sufficient model sparsity. The method involves developing a novel multi wavelet kernel by the construction of an autocorrelation function of multiwavelets and uses this kernel in context of linear programming SVR for predicting the LS.

2.4.2.6 Artificial Neural Network Approach

To address the extreme number of FEA required to achieve accuracy, a directional approach was developed, which was reported to significantly improve efficiency. This utilizes deterministic point sets to preserve the underlying joint probability distribution of the random vector describing the structure and adopts neural networks to focus the simulation efforts in the most crucial regions [55]. In [56], two adaptive stochastic search algorithms are used to locate and trace an implicitly defined function to construct an SM for RA. An ANN-SM was applied in the implementation, and it was claimed that the method could, in principle, be applied with any form of SM. In both algorithms proposed, the SM evolved continuously with sample selection and was used in the choice of new samples such that convergence is achieved rapidly to an accurate representation of the limit surface.

2.4.2.7 Radial Basis Function Approach

Bucher and Most [57], compared approximate response functions in terms of their capacities to reduce computational costs in SRA. The RS approaches are based on polynomial functions, radial basis functions (RBFs) and ANN. In the polynomial approach, the higher-order polynomial show severe oscillations, requiring too many support points, and this drawback could be addressed via the application of smoothing techniques eg., the moving least-squares method (MLS). In the ANN method, the output is linked with the input parameters via simple, flexible functions including linear, step or sigmoid functions that are combined by adjustable weights. The RBF approach also allows for flexible adjustment of the interpolation scheme. The availability of interpolating functions that can be augmented incrementally by allowing extra support points implies that it permits approximation sequences to be provided, ensuring quick convergence of its reliability estimates to the true value.

Zhang et al. [58], proposed an efficient RSM to evaluate structural reliability using evidence theory in order to overcome the associated high computational cost. They developed a DoE technique whose key issue is the search of the important control points at intersections of the LS and uncertainty domain. These points have a significant contribution to the accuracy of the subsequent RS. Based on these, a highly precise RBF to the actual LSS was introduced.

2.5 Probabilistic Fatigue and Fracture Mechanics Approaches

Since limit state design is a common trend in modern design, details of this shall be presented in this section [1]. The general design requirement is to provide structures with sufficient safety margins taking into account all types of uncertainties having effects on its integrity (ie. load and capacity variability, modelling idealizations, etc.). Limit state design can be defined simply as the load/ demand of a structural system should under no circumstances exceed its resistance/ capacity. For offshore and marine structures, various limit states are prescribed in design standards that should be assessed within a comprehensive design. According to the DNV [59], the four main types of limit states that should be considered are: (a) Serviceability limit state (SLS): Deformation and vibration limit states (b) Ultimate limit state (ULS): Buckling and stress limit states (c) Fatigue limit state (FLS) (d) Accidental limit state (ALS).

Significant cyclic loads induced by wind and wave imposed on OWT support structures make their design to be generally dominated by FLS. The assessment of the FLS is performed using two types of methods, i.e. the S-N curve method and fracture mechanics (FM) method. The S-N curve approach is based on experimental fatigue-test data. This approach is commonly used in practice and well described in standards for fatigue design of Offshore structures [32,59]. Based on the S-N curve approach, the number of loading cycles to failure, N , can be determined from [14]:

$$\log N = A - m \log \Delta S \quad (2-12)$$

where A and m represents the intercept, and the slope of the S-N curve on the log-log plot, respectively, and ΔS is the stress range. Design standards such as the DNVGL-ST-0126 prescribe values for the intercept A and slope m in Eq. (2-12). The PF of FRA, according to the S-N curve method, is given as [15]:

$$g_{f,SN} = \log N - \log N_t \quad (2-13)$$

where subscripts f and SN represents the FLS and S-N curve method respectively; N is the number of loading cycles to failure as given by Eq. (2-12), N_t is the expected number of loading cycles during the given design life.

FM method is applied at the design stage of offshore structures as this provides a platform for predicting the fatigue life and during the operational stage to allow the decision making process strategies for inspection scheduling and repair. Common amongst large and complex structures such as offshore tubular structures crack like imperfections, notches or

other forms of discontinuities exists. The basic concept of the FM approach revolves around is the characterization of the stress field in terms of a single parameter, ΔK , which is known as the *stress intensity factor* (SIF) near the crack [8,28]. This parameter is a function of both the stress σ and crack size a .

The FM approach is based on the models created to predict the crack growth in a material when variable loads are applied. The crack growth is a process not fully understood at the atomic level. The engineering analysis of this is studied using relationships between SIF and crack growth rates. The Paris law can be expressed as

$$\frac{da}{dN} = C.(\Delta K)^m \quad (2-14)$$

Where a is the crack length, N is the number of cycles, ΔK is the SIF range, and C and m are material constants. State-of-the-art numerical and experimental research on bilinear crack growth law phenomena can be found in [60–69]. The safety margin for fatigue reliability analysis based on LEFM is given by:

$$g_{f,FM} = \int_{a_0}^{a_c} \frac{1}{Y(a)^m (\sqrt{\pi a})^m} da - C \Delta S^m (N(t) - N_0) \quad (2-15)$$

where subscript f and FM represents the fatigue limit state and FM method, respectively; a_0 is the initial crack depth (or the crack depth at time t_0); a_c denotes the critical crack depth; $Y(a)$ is the compliance function, which is related to crack depth a ; m and C are Paris' law constants; $N(t)$ is the total number of stress cycles in the time period $[t_0, t]$; and N_0 is the initial number of stress cycles. The findings of the state-of-the-art-review studied herein will be presented later in Section 2.7.

2.6 Other Methods and Applications

2.6.1 Stochastic Finite Element Method (SFEM)

Component reliability methods are based on a failure function $g(\vartheta)$ in the space of basic random variables, which are collated in the vector θ (here θ is used for random field instead of X to prevent confusion between spatial variation and random field). It is easy to implement if $g(\vartheta)$ is explicitly defined or known. In practical cases, the failure function is usually unavailable explicitly in the closed-form, and the response is derived via FEA. Several computational techniques may be employed for the RA with implicit failure functions. The major techniques include Perturbation Techniques, Neumann expansion solution, RS

approach, and branch and bound techniques [2]. A state-of-the-art review on SFEM is presented in [70].

The perturbation techniques are desirable owing to their efficiency in computation times and accuracy. Theoretical background on perturbation method can be found in [2]. Li et al. [71], proposed a new class of hybrid perturbation-Galerkin methods to establish the response function (surface) to overcome the major challenge in the RA of the complex structure of being unable to find the response function from which the LS can be determined. Single-variable and double variable approximations are the main methods incorporating a combination of the perturbation technique and Bubnov-Galerkin projection, where several orders of summation terms of polynomial expansions are adopted as the Galerkin trial functions or basis vectors.

Feng et al. [72], presented a robust stochastic free vibration analysis for engineering structures involving hybrid, yet spatially variant, uncertain system parameters. Both the stochastic and non-stochastic representations of the spatial dependencies of the uncertainties are simultaneously incorporated within the unified analysis as distinguished from the conventional hybrid uncertain eigenvalue problem. It was asserted that the applicability and effectiveness of the proposed computational framework were demonstrated by the numerical investigations on various engineering structures.

In [73], a general FE based formulation was proposed for the assessment of the mean and mean-square response of stochastic structural systems with material properties defined by random fields governed by a flexibility-based formulation without involving approximations. Integral expressions of closed-form for the mean and mean-square value of the displacement response of structures which are stochastic and statically indeterminate was introduced. Two new quantities, variability response function (VRF) and the mean response function (MRF) for the mean-square response and the uncertain material properties were modelled using the stochastic field spectral density function which can be referred to as integral expressions. Towards achieving an efficient and accurate numerical evaluation of the VRF and MRF, a FEM-based fast MCS procedure (FEM-FMCS) was introduced.

2.6.2 Reliability Analysis of Systems

System RA could be conducted directly or as a follow up of a set of a single element or mode analysis. The first option is through NI or MC methods. It may be viable, in many cases to begin with an analysis of individual component and process the outcomes afterwards to

compute the POF for the system, and it may be evident that the methods of the series and parallel systems are capable of providing solutions to the combined system problems. For complicated structural systems, applying the FORM/ SORM and MC techniques directly could either be too computationally expensive or the LSF being unavailable explicitly in the closed-form. For realistic structures then, the response is obtained through a numerical technique such as FEA, whereby the derivatives are unavailable, and each evaluation of the implicit LSF is time demanding. A wide range of computational procedures can be used for the RA with implicit failure functions in the form of the Stochastic Finite Element Method (SFEM) [2]. Detailed explanation on Parallel System can be found in [2,28].

In the series system, failure of the weakest link results in failure of the entire system. Series systems are modelled commonly by assuming multiple failure modes of a component or multiple failure paths of a structure. A detailed explanation of this can be found in [2]. Gong and Zhou [74], evaluated the system reliability of series systems using a proposed improved equivalent component approach. The FORM context was considered for an analytical expression derived to estimate the unit normal vector related to the equivalent component. Hence, the computational efficiency for establishing the correlation coefficients between the equivalent component approach and the system is enhanced. At each combining step, the two components with the utmost correlation coefficient are combined in an adaptive combining process. The efficiency and accuracy of the enhanced equivalent component approach were demonstrated for a series system with unequally and equally correlated components.

Zhang et al. [75], described a framework for developing reliability-based system resistance factors suitable for use with a Direct Design Method (DDM), which is a system-based design-by-advanced analysis approach. A design-by-inelastic analysis method which relies on existing resistance factors originally developed from member reliability considerations was implemented for minimum system reliability requirements [58].

2.6.3 Time-Variant Reliability of Systems

Theoretical background on the transfer into T-V system method and on the outcrossing approach can be found in [2,28]. In many cases reliability aspects are T-V; for instance, some kind of degrading mechanism on the resistance side or fluctuating loads may be the reason. In [4], T-D RA of ageing structures was presented wherein uncertainties such as structural deterioration and non-stationarities in structural load process were taken into account. It was claimed that the improved approximate method, which requires only low-

dimensional integration reduces the cost of assessing T-V reliability over a service life extending to 50 years significantly. In [76], a T-V reliability method was formulated as a large scale series system consisting of T-V response functions obtained by discretizing T-V continuous response functions within the forecast time period. This is used instead of analysing outcrossing rates which have a limitation of being inaccurate for low boundary reliability with dependent outcrossing rates. In [77], an efficient cross-entropy-based adaptive IS method was proposed to facilitate the wide application of stochastic-process-based T-V reliability methods in complex problems. The LHS with proper correlation control is used to extend cross-entropy-based IS to T-V RA.

2.7 Critical Discussion

Various challenges as well as their respective solutions with respect to SRA methods are identified and presented in Sections 2.2-2.6 in this study. This section collates and discusses key aspects from the studies which stand out as particularly important. **Table 2-1-**

Table 2-4 summarises the most popular SR methods and their capabilities and limitations [5,8,11,12,16,19,25–28,47,70,78].

The developments over the last forty years with an emphasis on recent development in the FORM and SORM has been reviewed in great detail by Breitung [12], and show that the FORM and SORM are relevant and indispensable in the area of RA as applied to structural engineering. This is in agreement with previous studies carried out by Rackwitz [25]. The well-practised quantitative approaches to reliability-based risk analysis of analytical nature, such as the concept of LS and FORM/SORM or MCS methods, are still common practice [27]. The conventional SR methods such as FORM/SORM and MCS still remain the de-facto methods and serve as the basis for enhanced methods that overcome their inherent limitations. Recent research [70], shows that the FORM is the most efficient SRA method ahead of the SORM.

Due to the volume of research, developments in the area of SRA are tending towards the use of RS and SM/MM. The PF of most realistic engineering structures today are highly non-linear and implicit (i.e. cannot be solved without the use of FEA) and thus analytical methods are incapable of solving them efficiently. Also, the MCS cannot efficiently provide accurate solution of LS with very low failure probabilities. Despite the fact that numerical techniques such as IS, LHS, SS, have been developed to reduce computational costs, this

drawback among others still exist. There have been several alternative methods which involve a combination of two or more reliability methods to overcome these drawbacks. The RSM provides an efficient vehicle to combine the high fidelity FEA modelling with conventional SRA methods. SM SRA methods are ideal for cases requiring implicit PF to be evaluated point-wise using FEM. The PCE has been used as a regression technique to model accurately the global behaviour of computational models, while the KIM with high fidelity models local variations owing to its interpolation capabilities. Global methods such as the Active Learning Reliability Method combining Kriging and MCS (AK-MCS) and the EGRA [48] have been found to be very efficient, as they give accurate results for implicit time consuming unaffordable PFs, as demonstrated in [9]. For the treatment of problems such as complex geotechnical designs, and those involving high-frequency vibrations and of elastic stability, SFEM have been found to be ideal as it accounts for spatially varying stochastic structural heterogeneity [70,73]. Numerous studies were carried out on reliability analysis in other related areas such as in geotechnical engineering, fluid mechanics, rock engineering, etc. The scope of the present study is limited to only reliability assessment with respect to metal offshore jacket structures associated with structural engineering.

Applications of the T-D SRA for the design of modern metal structures such as those deployed offshore (i.e. in environments characterised by highly stochastic loads and resistance properties, thus necessitating the need for SRA to account for such uncertainties systematically) include [14,15,79–84]. In [85], the fatigue reliability of fixed offshore platforms was investigated by analysing different failure scenarios. The analysis was divided into a finite number of sub-scenarios in order to evaluate the occurrence probability of a special scenario. The Palmgren-Miner's rule and S-N curve were employed to estimate the accumulated fatigue damages in the LSF. Extensive research has been carried out in the area of probabilistic fracture mechanics approach to FRA, some of which include: According to [86], to accurately evaluate the effect of an inspection and repair strategy of structures subjected to degradation resulting from crack growth, application of FM models are required to describe crack propagation. The reliability methods applied to account for inherent uncertainties with respect to selecting an optimal tool for making the proper decision, which enables a balance between design criteria, and inspection and repair plans include SN and FM formulations. These include a crack growth formulation based on bi-linear crack growth law assuming both crack growth law segment to be correlated and non-correlated in the POF calculation. The FORM and SORM, as well as MCS, were used to illustrate the effect

of inspection in the updated reliabilities. It was reported that crack initiation time, initial crack size and the crack aspect ratio play significant roles in the calibration of FM methods.

Dong et al., [79], investigated the fatigue reliability of welded multi-planar tubular joints of the support structure of a fixed jacket offshore wind turbine in a water depth of 70m. The long-term statistical distribution of hot-spot stress ranges was fitted using a two-parameter Weibull function by combining time-domain simulation for the inherent environmental conditions (wind/ sea states) in operational condition. The SN-Miner-Palmgren approach based fatigue design criteria were satisfied by normalizing the load histories and thus, the estimated safety levels refer to fatigue design of tubular joints that meets design criteria. The FM analysis of crack growth was applied for the reliability analysis. The hot-spot stress range was increased assumed to be due to changes of the nominal stress and stress concentration factors produced by thickness thinning (wastage) effects of selected components with a general uniform corrosion model in order to account for the corrosion-induced crack growth rate. Also investigated include factors such as the effects of geometry function and corrosion-induced material degradation on the reliability evaluation. The influence of inspection and repair with and without considering corrosion were investigated based on the quality of inspection in terms of probability of crack detection curves. FM models are applied to describe crack propagation models, which are calibrated based on SN-data since the initiation of cracks and their initial stages at growth are subject to uncertainties which are hard to quantify.

A sub-category under this which is an area open to further investigations due to the sparse amount of research is the damage tolerance approach for probabilistic pitting corrosion fatigue life prediction performed by [15] wherein comprehensive mechanistic-based probabilistic models for pitting corrosion fatigue life prediction by including all stages were presented, and the FORM was implemented with the proposed models. In [15], a generic RA framework that combines parametric FEA modelling, RSM, and RA specifically for complex highly non-linear OWT jacket type support structures in the presence of highly stochastic variables, and taking into consideration, specifically, T-D phenomena such as fatigue as well as degradation mechanisms such as corrosion was developed. Two ANNs were trained to relate various stochastic variables for predicting the PF. The two ANNs were employed in order to have an intermediate predictor for a stochastic variable, which is more advantageous because of the added interpretability of results. An advantage of the proposed methodology is that the first ANN architecture enabled a significant reduction in the

computational cost, which would have been required to simulate global behaviour of the support structure thus allowing other global parameters to be incorporated.

Several studies have been performed on applying GA in SRA and on sensitivity analysis, and design optimization referred to as the stochastic/ structural reliability sensitivity analysis (SSA) and RBDO, respectively. The scope of this study is limited to only SRA methods due to the myriads of research performed in these areas (i.e. GA, SSA and RBDO). It should be noted that this review does not cover all the papers published on this subject, but attempted to present the main techniques, with the intent of producing an important document, which serves as a guide to designers/ researchers on this subject.

Table 2-1. Capabilities and limitations of the most common level III approximation structural reliability methods

Method		Capabilities	Limitations
First Order Reliability Method (FORM)	Mean Value First Order Second Moment Reliability Method	<ul style="list-style-type: none"> • Simplest and least expensive reliability method • A simplistic technique used in calculating reliability indices, using a minimum representation of basic variables 	<p>The applicability range of this method is diminished as a result of the following reasons:</p> <ul style="list-style-type: none"> • Non-linearity or large variations may not be handled by this method efficiently because linearization of the LSF about the mean values may result in inaccurate results. • The MVFOSM algorithm is dependent on different (mathematically equivalent) formulations of the same problem; for both non-linear and linear LSF expressions. • For cases where the LSS is characterized by irregular/ large curvatures (high non-linearity), the POF estimated by FORM, using the RI β, may yield inaccurate and unreliable results. • MVFOSM method is a straight forward procedure, while the HL method needs several iterations to converge, especially for non-linear problems
	Hasofer and Lind Method	FORM approximation gives adequate outcome when the function is nearly linear close to the MPP, and the LSS has only one minimal distance point.	
	Hasofer and Lind-Rackwitz Fiessler Method	Widely used approximate analytical method since it provides a good balance between efficiency and accuracy in realistic engineering RA.	<ul style="list-style-type: none"> • It may yield unstable results, such as severe oscillations and chaotic solutions for highly non-linear problems (gives non-convergence problems). • Cannot be used for implicit LS and also limited to only one dominant failure mechanism
Second-Order Reliability Method		Ideal for cases where the LSS has large or irregular curvatures (high non-linearity), the POF estimated by FORM, using the RI β , can produce inaccurate and unreliable results. By introducing second-order Taylor series expansions (or other polynomials), this drawback may be overcome.	<ul style="list-style-type: none"> • It is basically a more time consuming and complex process • For highly non-linear PF with a wide input data-sets the estimated FORM/ SORM RI results may not be sufficiently precise as a result of non-normal to normal transformations and multiple MPPs as well as the application of only first/ second-order terms to calculate the original PFs. • As a result of the parabolic approximation, there is an additional error in such SORMs besides the quadratic approximation error.

Table 2-2. Capabilities and limitations of the most common level III direct structural reliability methods

Method		Capabilities	Limitations
Analytical Integration		Ideal for simple failure surface	<ul style="list-style-type: none"> Only possible for some special cases of limited practical interest Due to rapidly increasing computational demands as the number of dimension increases (the so-called 'curse of dimensionality') it has not found great favour in reliability computations.
Numerical Integration		Standard routines are found in most computer systems	Not always feasible owing to the growth-off errors and excessive computational times
Crude Monte Carlo Simulation Technique (MCS)		Most versatile, clear and well understood exact method available Require no partial derivative of LSF; therefore, the method can be used for implicit LSF.	<ul style="list-style-type: none"> Computationally unaffordable/ exorbitant for real engineering problems (for very small POFs) Simplest MC approach for reliability problems but not the most efficient It becomes inefficient when the LS needs a continuous calculation procedure such as FEA in which case it will be impractical.
Variance Reduction Techniques	MCS with Importance Sampling Technique	<ul style="list-style-type: none"> Reduce computational time compared to the crude MCS Has been demonstrated to be very robust and effective for a range of possible LSF shapes. Increases the accuracy for the same number of runs 	<ul style="list-style-type: none"> IS distribution $h_v(\mathbf{z})$ may not be chosen well, such as being too flat or being skewed Extremely concave LSFs may result in inefficient sampling A maximum likelihood unique point $\mathbf{x}^*$ may not be identifiable: <ul style="list-style-type: none"> If $f_x(\mathbf{z})$ has a 'flat' contour region If the PF $G(\mathbf{z}) = 0$ coincides with a contour of $f_x(\mathbf{z})$ in a region of interest, or

Adaptive Sampling		<ul style="list-style-type: none"> • Involves a prior analysis to locate the design point for problems of high dimensionality in particular; a search algorithm with the constraint that the point must lie along the LS would fix the desirable location of $h_v(\blacksquare)$. It is also possible to modify $h_v(\blacksquare)$, depending on the information being obtained during the search process. • Can be applied for multiple failure mechanisms and small probabilities of failure. 	<ul style="list-style-type: none"> • If the PF $G(\blacksquare) = 0$ is non-smooth (e.g. Ripple-like) and has a series of candidate locations for x^* • There can be more than one point of local maximum likelihood such as when $f_x(\blacksquare)$ is not uni-modal • The application of IS is sometimes referred to as an art that must be applied with caution.
Conditional Expectation Techniques	Directional Simulation	<ul style="list-style-type: none"> • Has the advantage of simulation in polar coordinate standard normal (y) space. • Is recommended for convex safe sets • Is applicable specifically to LSS which are nearly spherical (in standard normal space y) • The amount of sampling required usually is reduced considerably compared to IS in Cartesian coordinates • The special case of hyperspherical LS surface in standard normal space, only one directional sample is required (to fix the radius) and would give the exact result immediately. 	Application of the directional sampling and adaptive sampling is limited to a moderate number of random variables
	Axis Orthogonal Simulation Technique	Is recommended for convex failure sets	The technique is not very efficient for one or a few planar LS.
			They typically require a large number of response function evaluations, which makes them impractical if the response function is expensive to evaluate.

Design Point Simulation	Makes use of the FORM Design point which makes it less cumbersome in the search for the POF	
Subset Simulation	<ul style="list-style-type: none"> Efficiently deals with small failure probabilities Converts the simulation of a rare event into sequence simulation of more frequent events. 	<ul style="list-style-type: none"> Additional complexity as it involves the use of Markov Chain MCS Method. Inefficient for expensive PF.

Table 2-3. Capabilities and limitations of the most common advanced approximation structural reliability methods

Method			Capabilities	Limitations
Parallel System			A parallel system fails when all the links (potential failure modes) fail. The most consistent function of the parallel system is for modelling the sequential failure of components in a single failure path leading to structural failure	Redundant members are introduced which introduces a computationally intensive procedure
Series System			Ideal for Pipelines	Failure of one component leads to failure of the system
Stochastic Finite Element Method	Perturbation Method		The perturbation techniques are desirable owing to their efficiency in terms of computation times and accuracy	Too mathematically intensive
	Neumann Expansion Solution		<ul style="list-style-type: none"> Can be referred to as a computational scheme to lessen the amount of calculation time and to increase the efficiency of standard techniques as FORM/ SORM and MC Is adopted to prevent repeated inversion of the random system-stiffness-matrix while undergoing the MC simulation approach. The matrix k_o has to be decomposed only once for all samples in conjunction with the MCS. Due to this single matrix decomposition, computing time can be significantly reduced. 	Determining the covariance matrix among all elements of the fluctuation part of the stiffness matrix involves prohibitively high computational effort.
	Response Surface Method		<ul style="list-style-type: none"> It is desirable when the simulation is used to determine reliability results Ideal for Implicit LSFs It is not restrained by the number of random variables It is simple to perform with high accuracy 	<ul style="list-style-type: none"> May sometimes be inefficient for highly non-linear failure function Restricted to small dimensions of uncertainty space Inefficient for large complex structures

Surrogate Models/ Response Surface Model/ Meta-Models	Branch and Bound Method		Are useful for the elastic-plastic analysis of frame structures where effects of plasticity like the formation of plastic hinges give sharp changes in the stiffness behaviour	<ul style="list-style-type: none"> If the initial point of choice in the RSM is unreasonable, and the objective function is highly non-linear, then the rate of convergence of the RSM is slow. Therefore, the RSM for SR estimation in a wide range of applications has been limited. 	Its application is limited
	Polynomial Regression Models		The most widely used due to their simple formulations and implementation	<ul style="list-style-type: none"> Higher-order polynomials tend to show severe oscillations They sometimes face non-convergence issues for cases with an increasing number of support points centred at the mean value of the basic random variables 	
	Approaches Based on:	Radial Basis Function	<ul style="list-style-type: none"> SM has the advantage of been more affordable compare with other exact methods Has the merit of defining failure conditions of structural systems such that RA can be conducted with high fidelity. Have been validated to be the best interpolation methods compared to others by using examples of different kinds of scattered data. 	Computationally efficient but at the expense of accuracy	
		Local Interpolation Model (Polyhedra)	<ul style="list-style-type: none"> These are highly flexible to local approximations and should converge in the long run to the exact LSF. It is possible to construct approximation whose reliability estimates converge fast to the true value, as a result of their availability which can be augmented incrementally by providing additional support points. 	It is an approximate method	

Artificial Neural Network	<ul style="list-style-type: none"> • Possess the capability of describing failure conditions of structural systems such that RA can be carried out with high fidelity. • They are flexible in nature and have the ability to capture complex non-linear relationships between input and output through appropriate learning. • Have practical advantages over classical RSM due to their superior mapping capabilities and the flexibility in the functional form 	<ul style="list-style-type: none"> • Overfitting could occur whereby the number of hidden nodes is too large for the number of training samples • Have the main challenge of suitably choosing the learning parameters that help restrain under or overfitting, as both are equally disastrous.
Support vector Machine	In comparison to ANNs, SVM employs the theory of minimizing the structure risk to avoid the problems of excessive study, calamity data, local minimum value etc.	Its implementation involves high computational efforts, and sufficient model sparsity cannot be guaranteed.
Moving Least Squares	<ul style="list-style-type: none"> • The optimization problem of the overdetermined system of equations can be solved by using the least-squares approach. • As a result of the approximate character of the classical MLS method, the exact representation of support point values cannot be achieved, which is a positive aspect. 	<ul style="list-style-type: none"> • If the input data is noisy, it is owing to the fact that due to the approximative character of the classical MLS method, the support point values cannot be represented exactly. • The application of this in the framework of RA this property result in significant errors in the calculation of the POF
Kriging Models	<ul style="list-style-type: none"> • Have more general approximation capability, i.e. predicts highly accurate POF values compared to the polynomial regression models • Have important features that have been explored in the context of SRA such as the interpolation capability, the flexibility to estimate arbitrary functions with high precision as well as being capable of providing a measure of local uncertainty for the model predictions. • Provides prediction uncertainty measure which has been used in the development of effective adaptive SMs for SRA with active refinement algorithms for the DoE. 	Significantly more complex compared to polynomial regression models

Table 2-4. Capabilities and limitations of the other common structural reliability methods

Method			Capabilities	Limitations
Stochastic Expansion	Non-Intrusive	Stochastic Response Surface Method	<ul style="list-style-type: none"> • Its an extension of the conventional RSM, the PF of structures are replaced with polynomials while the traditional one employs polynomial sequences, and the SRSM uses Polynomial Chaos. • Describes uncertainties in a non-explicit way, assuming the analysis code to be a “black box” such that access to the analysis code will not be required. • The mean square error is minimized by selecting the collocation points and from high probability regions, therefore, resulting in fewer function evaluations for enhanced precision • The method is applicable to the analysis of SR with any distribution type • Higher accuracy could be attained from the higher-order RS function 	<p>Its is widely used in chemical Engineering. Its application in Structural Engineering is still burgeoning.</p>
	Intrusive	Spectral Stochastic FEM	Gives more reliable results	<ul style="list-style-type: none"> • Complicated and demands access to simulation procedure • Linear and non-linear SFEM is not yet practical if the original random field is discretized into a high dimensional random vector
Time variant reliability Methods			<ul style="list-style-type: none"> • In a lot of cases, reliability aspects are T-V. For instance, some kind of degrading mechanism on the resistance side or fluctuating loads may be the reason. • Fatigue and corrosion phenomenon is T-V 	Practical application of T-V reliability methodology appears rather limited, partially because only very few computer codes are available

2.8 Conclusion

This work presents the state-of-the-art in methods used for structural reliability analysis (SRA) based on a systematic review focusing mainly on literature from 2005 to 2020. The paper focuses on presentations of methods and their variations, aiming to qualify their advantages and limitations with applicability to design of metal offshore jacket structures. Improvements to the fundamental analytical methods facing issues with highly non-linear performance function (PF) structures have been modified with conjugate search direction approach, Saddle Point Approximation (SPA), the introduction of the merit function, subset simulation (SS), evidence theory, among others. To reduce the computational burden of MCS, the approximation methods can be applied to estimate implicitly or explicitly the limit state functions (LSFs) involving Finite Element Analysis (FEA). Combinations of advanced approximation methods and RA methods are also found in literature as they can be suitable for complex, highly non-linear problems.

- The FORM has been improved by the development of the conjugate search direction, finite based Armijo search direction method, Hybrid Relaxed HL-RF, stability transformation method (STM) with chaos feedback control, STM with chaos feedback control, STM with chaotic conjugate search direction, among others. The combination of Maximum Entropy Fitting Method and the FORM was applied to problems of implicit LSFs. The SORM is an improvement on the FORM to provide solutions to highly non-linear LSFs. A new SORM for RA was developed using the SAP in order to overcome some of the issues inherent in the traditional SORM.
- The MCS method has been improved by the development of interval MC method which combines simulation process with interval analysis, new MC based methods involving the use of brute force MCS methods for complicated structural systems, IMC-IFEM, merging IS with directional simulation, etc. Improvements in variance reduction techniques have been achieved, such as the development of interval importance sampling (IS) method which applies the IS technique and imprecise probability, and the LHS based quasi-random polar sampling technique.
- The advanced approximation modelling methods include the well-established Response Surface Models/ Method (RSM) and the Surrogate Models (SM) as well as the Stochastic RSM (SRSM). The SRSM is a model for the RA of complex systems with low Probability of Failure (POF) for which approximate methods are inaccurate and for which Monte Carlo Simulation (MCS) is too computationally intensive. The efficiency of the RSMs developed for implicit LSFs studied herein

include, the Collocation Based SRS, novel SRS combining FEA, MPR and FORM/SORM, incorporating the SRS with Saddlepoint approximation (SPA), among others. Examples of SM include the Kriging, Adaptive Kriging, EGRA, Support vector machines, ANN, RBF, etc. These can be combined with conventional reliability methods for problems of implicit LSFs. Kriging and Adaptive Kriging interpolation models have been combined with the FORM, Line sampling, IS, SS, MCS, etc.

- This study focussed specifically on the probabilistic fatigue and fracture mechanics approaches because the fatigue limit state in most cases is the design-driving criterion for structural components of offshore jacket structures. Consequently, the SRA of structures considering pitting-corrosion fatigue phenomenon was identified as particularly of note and is recommended as an area open to further investigation.

Author Contributions: Conceptualization, methodology, software, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, A.A.S.; Conceptualization, methodology, formal analysis, investigation, resources, writing—review and editing, supervision, project administration, A.K; Methodology, formal analysis, investigation, resources, writing—review and editing, supervision, project administration, funding acquisition, A.M. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: Author Abdulhakim A. Shittu would like to acknowledge the Petroleum Technology Development Fund (PTDF), Nigeria, for doctoral study scholarship, award number: PTDF/ED/PHD/SAA/1142/17.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kolios, A. A multi-configuration approach to reliability based structural integrity assessment for ultimate strength, Cranfield University, 2010.
2. Karadeniz, H. Review of Structural Reliability Methods with Applicability in Practice. *Civ. Eng.* **2006**, *4*, 880653–880653.
3. Ditlevsen, O.; Madsen, H.O. Structural Reliability Methods. *Book* **2007**, 375.
4. Li, Q.; Wang, C.; Ellingwood, B.R. Time-dependent reliability of aging structures in the presence of non-stationary loads and degradation. *Struct. Saf.* **2015**, *52*, 132–141, doi:10.1016/j.strusafe.2014.10.003.
5. Choi, S.-K.; Grandhi, R.; Canfield, R. *Reliability-based Structural Design*; Springer: USA, 2006;
6. Li, G.; Lu, Z.; Li, L.; Ren, B. Aleatory and epistemic uncertainties analysis based on non-probabilistic reliability and its kriging solution. *Appl. Math. Model.* **2016**, *40*, 5703–5716, doi:10.1016/j.apm.2016.01.017.
7. Wei, P.; Song, J.; Bi, S.; Broggi, M.; Beer, M.; Lu, Z.; Yue, Z. Non-intrusive stochastic analysis with parameterized imprecise probability models : II . Reliability and rare events analysis. *Mech. Syst. Signal Process.* **2019**, *126*, 227–247, doi:10.1016/j.ymssp.2019.02.015.
8. Melchers, R.; Andre, T. *Structural reliability analysis and prediction*; 3rd ed.; Wiley: Hoboken, USA, 2018;
9. Huang, C.; El Hami, A.; Radi, B. Overview of Structural Reliability Analysis Methods — Part III : Global Reliability Methods. *Incert. fiabilité des systèmes multiphysiques* **2016**, *17*, doi:10.21494/ISTE.OP.2017.0115.
10. Huang, C.; El Hami, A.; Radi, B. Overview of Structural Reliability Analysis Methods —

- Part I: Local Reliability Methods. *Incert. fiabilité des systèmes multiphysiques* **2017**, 17, 1–10, doi:10.21494/ISTE.OP.2017.0115.
11. Nowak, A.S.; Collins, K.R. *Reliability of Structures*; Second Edi.; CRC Press, 2012;
 12. Breitung, K. 40 years FORM: Some new aspects? *Probabilistic Eng. Mech.* **2015**, 42, 71–77, doi:10.1016/j.probengmech.2015.09.012.
 13. Shi, P.; Mahadevan, S. Damage tolerance approach for probabilistic pitting corrosion fatigue life prediction. *Eng. Fract. Mech.* **2001**, 68, 1493–1507, doi:10.1016/S0013-7944(01)00041-8.
 14. Shittu, A.A.; Mehmanparast, A.; Wang, L.; Salonitis, K.; Kolios, A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Appl. Sci.* **2020**, 10, 860, doi:10.3390/app10030860.
 15. Shittu, A.A.; Mehmanparast, A.; Shafiee, M.; Kolios, A.; Hart, P.; Pilario, K.E. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting Corrosion-Fatigue: A Damage Tolerance Modelling Approach. *Wind Energy* **2020**, Early view, doi:10.1002/we.2542.
 16. Ayyub, B.M.; McCuen, R.H. *Probability, Statistics, and Reliability for Engineers and Scientists*; Third.; Taylor and Francis Group: 6000 Broken Sound Parkway NW, Suite 300, Boca Raton, 2011; ISBN 9781439895337.
 17. Low, B.K.; Tang, W.H. Efficient Spreadsheet Algorithm for First-Order Reliability Method. *J. Eng. Mech.* **2007**, 133, 1378–1387, doi:10.1061/(ASCE)0733-9399(2007)133:12(1378).
 18. Keshtegar, B.; Chakraborty, S. A hybrid self-adaptive conjugate first order reliability method for robust structural reliability analysis. *Appl. Math. Model.* **2018**, 53, 319–332, doi:10.1016/j.apm.2017.09.017.
 19. Keshtegar, B.; Meng, Z. A hybrid relaxed first-order reliability method for efficient structural reliability analysis. *Struct. Saf.* **2017**, 66, 84–93, doi:10.1016/j.strusafe.2017.02.005.
 20. Keshtegar, B.; Chakraborty, S. An efficient-robust structural reliability method by adaptive finite-step length based on Armijo line search. *Reliab. Eng. Syst. Saf.* **2018**, 172, 195–206, doi:10.1016/j.ress.2017.12.014.
 21. Yang, D. Chaos control for numerical instability of first order reliability method. *Commun. Nonlinear Sci. Numer. Simul.* **2010**, 15, 3131–3141, doi:10.1016/j.cnsns.2009.10.018.
 22. Keshtegar, B. Chaotic conjugate stability transformation method for structural reliability analysis. *Comput. Methods Appl. Mech. Eng.* **2016**, 310, 866–885, doi:10.1016/j.cma.2016.07.046.
 23. Pedroso, D.M. FORM reliability analysis using a parallel evolutionary algorithm. *Struct. Saf.* **2017**, 65, 84–99, doi:10.1016/j.strusafe.2017.01.001.
 24. Shi, X.; Teixeira, A.P.; Zhang, J.; Soares, C.G. Structural reliability analysis based on probabilistic response modelling using the Maximum Entropy Method. *Eng. Struct.* **2014**, 70, 106–116, doi:10.1016/j.engstruct.2014.03.033.
 25. Rackwitz, R. Reliability analysis — a review and some perspectives. *Struct. Saf.* **2001**, 23, 365–395.
 26. Huang, X.; Li, Y.; Zhang, Y.; Zhang, X. A new direct second-order reliability analysis method. *Appl. Math. Model.* **2018**, 55, 68–80, doi:10.1016/j.apm.2017.10.026.
 27. Leimeister, M.; Kolios, A. A review of reliability-based methods for risk analysis and their application in the offshore wind industry. *Renew. Sustain. Energy Rev.* **2018**, 91, 1065–1076, doi:10.1016/j.rser.2018.04.004.
 28. Karadeniz, H. *Stochastic Analysis of Offshore Steel Structures*; 2013; ISBN 9781849961899.
 29. Cardoso, J.B.; de Almeida, J.R.; Dias, J.M.; Coelho, P.G. Structural reliability analysis using Monte Carlo simulation and neural networks. *Adv. Eng. Softw.* **2008**, 39, 505–513, doi:10.1016/J.ADVENGSOFT.2007.03.015.
 30. Zhang, H.; Mullen, R.L.; Muhanna, R.L. Interval Monte Carlo methods for structural reliability. *Struct. Saf.* **2010**, 32, 183–190, doi:10.1016/j.strusafe.2010.01.001.
 31. Naess, A.; Leira, B.J.; Batsevych, O. Reliability analysis of large structural systems. *Probabilistic Eng. Mech.* **2012**, 28, 164–168, doi:10.1016/j.probengmech.2011.08.024.
 32. Gaspar, B.; Naess, A.; Leira, B.J.; Soares, C.G. System reliability analysis by monte carlo

- based method and finite element structural models. *J. Offshore Mech. Arct. Eng.* **2014**, 136, 1–9, doi:10.1115/1.4025871.
33. Jahani, E.; Muhanna, R.L.; Shayanfar, M.A.; Barkhordari, M.A. Reliability assessment with fuzzy random variables using interval monte carlo simulation. *Comput. Civ. Infrastruct. Eng.* **2014**, 29, 208–220, doi:10.1111/mice.12028.
 34. Dai, H.; Zhang, H.; Wang, W. A support vector density-based importance sampling for reliability assessment. *Reliab. Eng. Syst. Saf.* **2012**, 106, 86–93, doi:10.1016/j.ress.2012.04.011.
 35. Shayanfar, M.A.; Barkhordari, M.A.; Barkhori, M.; Barkhori, M. An adaptive directional importance sampling method for structural reliability analysis. *Struct. Saf.* **2018**, 70, 14–20, doi:10.1016/j.strusafe.2017.07.006.
 36. Zhang, H. Interval importance sampling method for finite element-based structural reliability assessment under parameter uncertainties. *Struct. Saf.* **2012**, 38, 1–10, doi:10.1016/j.strusafe.2012.01.003.
 37. Reh, S.; Beley, J.D.; Mukherjee, S.; Khor, E.H. Probabilistic finite element analysis using ANSYS. *Struct. Saf.* **2006**, 28, 17–43, doi:10.1016/j.strusafe.2005.03.010.
 38. Papaioannou, I.; Betz, W.; Zwirgmaier, K.; Straub, D. MCMC algorithms for Subset Simulation. *Probabilistic Eng. Mech.* **2015**, 41, 89–103, doi:10.1016/j.probengmech.2015.06.006.
 39. Schneider, R.; Thöns, S.; Straub, D. Reliability analysis and updating of deteriorating systems with subset simulation. *Struct. Saf.* **2017**, 64, 20–36, doi:10.1016/j.strusafe.2016.09.002.
 40. Bucher, C.; Most, T. A comparison of approximate response functions in structural reliability analysis. *Probabilistic Eng. Mech.* **2008**, 23, 154–163, doi:10.1016/j.probengmech.2007.12.022.
 41. Kolios, a J.; Brennan, F. Reliability Deterioration of Offshore/Marine Steel Structures due to Effects of Corrosion. In Proceedings of the Asranet 2012; London, 2012; p. 10.
 42. Huang, X.; Liu, Y.; Zhang, Y.; Zhang, X. Reliability analysis of structures using stochastic response surface method and saddlepoint approximation. *Struct. Multidiscip. Optim.* **2017**, 55, 2003–2012, doi:10.1007/s00158-016-1617-9.
 43. Gavin, H.P.; Yau, S.C. High-order limit state functions in the response surface method for structural reliability analysis. *Struct. Saf.* **2008**, 30, 162–179, doi:10.1016/j.strusafe.2006.10.003.
 44. Kim, D.H.; Lee, S.G. Reliability analysis of offshore wind turbine support structures under extreme ocean environmental loads. *Renew. Energy* **2015**, 79, 161–166, doi:10.1016/j.renene.2014.11.052.
 45. Rücker, W.; Faber, M.H. Support Structure Reliability of Offshore Wind Turbines Utilizing. *ASME 2010 29th Int. Conf. Ocean. Offshore Arct. Eng.* **2010**, 1990, 1–10, doi:10.1115/OMAE2010-20546.
 46. Wen, Z.; Pei, H.; Liu, H.; Yue, Z. A Sequential Kriging reliability analysis method with characteristics of adaptive sampling regions and parallelizability. *Reliab. Eng. Syst. Saf.* **2016**, 153, 170–179, doi:10.1016/j.ress.2016.05.002.
 47. Gaspar, B.; Teixeira, A.P.; Guedes Soares, C. Adaptive surrogate model with active refinement combining Kriging and a trust region method. *Reliab. Eng. Syst. Saf.* **2017**, 165, 277–291, doi:10.1016/j.ress.2017.03.035.
 48. Bichon, B.J. Efficient Surrogate Modeling for Reliability Analysis and Design, Vanderbilt University, 2010.
 49. Zhao, H.; Yue, Z.; Liu, Y.; Gao, Z.; Zhang, Y. An efficient reliability method combining adaptive importance sampling and Kriging metamodel. *Appl. Math. Model.* **2015**, 39, 1853–1866, doi:10.1016/j.apm.2014.10.015.
 50. Cadini, F.; Santos, F.; Zio, E. An improved adaptive kriging-based importance technique for sampling multiple failure regions of low probability. *Reliab. Eng. Syst. Saf.* **2014**, 131, 109–117, doi:10.1016/j.ress.2014.06.023.
 51. Huang, X.; Chen, J.; Zhu, H. Assessing small failure probabilities by AK – SS : An active learning method combining Kriging and Subset Simulation. *Struct. Saf.* **2016**, 59, 86–95, doi:10.1016/j.strusafe.2015.12.003.

52. Bichon, B.J.; Eldred, M.S.; Swiler, L.P.; Mahadevan, S.; McFarland, J.M. Efficient Global Reliability Analysis for Nonlinear Implicit Performance Functions. *AIAA J.* **2008**, *46*, 2459–2468, doi:10.2514/1.34321.
53. Pan, Q.; Dias, D. An efficient reliability method combining adaptive Support Vector Machine and Monte Carlo Simulation. *Struct. Saf.* **2017**, *67*, 85–95, doi:10.1016/j.strusafe.2017.04.006.
54. Dai, H.; Zhang, B.; Wang, W. A multiwavelet support vector regression method for efficient reliability assessment. *Reliab. Eng. Syst. Saf.* **2015**, *136*, 132–139, doi:10.1016/j.ress.2014.12.002.
55. Nie, J.; Ellingwood, B.R. Finite element-based structural reliability assessment using efficient directional simulation. *J. Eng. Mech.* **2005**, *131*, 259–267, doi:10.1061/(ASCE)0733-9399(2005)131:3(259).
56. Sundar, V.S.; Shields, M.D. Surrogate-enhanced stochastic search algorithms to identify implicitly defined functions for reliability analysis. *Struct. Saf.* **2016**, *62*, 1–11, doi:10.1016/j.strusafe.2016.05.001.
57. Bucher, C.; Most, T. A comparison of approximate response functions in structural reliability analysis. *Probabilistic Eng. Mech.* **2008**, *23*, 154–163, doi:10.1016/J.PROBENGMECH.2007.12.022.
58. Zhang, H.; Ellingwood, B.R.; Rasmussen, K.J.R. System reliabilities in steel structural frame design by inelastic analysis. *Eng. Struct.* **2014**, *81*, 341–348, doi:10.1016/j.engstruct.2014.10.003.
59. Dnv-Os-C101 Design of Offshore Steel Structures , General (Lrfd Method). *Det Nor. Verit.* **2011**, 2015.
60. Mehmanparast, A.; Taylor, J.; Brennan, F.; Tavares, I. Experimental investigation of mechanical and fracture properties of offshore wind monopile weldments: SLIC interlaboratory test results. *Fatigue Fract. Eng. Mater. Struct.* **2018**, *41*, 2485–2501, doi:10.1111/ffe.12850.
61. Mehmanparast, A.; Brennan, F.; Tavares, I. Fatigue crack growth rates for offshore wind monopile weldments in air and seawater: SLIC inter-laboratory test results. *Mater. Des.* **2017**, *114*, 494–504, doi:10.1016/j.matdes.2016.10.070.
62. Igwemezie, V.; Mehmanparast, A. Waveform and frequency effects on corrosion-fatigue crack growth behaviour in modern marine steels. *Int. J. Fatigue* **2020**, *134*, 105484, doi:10.1016/j.ijfatigue.2020.105484.
63. Igwemezie, V.; Dirisu, P.; Mehmanparast, A. Critical assessment of the fatigue crack growth rate sensitivity to material microstructure in ferrite-pearlite steels in air and marine environment. *Mater. Sci. Eng. A* **2019**, *754*, 750–765, doi:10.1016/j.msea.2019.03.093.
64. Igwemezie, V.; Mehmanparast, A.; Kolios, A. Current trend in offshore wind energy sector and material requirements for fatigue resistance improvement in large wind turbine support structures – A review. *Renew. Sustain. Energy Rev.* **2019**, *101*, 181–196.
65. Igwemezie, V.; Mehmanparast, A.; Kolios, A. Materials selection for XL wind turbine support structures: A corrosion-fatigue perspective. *Mar. Struct.* **2018**, *61*, 381–397, doi:10.1016/j.marstruc.2018.06.008.
66. Jacob, A.; Mehmanparast, A.; D'Urzo, R.; Kelleher, J. Experimental and numerical investigation of residual stress effects on fatigue crack growth behaviour of S355 steel weldments. *Int. J. Fatigue* **2019**, *128*, 105196, doi:10.1016/j.ijfatigue.2019.105196.
67. Jacob, A.; Oliveira, J.; Mehmanparast, A.; Hosseinzadeh, F.; Kelleher, J.; Berto, F. Residual stress measurements in offshore wind monopile weldments using neutron diffraction technique and contour method. *Theor. Appl. Fract. Mech.* **2018**, *96*, 418–427, doi:10.1016/j.tafmec.2018.06.001.
68. Bocher, M.; Mehmanparast, A.; Braithwaite, J.; Shafiee, M. New shape function solutions for fracture mechanics analysis of offshore wind turbine monopile foundations. *Ocean Eng.* **2018**, *160*, 264–275, doi:10.1016/j.oceaneng.2018.04.073.
69. Khajeian, A.; Mahmoudi, A.H.; Mehmanparast, A. Shot peening effects on residual stresses redistribution of offshore wind monopile multi-pass weldments. *Mar. Struct.* **2019**, *66*, 106–120, doi:10.1016/j.marstruc.2019.03.006.
70. Aldosary, M.; Wang, J.; Li, C. Structural reliability and stochastic finite element methods:

- State-of-the-art review and evidence-based comparison. *Eng. Comput. (Swansea, Wales)* **2018**, *35*, 2165–2214.
71. Li, Y.-J.; Huang, B.; Li, C.-Q. Hybrid perturbation-Galerkin methods for structural reliability analysis. *Probabilistic Eng. Mech.* **2017**, *48*, 59–67, doi:10.1016/j.probengmech.2017.05.001.
 72. Feng, J.; Wu, D.; Gao, W.; Li, G. Hybrid uncertain natural frequency analysis for structures with random and interval fields. *Comput. Methods Appl. Mech. Eng.* **2018**, *328*, 365–389, doi:10.1016/j.cma.2017.09.004.
 73. Papadopoulos, V.; Papadrakakis, M.; Deodatis, G. Analysis of mean and mean square response of general linear stochastic finite element systems. *Comput. Methods Appl. Mech. Eng.* **2006**, *195*, 5454–5471, doi:10.1016/j.cma.2005.11.008.
 74. Gong, C.; Zhou, W. Improvement of equivalent component approach for reliability analyses of series systems. *Struct. Saf.* **2017**, *68*, 65–72, doi:10.1016/j.strusafe.2017.06.001.
 75. Zhang, H.; Shayan, S.; Rasmussen, K.J.R.; Ellingwood, B.R. System-based design of planar steel frames, I: Reliability framework. *J. Constr. Steel Res.* **2016**, *123*, 135–143, doi:10.1016/j.jcsr.2016.05.004.
 76. Gong, C.; Frangopol, D.M. An efficient time-dependent reliability method. *Struct. Saf.* **2019**, *81*, 101864, doi:10.1016/j.strusafe.2019.05.001.
 77. Yang, D.Y.; Teng, J.G.; Frangopol, D.M. Cross-entropy-based adaptive importance sampling for time-dependent reliability analysis of deteriorating structures. *Struct. Saf.* **2017**, *66*, 38–50, doi:10.1016/j.strusafe.2016.12.006.
 78. Chojaczyk, A.A.; Teixeira, A.P.; Neves, L.C.; Cardoso, J.B.; Guedes Soares, C. Review and application of Artificial Neural Networks models in reliability analysis of steel structures. *Struct. Saf.* **2015**, *52*, 78–89, doi:10.1016/j.strusafe.2014.09.002.
 79. Dong, W.; Moan, T.; Gao, Z. Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection. *Reliab. Eng. Syst. Saf.* **2012**, *106*, 11–27, doi:10.1016/j.ress.2012.06.011.
 80. Yeter, B.; Garbatov, Y.; Soares, C.G. Fatigue reliability of an offshore wind turbine supporting structure accounting for inspection and repair. In *Analysis and Design of Marine Structures*; Soares, G., Sheno, E., Eds.; Taylor & Francis Group: London, UK, 2015; pp. 737–747.
 81. Yeter, B.; Garbatov, Y.; Soares, C.G. Reliability of Offshore Wind Turbine Support Structures Subjected to Extreme Wave-Induced Loads and Defects. In *Proceedings of the Proceedings of the ASME 2016 35th International Conference on Ocean, Offshore and Arctic Engineering*; Busan, South Korea, 2016.
 82. Yeter, B.; Garbatov, Y.; Guedes Soares, C. System reliability of a jacket offshore wind turbine subjected to fatigue. In *Proceedings of the Proceedings of the 5th International Conference on Marine Structures, MARSTRUCT*; Lisbon, 2017; pp. 939–950.
 83. Jiang, Z.; Hu, W.; Dong, W.; Gao, Z.; Ren, Z. Structural reliability analysis of wind turbines: A review. *Energies* **2017**, *10*, 1–25, doi:10.3390/en10122099.
 84. Shittu, A.A.; Mehmanparast, A.; Pilario, K.E.; Hart, P.; Kolios, A.J. Comparative study between SN and fracture mechanics approach on reliability assessment of offshore wind turbine jacket foundations. *Under Rev.* **2020**.
 85. Gholizad, A.; Golafshani, A.A.; Akrami, V. Structural reliability of offshore platforms considering fatigue damage and different failure scenarios. *Ocean Eng.* **2012**, *46*, 1–8, doi:10.1016/j.oceaneng.2012.01.033.
 86. Ayala-uraga, E.; Moan, T. Fatigue reliability-based assessment of welded joints applying consistent fracture mechanics formulations. *Int. J. Fatigue* **2007**, *29*, 444–456, doi:10.1016/j.ijfatigue.2006.05.010.



© 2020 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

3 COMPARATIVE STUDY OF STRUCTURAL RELIABILITY ASSESSMENT METHODS FOR OFFSHORE WIND TURBINE JACKET SUPPORT STRUCTURES

Abdulhakim Adeoye Shittu, Ali Mehmanparast, Lin Wang, Konstantinos Salonitis and Athanasios Kolios

Published: Applied Sciences, 2020, 10(3), paper number: 860

Statement of contributions:

Abdulhakim A. Shittu conducted the literature review, developed, and validated the model, performed the simulations, generated all the results, drafted and critically revised the manuscript. A. Mehmanparast, L. Wang, K. Salonitis, and A. Kolios provided supervision, reviewed and critically commented on the manuscript before submission.

Abstract: Offshore wind turbines (OWTs) are deployed in harsh environments often characterized by highly stochastic loads and resistance properties, thus necessitating the need for structural reliability assessment (SRA) to account for such uncertainties systematically. In this work, the SRA of an OWT jacket-type support structure is conducted, applying two stochastic methods to predict the safety level of the structure considering various design constraints. The first method refers to a commercial finite element analysis (FEA) package (DesignXplorer® from ANSYS) which employs direct simulations and the six sigma analysis function applying Latin hypercube sampling (LHS) to predict the probability of failure. The second method develops a non-intrusive formulation which maps the response of the structure through a finite number of simulations to develop a response surface, and then employs first-order reliability methods (FORM) to evaluate the reliability index and, subsequently, the probability of failure. In this analysis, five design constraints were considered: stress, fatigue, deformation, buckling, and vibration. The two methods were applied to a baseline 10-MW OWT jacket-type support structure to identify critical components. The results revealed that, for the inherent stochastic conditions, the structural components can safely withstand such conditions, as the reliability index values were found acceptable when compared with allowable values from design standards. The reliability assessment

results revealed that the fatigue performance is the design-driving criterion for structural components of OWT support structures. While there was good agreement in the safety index values predicted by both methods, a limitation of the direct simulation method is in its requirement for a prohibitively large number of simulations to estimate the very low probabilities of failure in the deformation and buckling constraint cases. This limitation can be overcome through the non-intrusive formulation presented in this work.

Keywords: stochastic modeling; reliability index; non-intrusive formulations; structural reliability analysis; offshore wind structures

3.1 Introduction

In line with the quest to battle against the energy crisis and global climate change, wind energy is found to provide a technically and economically feasible solution, making it the most promising renewable energy technology in Europe and beyond (i.e., China, United States of America (USA), etc.) [1]. Today, the vast majority of wind energy is generated from onshore wind farms. However, there is a limitation in the further growth of onshore wind farms as a result of visual impact and limited space available to deploy wind turbines. In comparison to land, there is more available space to deploy wind turbines at sea, and the wind shear is stronger at offshore locations, driving the wind industry to move offshore, currently aiming for offshore wind in Europe to reach 64.8 GW by 2030 [1–4].

With few exceptions, most of the existing offshore wind turbines (OWTs) are installed on monopile foundations in shallow waters (depths < 50 m). However, as turbines become larger (>5 MW) and as water depth increases beyond 35–50 m, monopiles become progressively uneconomical, primarily because of modal requirements that force structural dimensions to grow even beyond fabrication and installation capabilities currently available [5]. State-of-the-art research on monopile foundations can be found in References [6,7]. Space frame structures such as jackets, widely used in the petroleum industry, offer a lighter and yet stiff alternative to monopiles. Effective design of these structures from a turbine system dynamics perspective is a demanding task. Although jacket-type support structures could contribute to further developments in the offshore wind industry, research is still required to support their basic design and analysis [5,8], as well as to take into account the requirement for optimization due to both the serial production required and the nature of these unmanned structures. As a result of

application-based research, several new methods and patents were developed aiming to resolve some of these issues [9–18].

In a conventional structural analysis, the environmental loads, geometric dimensions, material properties, and parameters are treated as deterministic quantities, which are often expressed in the design through characteristic values incorporating partial safety factors for consideration of uncertainties. This type of analysis is adequate in cases where randomness is relatively small. However, structures used for offshore deployment are generally complex and subjected to high uncertainties introduced by the environment, manufacturing, and operational processes. Randomness in design parameters for such systems should be systematically accounted for via stochastic modeling, allowing for a better informed and potentially optimized design that would take into consideration the life cycle of the structure and associated time-variant mechanisms of damage. Reliability analysis enables an efficient approach to better understand the response of the system to variation of an input parameter, enabling the systematic modeling of uncertainties occurring from highly complex models, loading conditions, etc. [19]. In particular, for offshore jacket foundations, soil-structure interactions and particularities of marine environments introduce considerable uncertainties (e.g., soil properties, wind, wave, and current loads, etc.), leading to the requirement of employing proper reliability analysis methods. A structural reliability model of OWT support structures requires two key components, i.e., (1) a structural model describing the structural behavior of OWT support structures, and (2) a suitable reliability assessment method which finds the reliability index β (or the probability of failure P_f) of critical members with respect to the constraints [20].

Structural models for OWT support structures can be roughly classified into two groups, i.e., one-dimensional (1D) beam models and three-dimensional (3D) finite element analysis (FEA) models. In the 1D beam model, the support structure is discretized into a sequence of elastic Euler or Timoshenko beam elements. It is computationally efficient and capable of accurately modeling global structural behavior, such as deflections and modal frequencies [21]. However, it is incapable of accurately representing the structural responses at a local scale such as stress concentration effects [22]. In the 3D FEA model, the jacket foundations are usually defined by applying brick or shell elements. In comparison to the one-dimensional beam model, the three-dimensional finite element model has the capability of examining detailed stress distributions and accurately

capturing structural responses within the structure. The three-dimensional finite element analysis model was extensively applied to structural modeling of wind turbine structures due to its high fidelity [1,2,23–27]. Thus, the 3D FEA model is adopted in this study to determine the structural responses of OWT jacket foundations.

Due to the fact that OWT jacket support structures are embedded via piles into the soil, it is important to consider soil-structure interaction in order to adequately capture their structural response. A simple method to model the soil is the p-y method, in which the soil is modeled using equivalent springs with stiffness based on soil properties. However, this method underestimates the deflection and the modal frequency. An alternative way of modeling the soil is 3D FEA with brick elements, which is capable of providing accurate and reliable results [28,29]. Considering the accuracy, 3D FEA with brick elements is adopted to model the soil later on in this study.

Several studies [30–44] showed that structural reliability assessment is commonly applied to assess the safety level of OWT structures. Most reliability methods are established as time-invariant; however, in numerous instances, owing to the continuous degradation of the resistance of the structure through corrosion, fatigue, etc., or due to fluctuating loads in time, reliability models should be accounted for as time-variant [45,46]. At first, the structural reliability assessment focuses on the evaluation of the reliability of each component, assuming a series system formulation where a single point failure illustrates a global failure of the structure [40,47,48]. In a second level, however, the embedded redundancy in the system is evaluated through methods such as push-over analysis, which is again based on the calculation of component reliability. Level I methods are deterministic reliability methods that only use one characteristic value to describe each uncertain variable. Common design standard formats, such as load resistance and allowable stress, belong to this category. These methods correspond to standard deterministic design methods. They can be combined with more advanced, higher-order methods in the case of partial safety factors calibration, which can optimize their application [49]. The conventional structural reliability methods include level II (approximate) reliability methods or analytical techniques which consist of the first-order reliability method (FORM) [50] and the second-order reliability method (SORM) [51], as well as level III reliability methods which include Monte Carlo Simulations (MCS). In FORM, the limit state function is approached through Taylor's expansion, and the problem of evaluating the reliability of a complex system is translated into a problem of

mathematical optimization. SORM generally performs better in cases of highly nonlinear systems than FORM, while, in other cases, the two methods give similar results. MCS involves direct simulations and, hence, reduces the uncertainty in the results due to approximations in the solution algorithm. However, its application is constrained in the calculation of high probabilities for relatively non-complex engineering systems. MCS can be incorporated with variance reduction techniques, e.g., Latin hypercube sampling (LHS), weighted Latin hypercube sampling (WLHS), importance sampling, subset simulation, etc. [19,20,45,52].

The stochastic expansion consists of intrusive and non-intrusive formulations. An intrusive formulation is one whereby the representation of uncertainty is expressed explicitly within the analysis of the system. Practically, this refers to methods that use Karhunen-Leove expansion (K-L) and polynomial chaos expansion (PCE) to directly modify the stiffness matrix of a finite element analysis procedure, such as SSFEM (spectral stochastic FEM) and stochastic Galerkin FEM. On the other hand, non-intrusive formulations, such as stochastic response surface methods [46,49], represent uncertainties in a non-explicit way and treat the analysis code as a “black box” without requiring access to the source code. Both methods employed in this research constitute non-intrusive formulations.

The first method studied in this paper accounts for the use of a commercial tool (ANSYS DesignXplorer®), which considers randomness in input variables (such as material properties, boundary conditions, loads, and geometry) and characterizes them by the joint probability density function of the input variables. Mixed moments of order higher than two are assumed to be negligible, which means that the joint probability density function can be described by the marginal distribution functions and the correlation structure. Available tools offer several statistical distribution functions to specify the marginal distribution. The probabilistic methods implemented in the DesignXplorer® include Latin hypercube sampling, all versions of the central composite design of experiment (DOE) type, Box-Behnken design DOE type, variational technology, and Monte Carlo simulations on the response surface [53,54]. More information on these probabilistic methods can be found in References [48,54]. The benefit of the tool is in its user-friendly interface and direct link with FEM modeling. However, it relies on direct simulations, which is a limitation for the order of magnitude probabilities of interest for

offshore and marine applications, and which cannot be generalized and integrated with more specialized tools for more advanced analysis.

The second approach, which was developed by the authors, proposes a non-intrusive stochastic formulation, which links the structural model to a reliability analysis algorithm through approximation modeling. In this case, quadratic response surface modeling is adopted in order to map the response of the structure in the domain of stochastic variables. The benefit of this approach is that it allows for high-fidelity computational tools to be employed for the analysis in a modular way, thereby extending its applicability to various engineering problems requiring advanced modeling techniques, and further permitting coupling with analytical reliability methods such as FORM and SORM, allowing for low values of probability of failure to be calculated.

This work aims to carry out a comparison of the two methods described above for a typical OWT jacket-type support structure considering various design constraints and stochastic variables. This paper is the first of its kind to study the structural reliability of an OWT jacket-type support structure using two methods and then comparing the results, as there is no work which reported the use of the post-processing tool inbuilt in ANSYS applied to an OWT jacket-type support structure to determine the probability of failure, nor any work comparing results from the probabilistic FEA in ANSYS to a non-intrusive stochastic formulation, which is also documented in this paper. Furthermore, the proposed non-intrusive method is verified against the commercial package, allowing for further complex engineering problems to be investigated without the need for a fully integrated application-specific tool, rather than through a modular approach which can allow the use of simpler and more computational efficient tools.

3.2 Theoretical Background on the ANSYS DesignXplorer© Probabilistic Methods

3.2.1 Monte Carlo Simulation

As the name implies, Monte Carlo simulation techniques involve “sampling” at “random” to simulate artificially a large number of experiments and to observe the result. In the case of analysis for structural reliability, this means, in the simplest approach, sampling each random variable X_i randomly to give a sample value $\hat{x}_i$. The limit state function $G(x) = 0$ is then checked using the sample set of values $\hat{x}_i$. If the limit state function is violated (i.e., $G(\hat{x}_i) \leq 0$), the structure or structural element “fails”. The experiment is

repeated many times, each time with a randomly chosen vector $\hat{x}$ of $\hat{x}_i$ values. If N trials are conducted, the probability of failure is given approximately as follows [55]:

$$p_f \approx \frac{n(G(\hat{x}_i) \leq 0)}{N}, \quad (3-1)$$

where $n(G(\hat{x}_i) \leq 0)$ is the number of trials n for which $(G(\hat{x}_i) \leq 0)$. Obviously, the number N of trials required is related to the desired accuracy for p_f . It is clear that, in the Monte Carlo method, a game of chance is constructed from known probabilistic properties in order to solve the problem many times over, and from that to deduce the required result (i.e., the failure probability).

3.2.2 Direct Sampling (“Crude” Monte Carlo)

The technique sketched above is the simplest Monte Carlo approach for reliability problems but not the most efficient. The basis for its application is outlined below. The probability of limit state violation may be expressed as follows [56]:

$$p_f = J = \int \dots \int I[G(x) \leq 0] f_X(x) dx, \quad (3-2)$$

where $I[]$ is an “indicator function” which is equal to one if $[]$ is “true” and zero if $[]$ is “false”. Thus, the indicator function identifies the integration domain. Equation (3-1) represents the expected value of $I[]$. If x_j represents the j -th vector of random observations from $f_X()$, it follows directly from sample statistics that Equation (3-3),

$$p_f \approx J_1 = \frac{1}{N} \sum_{j=1}^N I[G(\hat{x}_j) \leq 0], \quad (3-3)$$

is an unbiased estimator of J . Thus, Equation (3-3) provides a direct estimate of p_f . In exploiting this procedure, three matters are of interest: how to extract most information from the simulation points, how many simulation points are needed for a given accuracy, or, conversely, how to improve the sampling technique to obtain greater accuracy for the same or fewer sample points [55].

The fundamentals of the Monte Carlo simulation method are well documented in literature [48,57]. The key functionality of Monte Carlo simulation techniques is the generation of random numbers with a uniform distribution from 0–1 [54]. The DesignXplorer© uses the advanced Mersenne Twister (MT) algorithm [58]. The MT

algorithm is adopted for generating uniform pseudorandom numbers. In order to accommodate Mersenne-prime period, the MT is a modified variant of a previous generator, the twisted generalized feedback shift register (TGFSR). The MT generator was implemented in portable C-code and passed stringent statistical tests, including diehard. Its merits are due to the efficient algorithms that are unique to polynomial calculations over the two-element field [58]. ANSYS also uses the inverse probability method [48] to generate random numbers with arbitrary distributions. The implementation of the inverse cumulative probability function was verified with the results published by Kececioğlu [59] with matching results even for probabilities as low as 10^{-24} . It uses the Latin hypercube sampling technique [60,61] to make the sampling process more efficient, as well as to ensure that the tails of the distribution of the input variables are better represented.

The interpretation of the results of a Monte Carlo simulation analysis is based on statistical methods. The statistical procedures to calculate, for example, mean values and standard deviations, and to derive histogram plots are available in textbooks on statistics and probabilistic methods (e.g., Reference [62]). For the cumulative distribution function (CDF), the data are sorted in ascending order, and the CDF of the i -th data point, here denoted with F_i , can be derived as follows [54]:

$$\sum_{k=i}^N \frac{N!}{(N-k)!k!} F_i^k (1-F_i)^{N-k} = 50\%. \quad (3-4)$$

In DesignXplorer®, this equation is solved numerically for F_i . From the CDF curve, failure probabilities, as well as the inverse probability, can be derived.

In ANSYS, sensitivities are evaluated based on correlation coefficients [62]. The stronger a result parameter is correlated with a particular input variable, the more sensitive the result parameter is with respect to the input variable.

3.2.2.1 Accuracy and Validity

Monte Carlo simulation methods have two major sources of inaccuracy. Of course, the number of samples cannot be infinite, but must be limited. The error due to the limitation of the number of samples can be easily quantified. As described in Reference [62], confidence intervals from statistical results of a Monte Carlo simulation can be easily obtained. In the context of finite element analysis, another source of error, which is

typically overlooked, is the error due to re-meshing the geometry if geometric uncertainties are included in the probabilistic model. Furthermore, minute changes in the geometry can cause the mesh density in critical areas of the geometry to change in a non-continuous fashion. This leads to a change in the finite element results much larger than would be expected for a small geometry change. This error due to re-meshing cannot be easily quantified, but it can be minimized, if mesh controls are applied such as specifying the number of mesh divisions in critical areas of the geometry. However, this is a manual and often time-consuming operation. A method avoiding the influence of the meshing error involves variational technology.

3.2.2.2 Advantages and Disadvantages

The Monte Carlo simulation method does not make any simplification or assumptions in the deterministic or probabilistic model. The only assumption it does in fact make is that the limited number of samples is representative to quantify the randomness of the result parameters. The error associated with this assumption is well quantifiable as outlined above. With an increasing number of samples, the Monte Carlo simulation method converges to the true and correct probabilistic result. The Monte Carlo simulation is, therefore, widely used as the benchmark to verify the accuracy of other probabilistic methods. Another advantage is the fact that the required number of simulations is not a function of the number of input variables.

The disadvantage of the Monte Carlo simulation method is its computational cost. As a rule of thumb, addressing low probabilities of failure requires about $N_{sim} \approx \frac{100}{P_f}$ simulation loops, where P_f is the targeted failure probability. Hence, if the targeted failure probability is low, then the required number of samples may be prohibitively large, making the Monte Carlo simulation method impractical for real engineering problems.

3.2.2.3 Variance Reduction

According to Reference [55], the variance σ^2 directly affects the variance of J_1 , and the number of samples N inversely affects the variance of J_1 . This means that the standard deviation of $\hat{j}$ and, hence, of the Monte Carlo estimate decreases in proportion to $N^{-\frac{1}{2}}$. By comparison, for one-dimensional integration, the error in standard deviation reduces as N^{-2} for the trapezoidal rule and N^{-4} for Simpson's rule [63]. Obviously, the slow convergence of the "crude" Monte Carlo method is a significant disadvantage for its

practical application. One approach involves ways to reduce the variance σ^2 for the estimate of the probability of failure J . These are the so-called “variance reduction” techniques [64]. Apart from increasing the number of samples, variance reduction can be achieved only by using additional (a priori) information about the problem to be solved. The Latin hypercube sampling technique is an example of various variance reduction techniques. A good overview of the various strategies for variance reduction in general Monte Carlo work was given by References [64,65] in relation to some techniques for structural reliability calculations.

3.2.3 Six Sigma Analysis (SSA) Theory

3.2.3.1 Sample Generation

For SSA, the sample generation is based on the Latin hypercube sampling (LHS) technique by default. In the properties view for a six sigma analysis cell, sampling type can be set to either LHS or WLHS (weighted Latin hypercube sampling). LHS is a more advanced and efficient form of Monte Carlo analysis methods. With LHS, the points are randomly generated in a square grid across the design space, but no two points share input parameters of the same value. This means that no point shares a row or a column of the grid with any other point. Generally, LHS requires 20% to 40% fewer simulations loops than the direct Monte Carlo technique to deliver the same results with the same accuracy. However, that number is largely problem-dependent [53].

3.2.3.2 Latin Hypercube Sampling

The Latin hypercube method, originally presented in Reference [66], is a method that can represent multiple variables avoiding overlapping datasets. According to Reference [55], stratified and Latin hypercube sampling methods use the common idea that the sampling space be divided into strata (or hypercubes) and that only a few of the many possible samples may be selected in each strata (or hypercube) for inclusion in the estimation of the integral J . Application of the method initiates by dividing the distribution of each stochastic variable in n , non-overlapping intervals with equal probability. For each variable, one value should be randomly selected from each interval, and the analysis point derived from each dataset is then associated. The homogeneous allocation of intervals on the probability distribution function yields relatively small variance in the response, compared to the conventional Monte Carlo sampling. At the same time, the analysis is much less computationally demanding to generate [49].

The samples used from within each stratum (or hypercube) can be randomly selected from those that would otherwise be used; alternatively, for example, the mean or central point might be used as the one representative value. The evaluation of J then uses these selected values, weighted by their probability of occurrence. Latin hypercube sampling considers all the random variables [55,64,67,68].

For convenience, consider the special case in which all the random variables x_i ($i = 1, \dots, n$) are each divided into the same number of strata, say N . It is convenient also to make the divisions such that the probability of x_i falling in each stratum is $1/N$. Now, select a representative value for each stratum and for each random variable. In principle, more values could be selected, but this can also be achieved by using a greater number of strata. To estimate J , the procedure is to use just one of the N representative values for each random variable x_i (that is, selected from one of the strata) in combination with a selected representative value from each of the other random variables. This collection of representative values forms a sample set. The process is repeated, selecting from the remaining representative values, thereby forming another sample set, and so on. In the end, there will be N sample sets. These can be interpreted directly as the number N of sample vectors selected in Monte Carlo sampling and, thus, can be used directly in Equation (3-1), with evaluations of the limit state function using the present sample sets to estimate J (and, thus, p_f). Latin hypercube sampling can also be combined with other variance reduction techniques [68], such as importance sampling, although it is generally considered to be most suitable for small-scale simulation problems [55,56,69].

3.2.4 ANSYS DesignXplorer© for Structural Reliability Analysis

In order to perform the SRA, a stochastic parametric FEA model is firstly built in the ANSYS environment such that the different input parameters are assigned their corresponding distributions. Then, the developed FEA model is employed in performing a series of FEA simulations on the OWT support structure through the DoE module packaged in the DesignXplorer© facility in ANSYS, in order to map the response domain and then derive an appropriate response surface model. The purpose of the response surface is to interpolate the values in the multiple dimensions characterized by the DoE. There are several types of response surfaces as packaged in DesignXplorer© [53] which include the genetic aggregation, standard response surface full second-order polynomials, kriging algorithms, non-parametric regression, and the sparse grid. However, in this study, only the standard response surface full second-order polynomials

with manual refinements is applied, along with the selection of the specification of three verification points. The response surface is interpolated from design points in the DoE. Also packaged within the response surface module is the goodness of fit metric, which is calculated for the DoE points and can be calculated for verification points to check how accurate the response surface can predict the design points. In all limit state cases, the predicted vs. observed chart should be checked to show the goodness of fit data for one or more outputs. Furthermore, the output data should be observed in order to ascertain whether most of the points fall on or near the line, which implies that the response surface predicts the values for most of the design points within its range including the verification points accurately. This indicates that the response surface is a good fit for the DoE points.

In this study, the six sigma analysis function of the DesignXplorer© module in ANSYS is used for the probabilistic assessment. Latin hypercube sampling (LHS) with number of samples equal to 1×10^7 is defined and applied to all the design constraint cases. The cumulative distribution function (CDF) is used to assess the probability of failure and, hence, the reliability of the component. The cumulative distribution function value at any given point expresses the probability that the respective parameter value remains below that point. Whether this probability represents the failure probability or the reliability of the component depends on how failure is defined [53]. The corresponding reliability index β is evaluated through appropriate statistical transformation [55].

3.3 Development of a Non-Intrusive, Modular Formulation for Structural Reliability Assessment

3.3.1 A Modular Structural Reliability Assessment Algorithm

From the same simulations executed on the ANSYS DoE tool presented in Section 3.2.3, the results are imported into a MATLAB code that was developed for response surface modeling, which is presented in Section 3.3.2 [1,2]. **Figure 3-1** depicts the flow chart of structural reliability assessment of the non-intrusive formulation [1,2]. In brief, the analysis starts from the definition of the system, associated limit states, and determination of which variables will be considered as stochastic in the analysis. Next, a number of FEA simulations are executed by varying inputs and recording outputs related to limit states in order to map the response of the structure in the domain of stochastic variables. An appropriate method is then selected in order to approximate the response of the system and link output variables with global inputs (such as wind and wave loads).

Finally, the reliability index is calculated using MCS or FORM methods. In this instance, the iterative FORM algorithm is adopted to allow for the calculation of low probabilities of failure.

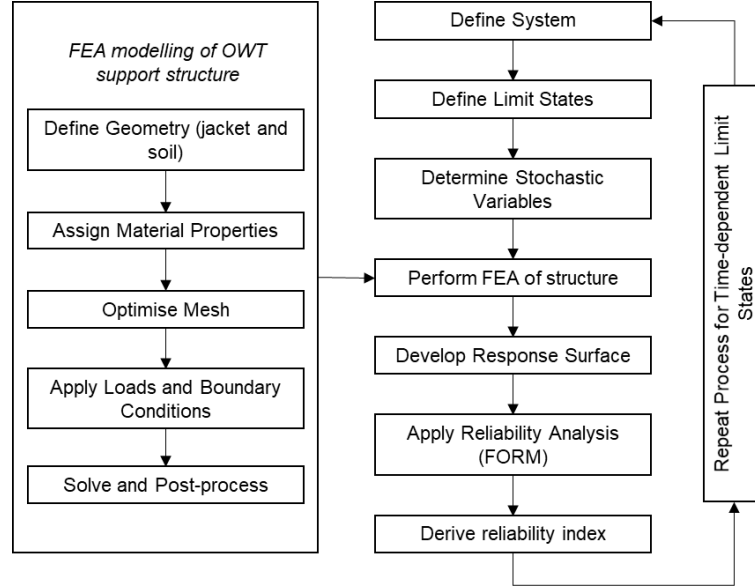


Figure 3-1. Flow chart of the non-intrusive formulation method [2].

3.3.2 Multivariate Regression

Regression analysis is a statistical process for establishing the relationship between a dependent variable and one or more independent variables. Taking the ultimate limit state (ULS) stress constraint as an example, the dependent variable (i.e., maximum von Mises stress, $\sigma_{VM,max}$) and independent variables (i.e., thrust load x_1 , tilting moment x_2 , torsional moment x_3 , total hydrodynamic load (wave and current) x_4 , soil 1 Young's modulus x_5 , soil 2 Young's modulus x_6 , soil 3 Young's modulus x_7 , and weight of rotor-nacelle assembly (RNA) x_8) are assumed to have the following functional relationship:

$$\sigma_{VM,max} = [a_0, a_1, \dots, a_{16}] \begin{bmatrix} 1 \\ x_1 \\ x_1^2 \\ \cdot \\ \cdot \\ \cdot \\ x_8 \\ x_8^2 \end{bmatrix}, \quad (3-5)$$

where $(a_0, a_1, \dots, a_{16})$ are 17 regression coefficients for a quadratic regression. For other types of constraints, i.e., deformation, buckling, vibration, and fatigue, expressions similar to Equation (3-5) can be derived. Multivariate regression can be used to obtain the regression coefficients for different limit states [49].

Taking the stress constraint case as an example, 300 stochastic FEA simulations were performed, obtaining 300 samples. The R -square value obtained in the regression analysis performed in this case was consistently higher than 0.95, which is relatively high and indicates a satisfactory multivariate regression to be used in this study.

3.3.3 FORM (First-Order Reliability Method)

Having obtained the performance function from regression, FORM is used to calculate the reliability index β . The FORM Hasofer and Lind algorithm is summarized below [70].

1. Define the performance function for different limit states. For example, in the ULS (stress constraint) case, Equation (3-5) is substituted into Equation (3-21), which yields the following performance function:

$$g_u(x) = \sigma_{VM,allow} - [a_0, a_1, \dots, a_{16}] \begin{bmatrix} 1 \\ x_1 \\ x_1^2 \\ \cdot \\ \cdot \\ \cdot \\ x_8 \\ x_8^2 \end{bmatrix}. \quad (3-6)$$

2. Set the mean value point as an initial design point, i.e., $x_{i,k} = \mu_{x_i}$ $i = 1, 2, \dots, n$, and calculate the gradients $\nabla g(X_k)$ of the limit-state function at this design point. Here, $x_{i,k}$ refers to the i -th element in the vector X_k of the k -th iteration, and μ_{x_i} is the mean value of the i -th element.
3. Calculate the initial reliability index β using the mean-value method, i.e., $\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}}$ and its direction cosine α .

$$\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}} = \frac{g(\mu_X)}{\left[\sum_{i=1}^n \left(\frac{\partial g(\mu_X)}{\partial x_i} \right)^2 \cdot \sigma_{x_i}^2 \right]^{\frac{1}{2}}}. \quad (3-7)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (3-8)$$

4. Compute a new design point X_k and U_k , function value, and gradients at this new design point.

$$x_{i,k} = \mu_{x_i} + \beta \sigma_{x_i} \alpha_i. \quad (3-9)$$

$$u_{i,k} = \frac{x_{i,k} - \mu_{x_i}}{\sigma_{x_i}}. \quad (3-10)$$

5. Compute the reliability index β and direction cosine α_i using Equations (3-9) and (3-10), respectively.

$$\beta = \frac{g(U^*) - \sum_{i=1}^n \frac{\partial g(U)}{\partial x_i} \sigma_{x_i} u_i^*}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(U^*)}{\partial x_i} \sigma_{x_i} \right)^2}}. \quad (3-11)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (3-12)$$

Repeat steps 4–5 until the convergence of the reliability index β is achieved.

3.4 Design Load Analysis

3.4.1 Sources of Loads

OWTs are exposed to several load sources usually imposed by their environment. In design codes, such as DNV-OS-J101 [71] and IEC 61400-3 [72], loads which are relevant to the design of OWT jacket support structures are outlined. Calculations and formulations of each load produced by the environment in this study are based on DNV-RP-C205 [73]. The loads relevant to OWT support structures can be roughly classified into six groups, i.e., (1) aerodynamic loads transferred from the rotor, (2) wind loads on the tower, (3) inertia loads, (4) current loads, (5) wave loads, and (6) hydrostatic loads [24]. These loads are illustrated in **Figure 3-2**.

Gravitational and inertia loads are static and dynamic loads which result from seismic activity, the entire structure's weight and imposed equipment on the structure under operation, and the exerted forces on the structure due to operations [74]. The inertia loads, as a result of the support structure and rotor-nacelle assembly (RNA) weight at the tower top, can have a significant impact on buckling and considerably influence the eigen-frequencies of the OWT support structure [24].

Aerodynamic loads are dynamic and static loads resulting from the airflow interaction with the moving and stationary wind turbine components. The load magnitude varies, and this depends on the air density, the mean wind speed and turbulence across the rotor plane, and the aerodynamic shapes of the components of the wind turbine and their interactive effects. These loads can be computed using aeroelastic models [74]. The aerodynamic loads imposed by the rotor are transmitted to the top of the tower and are usually decomposed into a load matrix defined in the referential axis of the wind turbine. According to [75], the main lateral aerodynamic loads acting on an OWT structure are the 1P (rotor frequency), and the 2P/3P (blade-passing frequency) loads. The vibration causes the 1P load at the hub level due to the mass and aerodynamic imbalances of the rotor. This load has a frequency equal to the rotational frequency of the rotor (referred to as 1P loading). Since most of the industrial wind turbines are variable-speed machines, 1P is not a single frequency but a frequency band between the frequencies associated with the lowest and the highest rpm (revolutions per minute). At the same time, the Blade-passing load (2P/3P) are loads on the tower due to the vibrations caused by blade shadowing effects (referred to as 2P/3P). As the blades of the turbine pass through the front of the tower, the temporary shadowing effects reduce the thrust on the tower. This is a dynamic load having a frequency equal to three times the rotational frequency of the turbine (3P) for the three-bladed wind turbines. For a two-bladed turbine, this will be two times (2P) the rotational frequency of the turbine (1P). The 2P/3P loading is also a frequency band like 1P and is simply obtained by multiplying the limits of the 1P band by the number of the turbine blades. Further details on these can be found in [75,76]. The reader is referred to Section 3.6.1.5 for an explanation of how this concept is applied in this study. The fatigue loads were determined by employing the damage equivalent load (DEL) method, which was described in Reference [77]. The support structure was subjected to a thrust load directed along the diagonal of the jacket base and applied at the assumed RNA center of mass (CM). This loading set-up resembled a yaw error situation and produced an additional torsional moment at the tower top. The presence of

a horizontal offset for the RNA CM led to a gravity moment at the tower top [8]. Wave load and rotor thrust vectors were directed along the jacket base diagonal, causing maximum compression and tension on the opposite legs [5].

Environmental loads are those caused by environmental phenomena, i.e., the set produced by wave force, current force, and wind force. Wave loads are dynamic loads produced by waves and their interaction with the OWT support structure. Le Mehaute's graph indicates the validity range of each wave theory and can be employed to determine the most applicable theory for given characteristics of waves, such as wave period (T), wave height (H), and water depth (d) [74]. The regular wave theories are ideal for designs where a single wave method is adopted, and this is a widely used method in offshore structure design. In this case, a regular wave with the appropriate period and height is used to represent an extreme wave. This method provides an easy analysis in estimating the extreme response of offshore structures. On the other hand, the random ocean wave is defined by an energy density spectrum. The ocean wave energy content and its distribution over a random wave frequency range are described by the wave energy spectrum. Therefore, the random wave design method may be ideal for designing floating structures [78]. In this study, the wave profile data presented in **Table 3-1** fall within the area of validity of the Stokes third-order wave theory. Stokes wave theory is one of the most commonly used methods in the analysis of offshore structures because of its accuracy in predicting the kinematic properties of the wave.

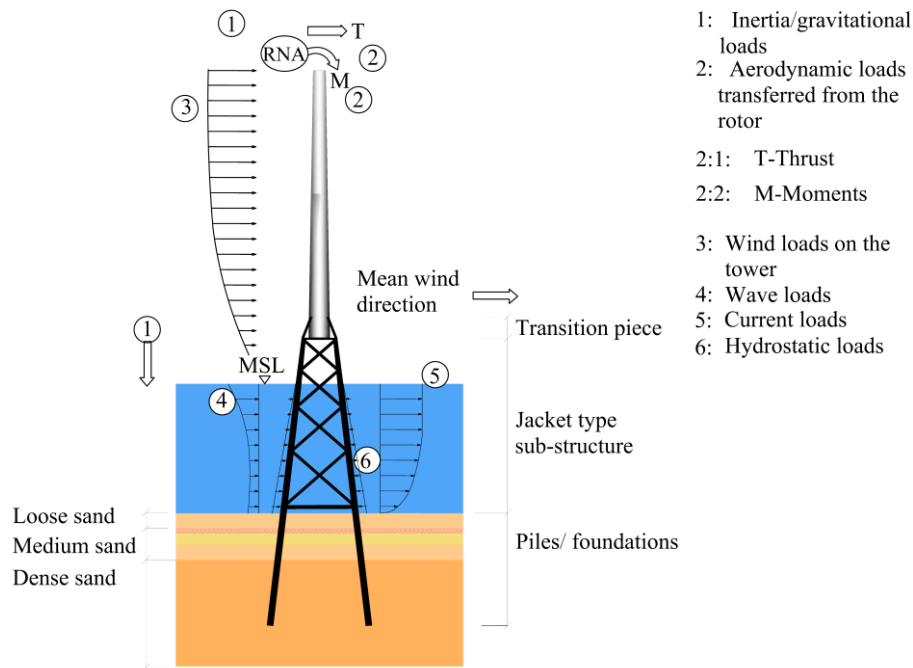


Figure 3-2. Representation of the loads on the support structure of the offshore wind turbine (OWT) and jacket geometry embedded in layered soil.

Table 3-1. Water levels and wave data of interest for the K-13 deep-water site [5].

Parameter	Value
Lowest astronomical tide, LAT (m)	-1.06
Tidal range, Δz_{tide} (m)	2.22
Storm surge, Δz_{surge} (m)	2.13
Air gap, Δz_{air} (m)	1.5
Significant wave height, H_s (m)	9.4
Maximum 50-year wave height, $H_{50,max}$ (m)	17.48
Maximum wave period range, T_{50} (s)	10.8–14
Maximum wave height above still water for deck height calculation, ξ_w (m)	11.36

A typical bottom-fixed jacket offshore structure is considered to be dominated by drag owing to the wavelength, water depth, structural shape, and size; thus, Morison's equation is adopted. An assumption that the total force due to waves acting on a structure can be computed by the linear superimposition of the drag and inertia forces is made in Morison's equation. For Morison's equation to be applied to determine the wave loads

acting on the structure, the member diameter, D , has to be less than one-fifth of the wavelength, λ , i.e.,

$$D \leq 0.2\lambda. \quad (3-13)$$

For slender members such as jacket members submerged in water, both current and wave loads can be determined using Morison's equation [71].

$$F = F_d + F_m = \frac{1}{2} \rho_w C_d D |u_x| u_x + \rho_w C_m \frac{\pi D^2}{4} a_x, \quad (3-14)$$

where the drag force is the first term while the inertia force is the second term; ρ_w is the density of water; C_d and C_m are the drag and inertia coefficients of the pile, respectively, and their corresponding values are 1.25 and 2.0, respectively [5]; D is the cylinder diameter; a_x and u_x are the horizontal wave-induced or current-induced acceleration and velocity of water, respectively, which were derived from the Stokes third-order theory.

Current loads are dynamic loads which are produced by the flow of water from external sources, apart from surface waves. Current can cause drag loads on the support structure. The current velocity $u_c(z)$ is described by a sub-surface current exponential profile from the mean sea level (MSL) to the seabed, d . The total current velocity of a submerged, stationary, tubular member, in the absence of vortex shedding, can be calculated as follows:

$$u_c(z) = u_{c,MSL} \left(\frac{d+z}{d} \right)^{1/7}, \quad (3-15)$$

where $u_{c,MSL}$ is the current velocity at MSL, and d is the depth of water from MSL to the seabed. The wave particle velocity and the current velocity are summed up in Morison's drag term in Equation (3-14), assuming that the wave and current are aligned.

The wind loads on the tower structure are a result of the drag and a function of the average wind velocity $\bar{V}(z)$. The wind shear is generally represented by a power law profile, defined by the following equation:

$$\bar{V}(z) = \bar{V}_r \left(\frac{z}{z_r} \right)^\alpha, \quad (3-16)$$

where $\bar{V}_r$ denotes the reference wind speed at the elevation of nacelle altitude Z_r , and α is the roughness coefficient with a value of 0.115 for the offshore site [24]. Wind loads acting along the tower can be calculated as follows:

$$F_{tower}(z) = \frac{1}{2} \rho_a C_{D,T} D(z) \bar{V}_r^2(z), \quad (3-17)$$

where $C_{D,T}$ is the coefficient of drag of the tower, with a typical value of 1.0 [24], and $D(z)$ represents the external diameter of tapered tower at height z . Having determined the wind loads, the moments due to the action of the wind loads can then be calculated.

Hydrostatic pressure, which acts on the submerged sections of the jacket support structure, is a constant normal load and varies with the depth of water. The hydrostatic force can be expressed as

$$F_h = \rho_w g h, \quad (3-18)$$

where F_h is the hydrostatic force, g is the acceleration due to gravity, and h is the depth of the water.

3.4.2 Site Specifications and Design Load Cases

The design load cases should take into account a set of design situations considering the most critical conditions that an OWT support structure can be subjected to, combining extreme or standard external conditions with operational states of the wind turbine or other operational modes (such as installation, transportation, fault, or maintenance) [74]. For the structural design of OWTs, IEC61400-3 [72] outlines 32 DLCs (design load cases) consisting of all operational modes of an OWT, which include start-up, standard operation, shut down, and 50-year extreme conditions. These DLCs can be roughly categorized into two main groups, namely, ultimate and fatigue. Basically, the typical load cases adopted in the structural design of OWTs are mainly the fatigue load considering normal sea conditions and the ultimate load considering 50-year extreme conditions. Both the fatigue and the ultimate load cases are considered in this study.

3.4.2.1 Fatigue Load Case

Due to the nature of rotor operation, as well as hydrodynamic loading, a significant source of periodic loadings is imposed during the lifetime of an OWT. OWT support structures are, thus, prone to fatigue failure [24,79]. A widely used fatigue DLC correlates

to an operating state within the normal sea state (NSS) and normal turbulence model (NTM), where the site is assumed to have no current and both the wave height and the cross zero period are obtained via a probability density function of the site. DLC 1.2, as prescribed in the IEC standard [72], are generally regarded as the governing fatigue DLCs for OWT support structures; therefore, they are considered in this study as fatigue load cases [24,80]. According to the IEC standard [81,82], the safety factor for fatigue load is equivalent to 1.0.

3.4.2.2 Ultimate Load Case

For the extreme hydrodynamic loads experienced by the OWT, that produced by the 50-year return period is widely considered as a critical ultimate load case. It was demonstrated from a previous study that wind loading generally governs the design of OWTs rather than hydrodynamic loading [83]. Therefore, the critical load case for ULS is mostly assumed to be defined by the parked turbine, under the 50-year EWM (extreme wind model) with 50-year RWH (reduced wave height) and ECM (extreme current model). The loading characteristics, as described above, correspond to the IEC 61400-3 [72] DLC 6.1b and 2.1 GL regulation [84], respectively. Load safety factors for gravitational and other loads (such as environmental loads) are given as 1.1 and 1.35, respectively [81,82].

3.4.2.3 Site Specifications

The information available from a previous study for a deep-water site located off the coast of Netherlands designated as the K-13 deep-water site [82] was adopted for this study, as listed in **Table 3-1**.

3.5 Baseline 10 MW OWT

There is continued interest in increasing the size of offshore turbines given the high cost of the support structure and associated operation and maintenance (O&M) activities. The baseline 10-MW OWT [5,8,85] is an envisioned simple reference 10-MW turbine scaled from a 5-MW NREL (national renewable energy laboratory) reference turbine [86]. The main properties were calculated through basic mechanics considerations and scaling laws. The RNA (rotor-nacelle assembly) is supported by an 88.4-m tapered tubular tower. Its basic characteristics are summarized in **Table 3-2**, and further details can be found in References [5,8].

Table 3-2. Main properties of the baseline 10-MW OWT model [5].

Item	Value
Rated power (MW)	10
Blade length (m)	87.70
Hub radius (m)	3.05
Rotor diameter (m)	181
Tip radius (m)	90.74
Rotor-nacelle assembly mass (kg)	1,072,000
Blade vertical clearance (m)	2
Precone (°)	3
Shaft tilt (°)	-5
Overhang (m)	-9.10

3.5.1 Parametric FEA

A parametric finite element analysis model of the OWT support structure and the soil system was developed using ANSYS software package, a widely used multi-purpose finite element analysis software. The parametric FEA model enables modeling OWT support structures with stochastic variables, such as environmental loads and material properties. The environmental loads, i.e., wind, wave, and current loads, are applied to the structure in an uncoupled way, ignoring the fluid-structure interactions, as illustrated in **Figure 3-2**. The parametric FEA model is applied to the jacket support structure of the baseline 10-MW OWT, of which the main parameters are summarized in **Table 3-3**. The geometry, material, mesh, and boundary conditions used in the FEA model are presented in the upcoming subsections.

Table 3-3. Baseline 10-MW support structure parameters [5,8,82,85]. MSL—mean sea level; OD - outer diameter; TP - transition piece; RNA—rotor-nacelle assembly; UL—ultimate limit; FL—fatigue limit.

Parameter	Value
Deck height above MSL (m)	16
Water depth (m)	50
Leg OD (m)	1.74

Leg wall thickness (m)	0.030
Number of bays	4
Jacket batter	8.47
Height of TP (m)	7
Number of legs	4
Pile OD (m)	1.59
Pile wall thickness (m)	0.037
Mud brace OD (m)	0.762
Mud brace wall thickness (m)	0.017
x-brace outer diameter (m)	0.61
x-brace wall thickness (m)	0.016
RNA mass (kg)	1,072,000
Tower length (m)	88.4
Tower-top OD (m)	3.85
Tower-top thickness (m)	0.03
Tower-base OD (m)	7
Tower-base thickness (m)	0.055
Thrust associated with rated power UL case (kN)	1700
Maximum rotor thrust taking into account dynamic amplification UL case (kN)	3400
Thrust FL case (kN)	203
Torsional moment UL case (kN·m)	7876
Torsional moment FL case (kN·m)	3483
Tilting moment UL case (kN·m)	38,567
Tilting moment FL case (kN·m)	3687

3.5.1.1 Geometry

The configuration of the jacket is usually a structure with four legs, inter-connected with bracings welded with diameters up to 2 m. A transition piece is connected to the tower bottom and transfers the forces from the tower into the jacket structure, which is anchored via piles or suction caissons to the seabed at each leg. The jacket structure

has a vertical height of 66 m, and it is joined with the tower through a 7-m-long transition piece. The transition piece is envisioned as a deck reinforced by stringers, which hosts a central cylindrical shell supported by four tubular struts. The piles are embedded 42 m in the soil and are intended to be driven through the legs and, thus, feature a batter angle [5,8].

3.5.1.2 Mesh

A crucial step in the coupling of the model to be applied for the FEA is the mesh generation. The ANSYS software package provides a powerful and reliable structure mesh generator capable of developing a mesh, which is consistent in all of the structure with minimal computational requirement.

In order to ensure accuracy of results, a mesh sensitivity study was carried out [1,24]. This is depicted in **Table 3-4** and **Figure 3-3**. From the mesh sensitivity study, the equivalent (von Mises) stress converged at the mesh size of 2 m for the soil and 0.5 m for the support structure, corresponding to a total number of elements of 190,222. Therefore, 2 m and 0.5 m are deemed as appropriate mesh sizes for the soil and the support structure, respectively. As can be observed, the maximum displacement and buckling load multiplier are not sensitive to change in mesh size. The generated mesh for the FEA model is depicted in **Figure 3-4**.

Table 3-4. Mesh sensitivity.

Soil Element Size (m)	Jacket Structure Element Size (m)	Number of Element s	Maximum von Mises Stress (Pa)	Maximum Displacement (m)	Buckling Load Multiplier
8	2	8047	2.5297×10^8	1.2492	3.7286
4	1	36,164	2.5328×10^8	1.2492	3.7286
2	0.5	190,222	2.5346×10^8	1.2492	3.7286
1	0.25	1,298,092	2.5353×10^8	1.2492	3.7286

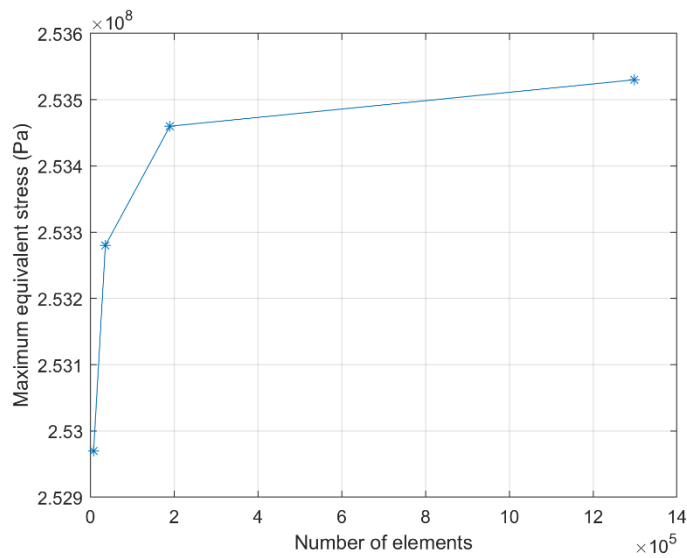


Figure 3-3. Mesh convergence test.

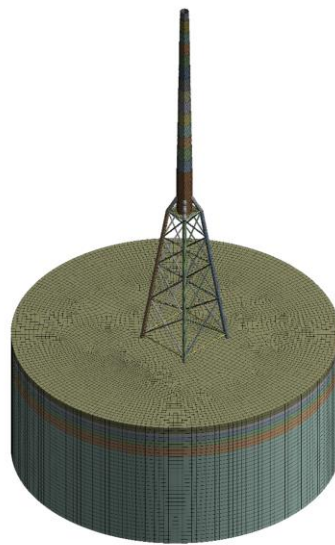


Figure 3-4. Three-dimensional (3D) display of meshing performed on the structural model.

3.5.1.3 Material

The jacket structure is made of S355 structural steel with a density of 8500 kg/m³ (increased by 8% to cover for secondary steel appurtenances, coatings, and welds that are not covered for in the thickness data of the support structure), Young modulus of 210

GPa, a Poisson's ratio of 0.3, and a nominal yield strength of 355 MPa. The tower and the transition piece are made of structural steel of the same properties [5,24].

3.5.1.4 Soil Profile

Other than the OWT support structure, a crucial section of the detailed parametric model comprises the soil-structure interaction, which is a factor of design of significant importance for the structural response of the piles-jacket-tower assembly. The soil modeled in the FEA model is cylindrical in shape, with a diameter of 140 m and height of 50 m and consisting of six different strata (see **Table 3-5**). The soil material is modeled using the Drucker-Prager strength linear model [87]. This model is used to calculate the yield strength of each soil strata. The yield strength of the soil, σ_{ys} , according to the Drucker-Prager model, is given by

$$\sigma_{y,s} = \frac{6c \cos \phi}{\sqrt{3}(3 - \sin \phi)}, \quad (3-19)$$

where ϕ represents the internal friction angle, and c represents the cohesion value. The coefficient of friction C_f between the soil and the pile is determined as follows [28]:

$$C_f = \tan\left(\frac{2}{3}\phi\right). \quad (3-20)$$

Table 3-5. K-13 deep-water site's soil profile [5].

Depth below Seabed (m)	Unit Weight N/m^3	Friction Angle ($^\circ$)	Shear Strength (N/m^2)	Young's Modulus (MPa)
0–3	10,000	36	60,000	30
3–5	10,000	33	60,000	30
5–7	10,000	26	60,000	50
7–10	10,000	37	60,000	50
10–15	10,000	35	60,000	50
15–50	10,000	37.5	60,000	80

3.5.1.5 Boundary Conditions

The wind and wave loads are applied to the surface of the tower and the surface of support structure submerged into the water, respectively. Additionally, the following three boundary conditions are also defined: (1) the bottom of the soil model is fixed against

translation in all directions; (2) lateral boundaries of the soil model are fixed against lateral translation; (3) an augmented Lagrangian formulation-based frictional contact [88,89] is established between the soil and pile with suitable friction coefficients in order to enable soil-structure interaction. See **Figure 3-5**.

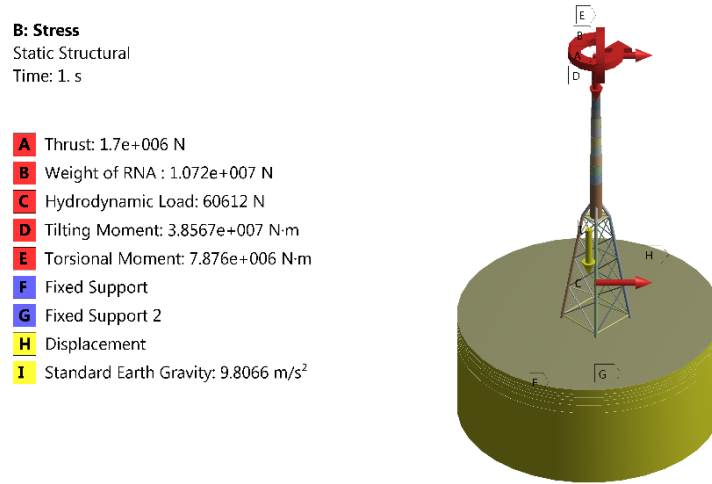


Figure 3-5. The 3D display of structural model with applied loads and boundary conditions.

3.5.2 Validation of the FEA

3.5.2.1 Modal Analysis

The modal frequencies of the OWT support structure calculated from the present FEA model are compared against those reported in the literature. The comparison results are presented in **Table 3-6**. As can be observed in **Table 3-6**, the first two frequencies of both fore-aft and side-to-side bending modes calculated from the present FEA model show good agreement with those reported in References [8,85], with the maximum percentage difference (11.11%) observed for the second side-to-side bending mode. This confirms the validity of the present FEA model. See **Figure 3-6**.

Table 3-6. Comparison of the support structure mode frequencies with reference values.

Mode Frequencies (Hz)	Present	References [8,85]	% Difference
1st side-to-side bending	0.21346	0.21320	0.12%
1st fore-aft bending	0.22297	0.21629	2.99%
2nd side-side bending	1.1602	1.0313	11.11%

2nd fore-aft bending	1.5292	1.6561	-8.29%
----------------------	--------	--------	--------

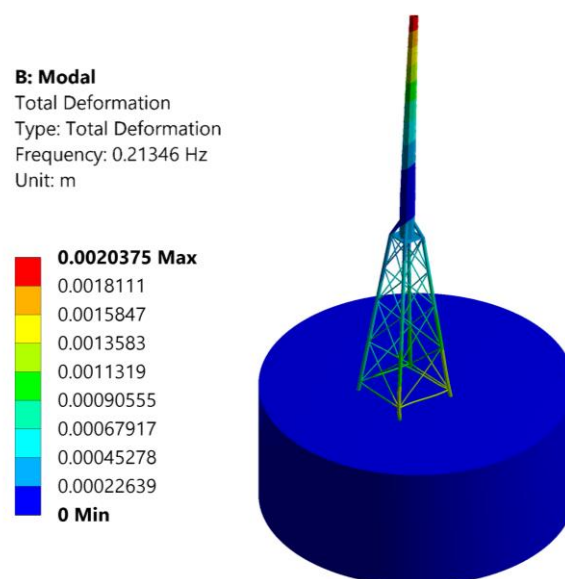


Figure 3-6. Display of structural model's modal analysis results showing the first mode frequency.

3.5.2.2 Deflections in Static Analysis

This section of the validation aims to examine the deformation behavior of the support structure in a static analysis. In the literature [5,8], the RNA weight and a 3.4-MN thrust load were applied on the tower top. The displacements at the RNA elevation and the base of the tower are compared with reference values, and results are presented in **Table 3-7**. Under the loaded condition, the deflections at the RNA and at the tower base are measured with respect to the location of the RNA and the center of the tower base, respectively.

As can be observed from **Table 3-7**, the results of the present FEA model match well with those reported in Reference [8], for deflections at both the RNA and the tower base, with a maximum difference of 3.44% observed for the deflection at the tower base. This further confirms the validity of the present FEA model. See **Figure 3-7**.

Table 3-7. Static deformation of the baseline 10 MW on jacket.

Load Case	Displacement at RNA	Displacement at the Tower Base
-----------	---------------------	--------------------------------

Mass/thrust	Present	Reference [8]	% Difference	Present	Reference [8]	% Difference
RNA/3.4 MN	1.263 m	1.2688 m	-0.46%	1.6085 $\times 10^{-1}$	1.6639 $\times 10^{-1}$	-3.44%

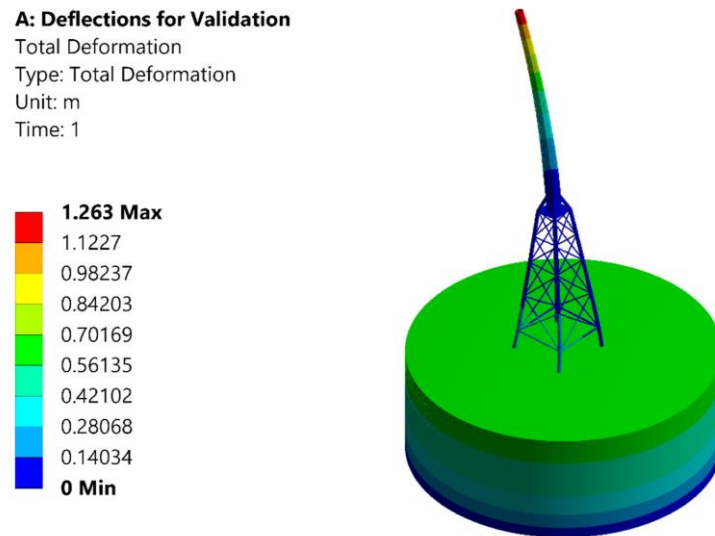


Figure 3-7. Display of results of total deformation showing the deflection at the RNA level.

3.6 Implementation of Structural Reliability Assessment on the OWT Support Structure

In this section, the structural reliability of the OWT support structure is assessed considering three limit states according to DNV-OS-J101, i.e., (1) ultimate limit state (ULS), (2) fatigue limit state (FLS), and (3) serviceability limit state (SLS). The fully parametric FEA model presented in Section 3.5.1 is used to perform FEA modeling taking account of stochastic variables. The results are then post-processed using two methods, i.e., (i) using the probabilistic FEA tool packaged in ANSYS referred to as the DesignXplorer©, and (ii) applying the non-intrusive formulation as described in Section 3.2 and References [2,49].

3.6.1 Constraints and Design Criteria

In the design of OWT support structures, three limit states should be considered according to DNV-OS-J101, i.e., (1) ULS (ultimate limit state), which accounts for the maximum load-carrying capacity (i.e., buckling and yielding stress), (2) FLS (fatigue limit state), which accounts for failure as a result of cyclic loads, and (3) SLS (serviceability limit state), which accounts for tolerance criteria (i.e., vibrations and deflections) applicable to standard use. Thus, the structural reliability of OWT support structures in this study takes into consideration five design criteria, i.e., stress (ULS), vibration (SLS), buckling (ULS), deformation (SLS), and fatigue (FLS).

3.6.1.1 Stress Constraint

The ULS (ultimate limit state) defines the ability of the structure to resist yielding. In terms of ultimate limit state, the maximum stress in the support structure $\sigma_{VM,max}$ should not exceed the allowable stress limits $\sigma_{VM,allow}$. The limit state function for the von Mises criterion can be expressed as follows:

$$g_u(x) = \sigma_{VM,allow} - \sigma_{VM,max}. \quad (3-21)$$

The allowable stress $\sigma_{VM,allow}$ can be expressed as follows:

$$\sigma_{VM,allow} = \frac{\sigma_y}{\gamma_m}, \quad (3-22)$$

where σ_y is the yield strength, with a value of 355 MPa for steel S355, and γ_m is the material safety factor, with a value of 1.1 suggested by DNV-OS-J101 standard [71]. Thus, the allowable stress $\sigma_{VM,allow}$ is 323 MPa.

3.6.1.2 Fatigue Constraint

The fatigue limit state is a crucial phenomenon in OWT support structures as they are subjected to significant cyclic loads. OWT support structures normally have a long service period that may exceed 20 years. This, in conjunction with the inspection intervals, affects the reliability requirement of the jacket structural design. According to the S-N curve method, the number of loading cycles to failure N , can be obtained by

$$\log N = A - m \log \Delta S, \quad (3-23)$$

where A and m are the intercept and the slope of the S-N curve on the log-log plot, respectively; ΔS is the stress range. The two parameters in Equation (3-23), i.e., intercept A and slope m , are generally given by design standards, e.g., DNVGL-ST-0126 [29]. The performance function of fatigue reliability assessment based on the S-N curve method can be expressed as follows:

$$g_{f,SN} = \log N - \log N_t, \quad (3-24)$$

where subscripts f and SN denote the fatigue limit state and S-N curve method, respectively; N is the number of loading cycles to failure given by Equation (3-23), and N_t is the number of loading cycles expected during the given design life. The number of cycles during the design life N_t may be determined as a function of rated rotor speed n_{rated} and availability η_a (98.5%) on the location chosen [24,90]. Therefore, considering a design life of 20 years, the number of cycles can be expressed as follows:

$$N_t = \eta_a \cdot n_{rated} \times (20[\text{year}] \times 365[\text{day/year}] \times 24[\text{hour/day}] \times 60[\text{min/hour}]) \quad (3-25)$$

The minimum fatigue safety ratio $f_{sr,min}$ must be greater than the allowable fatigue safety ratio $f_{sr,allow}$, which is equivalent to the product of one and the material PSF (partial safety factor) $\gamma_{m,f}$ for fatigue.

$$f_{sr,min} \geq f_{sr,allow}. \quad (3-26)$$

Since the material's PSF for fatigue limit state is 1.15 [29], $f_{sr,allow}$ is equivalent to 1.15. Hence, the limit state function based on the fatigue safety ratio can be expressed as follows:

$$g_{f,fsr} = f_{sr,allow} - f_{sr,min}. \quad (3-27)$$

3.6.1.3 Deformation Constraint

Excessive deflections influence the serviceability of OWT support structures and, therefore, should be avoided. The allowable deflection d_{allow} must exceed the maximum deflection d_{max} to ensure overall structural stability. This can be expressed as

$$d_{allow} > d_{max}. \quad (3-28)$$

The limit state function for deflection criteria can be expressed as

$$g_d(x) = d_{allow} - d_{max}. \quad (3-29)$$

According to [76], the jacket and OWT tower can be represented as Euler-Bernoulli beams and then later replaced with a single beam. The allowable deflection d_{allow} is given by the following empirical equation as suggested by DNV-OS-J101 [71]:

$$d_{allow} = \frac{L}{200}, \quad (3-30)$$

where L is the height of the jacket.

3.6.1.4 Buckling Constraint

The slenderness of the support structure coupled with the large RNA mass at the tower top forces the investigation of the risk of instability as a result of buckling. The ULS static analysis results are employed as pre-stress loads. The load multiplier L_m , which is defined as the critical load divided by the present load applied, should exceed the permissible load multiplier, $L_{m,allow}$ in order to avoid failure. This design criterion is given as

$$L_m \geq L_{m,allow}. \quad (3-31)$$

According to the DNV standard [29], 1.4 is adopted as the $L_{m,allow}$ value in this study. The limit state function for buckling criteria can, thus, be expressed as

$$g_b(x) = L_m - L_{m,allow}. \quad (3-32)$$

3.6.1.5 Vibration Constraint

One of the critical concerns for OWTs on jacket support structures is the resonance phenomenon. In order to guard against such a phenomenon, the first eigen-frequency f_{1st} of the OWT support structure must be separated sufficiently from rotor induced frequencies f_{1P} and blade-passing frequency f_{3P} . A soft-stiff structural design, whereby the modal frequency lies between the rotor upper bound f_{1P} (f_{1PH}) and lower bound f_{3P} (f_{3PL}) frequencies, is presently the most usual and cost-effective design for a jacket. Therefore, the resonance constraint should be expressed as follows [5,24,91]:

$$f_{1PH} \leq f_{1st} \leq f_{3PL}, \quad (3-33)$$

$$0.133 \leq f_{1st} \leq 0.233. \quad (3-34)$$

The limit state function for the resonance criterion at the rotor upper bound can, thus, be expressed as

$$g_r(x) = f_{1st} - f_{1PH}. \quad (3-35)$$

On the other hand, it is expressed at the rotor upper bound as follows:

$$g_r(x) = f_{3PL} - f_{1st}. \quad (3-36)$$

The lower g -function value is chosen to be applied in the reliability assessment.

3.6.2 Stochastic Variables and FEA

The stochastic variables considered in this study are presented in **Table 3-8**. Eight stochastic variables were considered for all cases (i.e., wind thrust, tilting moment, torsional moment, the weight of RNA, hydrodynamic load, and three Young's moduli were considered at three soil strata). The total hydrodynamic load is considered differently, based on its dependence on the wave height, wave period, and current speed. To find the peak hydrodynamic force acting on the system, a Weibull distribution is applied to the significant wave height and the current speed, while the lognormal distribution is applied to the wave period [2,92,93]. The distribution is then fitted into a Weibull-equivalent distribution. In the presence of observed data, distribution fitting algorithms (such as Akaike information criterion, Bayesian information criterion, and Kolmogorov-Smirnov) are often employed to determine the shape coefficients of the most appropriate statistical distributions [19]. The coefficient of variation (COV) of all stochastic variables was assumed to be 0.1 except for the stochastic variables with Weibull distribution. The mean values of these stochastic variables are presented in **Tables 3-2, 3-4, and 3-5**. This is summarized in **Table 3-9**, which depicts the means and the corresponding standard deviations. Having defined the stochastic variables, the FEA model presented in Section 3.5.1 is then used to perform FEA simulations of the OWT support structure with the help of the design of experiments (DoE) module in ANSYS. It enables the input parameters to be designated as stochastic parameters, having different types of distributions. DoE indicates the variation of design points with the output parameter.

Table 3-8. Stochastic variables.

Description	Distribution Types
-------------	--------------------

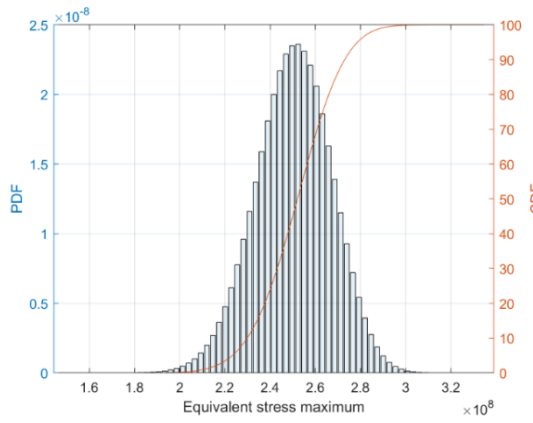
Wind thrust	Normal [2,92,93]
Tilting moment	Normal [2]
Torsional moment	Normal [2]
Weight of RNA	Normal [92,93]
Young's modulus of soils	Normal [2,92,93]

Table 3-9. Characteristics of design variables.

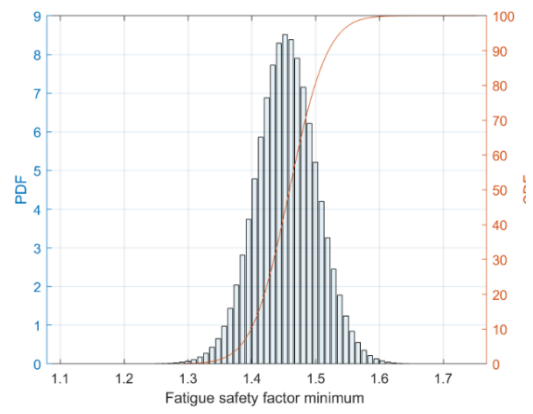
Description	Ultimate Load Case		Fatigue Load Case	
	Mean	Standard Deviation	Mean	Standard Deviation
Wind thrust (kN)	1700	170	203	20.3
Tilting moment (kN·m)	38,567	3856.7	3687	368.7
Torsional moment (kN·m)	7876	787.6	3483	348.3
RNA mass (kg)	1,072,000	107,200	1,072,000	107,200
Young's modulus of soil stratum 1 (MPa)	30	3	30	3
Young's modulus of soil stratum 2 (MPa)	50	5	50	5
Young's modulus of soil stratum 3 (MPa)	80	8	80	8

3.7 Results and Discussion

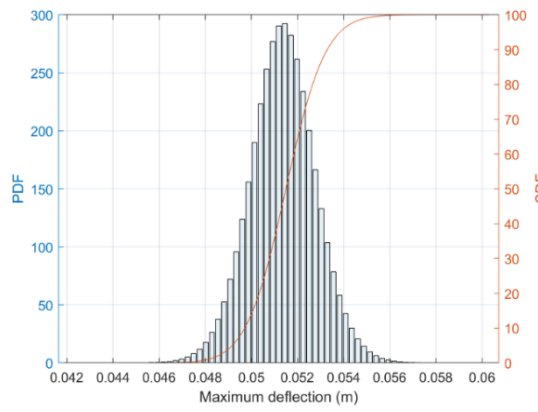
Figure 3-8a-e depict the probability density function (PDF) histogram and cumulative density function (CDF) of the output parameters for each design constraint from **DesignXplorer®**.



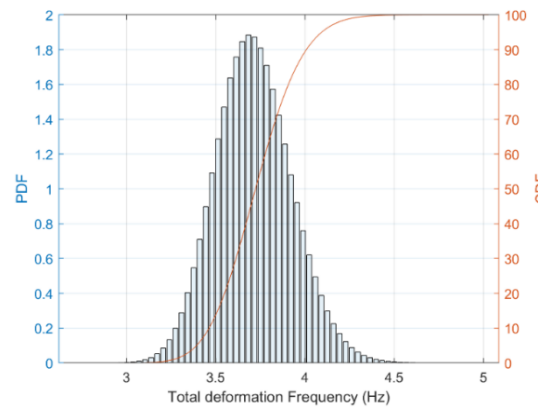
(a)



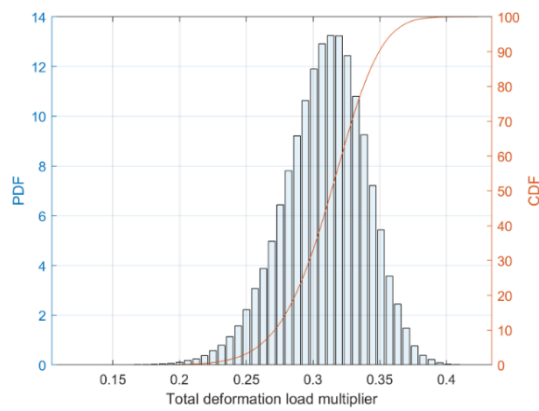
(b)



(c)



(d)



(e)

Figure 3-8. Cumulative density function (CDF) and histogram for the output parameter: (a) maximum von Mises stress (stress constraint case); (b) fatigue

safety factor minimum (fatigue constraint case); (c) maximum deformation; (d) first eigen-frequency (vibration constraint case);, (e) total deformation load multiplier (buckling constraint case)-DesignXplorer©.

For the stress constraint case (ULS), the probability that maximum equivalent stress remains less than $\sigma_{VM,allow} = 323$ MPa, $P_f(\sigma_{VM} \leq 323MPa)$, is about 0.99999867 which means that there is $1 - 0.99999867 = 1.327655 \times 10^{-6}$ probability that the von Mises stress exceed the limit value of 323 MPa, i.e., $P_f(\sigma_{VM} > 323MPa) = 1.327655 \times 10^{-6}$. Therefore, the probability of failure of the critical component of the structure is 1.327655×10^{-6} considering the ULS (stress constraint) design criteria. The corresponding reliability index value is $\beta = 4.7$.

For the fatigue constraint case (FLS), the probability that the minimum safety factor is less than $f_{sr,allow} = 1.15$, $P_f(f_{sr} \leq 1.15)$, is about 5.6461×10^{-7} . Therefore, the probability of failure of the critical component of the structure is 5.6461×10^{-7} considering FLS design criteria (using time-invariant analysis). The corresponding reliability index value is $\beta = 4.87$.

For the deformation constraint (SLS), the DesignXplorer© simulation could not produce results within the region of $P_f(d \leq 0.54)$, i.e., $d_{allow} = 0.54$. The value $P_f(d > 0.54)$, which is the value of the probability of failure, is expected to be very small, and this is identified as a limitation of the direct MCS requiring a prohibitively large number of simulations to estimate results of this magnitude. Similarly, for the buckling constraint case (ULS), the simulation could not produce the results within the region of $P_f(L_m \leq 1.4)$, as this value is expected also to be very small.

For the vibration constraint (SLS), the probability of failure of the critical component of the structure $P_f(f_{1st} \leq 0.133)$ is about 0.1276×10^{-4} , and the corresponding $\beta = 4.21$.

The results obtained from the non-intrusive formulation for each design constraint are depicted in **Figure 3-9** and **Table 3-10**. The results obtained from a time-invariant fatigue reliability assessment employing the FORM are the reliability index, $\beta = 5.077$, and probability of failure, $P_f = 0.192 \times 10^{-6}$.

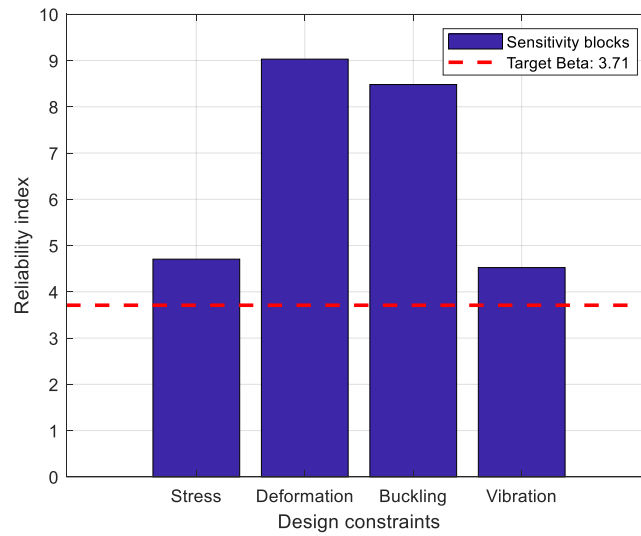


Figure 3-9. Reliability index of different design constraints (non-intrusive formulation).

Table 3-10. Computed probability of failure and safety index values using first-order reliability method (FORM) for different limit states.

Design Constraint	Computed Failure	Probability of	Computed Index	Safety
Stress constraint (ULS)		0.127×10^{-5}	4.706	
Deflection constraint (SLS)		0.869×10^{-19}	9.030	
Buckling constraint (ULS)		0.113×10^{-16}	8.481	
Vibration constraint (SLS)		0.570×10^{-5}	4.389	

As evident from the results above, the reliability assessment performed on the structure shows that the present model, as designed and for the modeling of the stochastic variables considered, satisfies the recommended reliability assessment criteria, as the reliability indices for all the design constraints considered are within the design thresholds. The target reliability index for OWT support structures is typically 3.71, corresponding to a probability of failure of 10^{-4} according to the DNV [93].

In this work, the time-variant fatigue reliability assessment was carried out using the fatigue analysis guidelines in the DNV standard [71,94], and this is presented in **Figure**

3-10. In this study, the thickness-corrected cathodic-protected D curve given by DNV-OS-J101 [71] is chosen for fatigue analysis. The intercept (A) and slope (m) of the S-N curve used for studying the fatigue life of steel structure in seawater for $N > 10^6$ are given as 15.606 and 5, respectively. From the time-variant fatigue reliability index curve, it can be observed that the structure maintains a reliability index of 3.92, exceeding the defined threshold of target reliability as specified by DNV for the nominal 20 years of operation. It can be observed that the fatigue limit state dominates the design of OWT support structures, as the reliability index for the fatigue limit state is lower than other reliability index values (see the time-variant fatigue reliability assessment at time = 20 years).

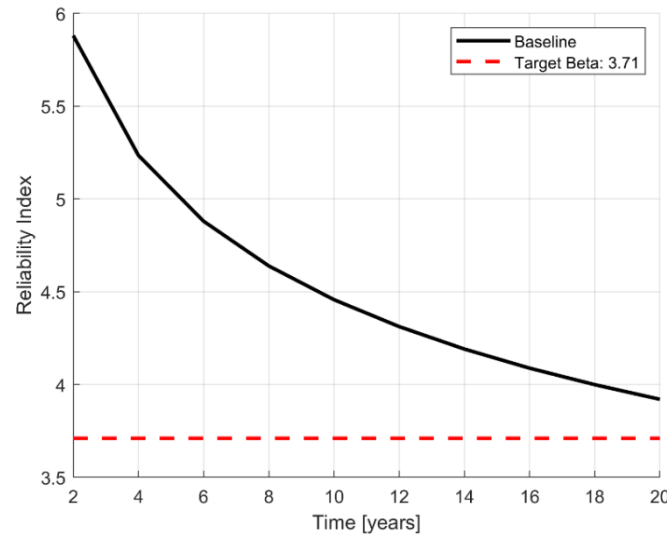


Figure 3-10. Fatigue reliability assessment (non-intrusive formulation).

As observed in **Table 3-11**, the values of safety index, β , predicted by the non-intrusive reliability analysis formulation were marginally higher than those predicted by the ANSYS probabilistic analysis for the different design constraints. However, the difference in the predicted reliability index values from both methods remains consistently below 5%; hence, the agreement of the two methods can be considered sufficient. Furthermore, considering the observed time required, the FORM simulations run instantly compared to the LHS (as packaged in the ANSYS DesignXplorer©), which requires about 15 min to run on a high-performance computer (i.e., for the 1×10^7 samples).

Additionally, a case study is performed to investigate the effects of COV of the stochastic variables on the fatigue reliability index. In this case, two additional values of COV are

considered, i.e., a 5% increase and 5% decrease. The calculated fatigue reliability index over 20-year service life with different values of COV is depicted in **Figure 3-11**. As can be seen from **Figure 3-11**, the reliability index is sensitive to the value of COV. The higher value of COV means higher uncertainties in stochastic variables, resulting in lower reliability.

Table 3-11. Comparison between the reliability index values computed by the two methods.

Design Constraint/Limit State	Reliability Index (ANSYS)	Reliability Index (Non-Intrusive Formulation)	Percentage Difference (%)
Stress constraint (ULS)	4.696	4.706	-0.21%
Fatigue constraint (FLS) (time-invariant analysis)	4.870	5.077	-4.25%
Deformation constraint (SLS)	-	9.030	
Buckling constraint (ULS)	-	8.727	
Vibration constraint (SLS)	4.211	4.389	-4.23%

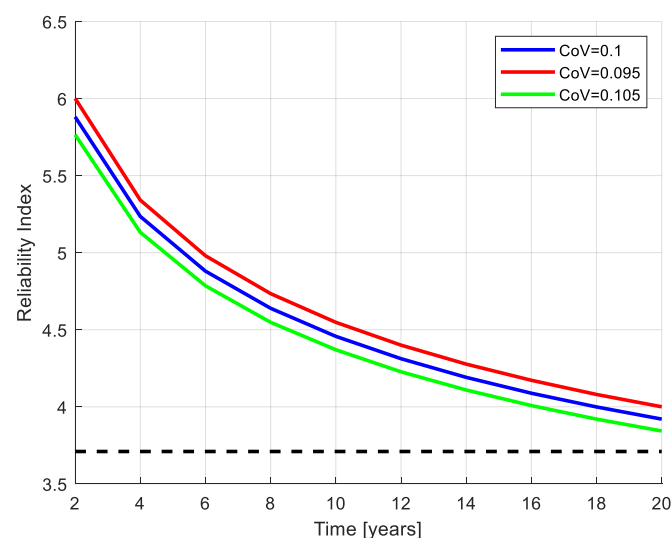


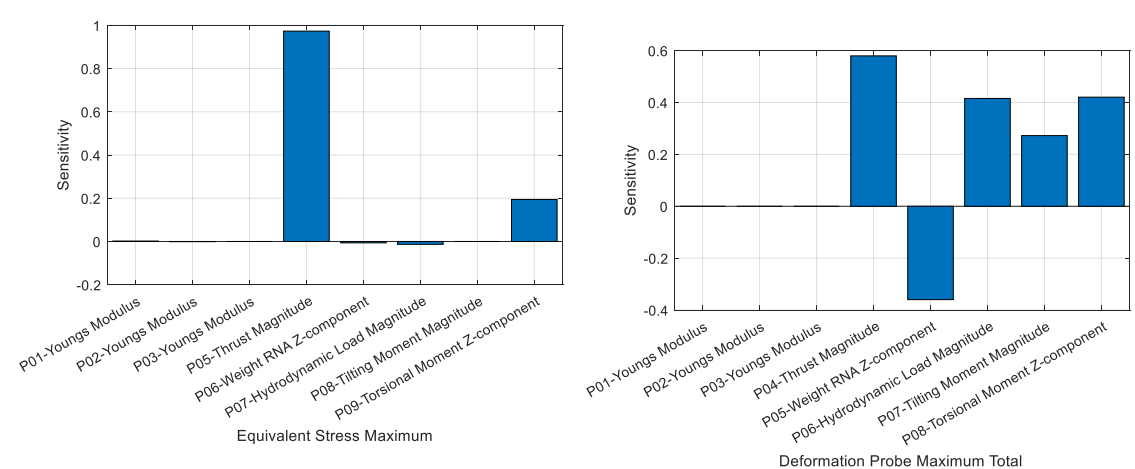
Figure 3-11. Fatigue reliability index with different coefficients of variation (COVs).

A global sensitivity analysis is also presented from the ANSYS probabilistic analysis for each of the design constraints through post-processing the results. These depict the most critical and important parameters that can radically change the response and reliability performance of the structure. **Figure 3-12a-e** show how sensitive the input design variables are to the structure based on the different design criteria. The bar heights indicate sensitivity in these charts.

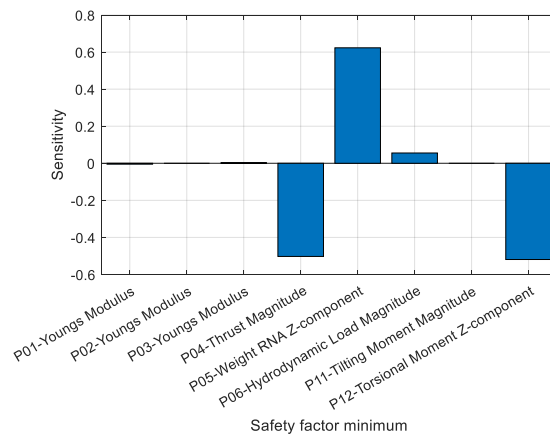
In **Figure 3-12a**, for the probability distribution of the maximum equivalent von Mises stress, it can be observed that the thrust magnitude and the torsional moment are positively correlated with direct impact. The RNA weight and the hydrodynamic load are negatively correlated and have little influence but inversely. The Young's modulus of the soil system and the tilting moment are neutral and have limited or no impact.

In **Figure 3-12b**, for the probability distribution of the deformation at the jacket top, it can be observed that four variables are positively correlated with direct impact. These are the thrust load, hydrodynamic load, and tilting and torsional moments, which have significant influence. The Young's modulus of the soil system has little or no impact. The RNA weight is negatively correlated and has a significant impact.

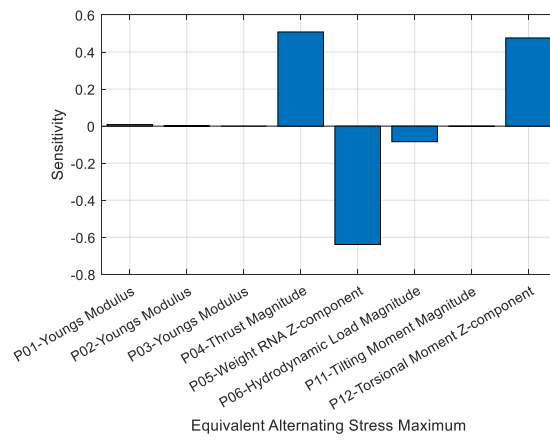
In **Figure 3-12c**, for the probability distribution of the minimum output parameter safety factor, it can be observed that Young's modulus of the soil system is neutral and has little or no impact. The RNA weight and hydrodynamic load are positively correlated with direct impact; the RNA weight has significant influence while the hydrodynamic load has quite some impact. The thrust and the torsional moments are negatively correlated and have significant influence but inversely. The tilting moment has very little or no impact.



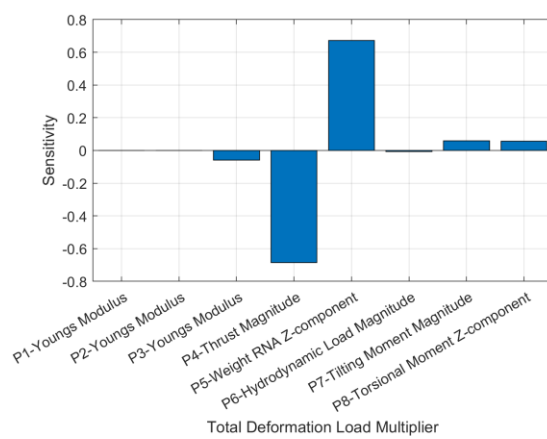
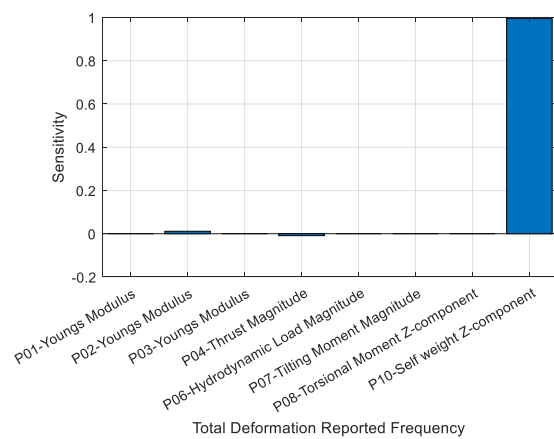
(a)



(b)



(c)



(d)

(e)

Figure 3-12. Global sensitivity chart: (a) stress design constraint (ULS); (b) deformation design constraint (SLS); (c) fatigue design constraint; (d) buckling constraint (ULS); (e) vibration constraint (SLS).

As can be seen from **Figure 3-12d**, the RNA weight and the thrust load have the highest impact and are positively and negatively correlated, respectively, with the other variables having little or no impact on the load multiplier probability distribution. It can also be observed that, in **Figure 3-12e**, the structure self-weight has the highest direct impact, with the thrust load and the second soil strata having very little inverse impact on the distribution of the output parameter, the first eigen-frequency, and, hence, the reliability of the structure.

3.8 Conclusions

In this study, a comparative analysis on the structural reliability of an OWT support structure between a commercial package and a purpose-developed, non-intrusive stochastic formulation was presented. Both methods start by defining the limit states taking account of the various design constraints. The design constraints considered in this study were as follows: stress (ULS), fatigue (FLS), deformation (SLS), buckling (ULS), and vibration (SLS). A 3D (three-dimensional) parametric FEA (finite element analysis) model of a typical OWT jacket-type support structure was developed, taking account of soil-structure interaction and stochastic variables (i.e., soil properties, wind, wave, and current loads). The series of FEA simulation results were post-processed using two methods. In the first method, the design of experiment and response surface module in the DesignXplorer© were used in order to map the response domain and then derive an appropriate response surface model. The probabilistic assessment was performed using the six sigma analysis function employing the Latin hypercube sampling method in computing the probability of failure, which was then translated to a reliability index. In the second method, multivariate quadratic regression was employed to derive the performance function expressed in terms of global stochastic variables using results from the FEA simulations. Next, FORM was employed to calculate the reliability index and then the probability of failure.

The following conclusions can be drawn from the present study:

- The two methods, i.e., the probabilistic tool package in ANSYS and the developed non-intrusive formulation, match well on the calculated reliability indices calculated

for all limit states, cross-verifying applicability of both methods for the structural reliability assessment of OWT support structures.

- The proposed non-intrusive formulation for SRA allows faster calculations, assessment of time-variant fatigue reliability assessment, and calculation of low values of probability of failure in complex engineering systems such as offshore and marine structures.
- This study also allowed for verification of the non-intrusive formulation, which can allow multiple problems of complex nature to be solved probabilistically, alleviating the need for an integrated, application-specific tool to be developed, instead of with the proposed modular formulation.

Funding: This work was supported by a grant from the Supergen Wind Hub EP/L014106/1, from the UK Engineering and Physical Sciences Research Council (EPSRC), under the Flexible Funding Scheme for the University of Strathclyde.

Acknowledgments: Author Abdulhakim Shittu would like to acknowledge the Petroleum Technology Development Fund (PTDF), Nigeria, for financial support.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Kolios, A.; Wang, L. Advanced Reliability Assessment of Offshore Wind Turbine Monopiles by Combining Reliability Analysis Method and SHM/CM Technology. In Proceedings of the 28th International Ocean and Polar Engineering Conference, Sapporo, Japan, 10–15 June 2018; pp. 1412–1419.
2. Wang, L.; Kolios, A. A Generic Framework for Reliability Assessment of Offshore Wind Turbine Monopiles Considering Soil-Solid Interaction and Harsh Marine Environments. In Proceedings of the 5th International Conference on Marine Structures, MARSTRUCT, Lisbon, Portugal, 8–10 May 2017.
3. EWEA. *EWEA Offshore Wind in Europe—Walking the Tightrope to Success*; The European Wind Energy Association: Brussels, Belgium, 2015.
4. Ioannou, A.; Angus, A.; Brennan, F. A lifecycle techno-economic model of offshore wind energy for different entry and exit instances. *Appl. Energy* **2018**, *221*, 406–424.
5. Damiani, R.; Song, H. A Jacket Sizing Tool for Offshore Wind Turbines within the Systems Engineering Initiative. In Proceedings of the Offshore Technology Conference, Houston, TX, USA, 6–9 May 2013.
6. Wang, X.; Zeng, X.; Yang, X.; Li, J. Feasibility study of offshore wind turbines with hybrid monopile foundation based on centrifuge modeling. *Appl. Energy* **2018**, *209*, 127–139.
7. Wang, X.; Zeng, X.; Yang, X.; Li, J. Seismic response of offshore wind turbine with hybrid monopile foundation based on centrifuge modelling. *Appl. Energy* **2019**, *235*, 1335–1350.
8. Damiani, R.R.; Song, H.; Robertson, A.N.; Jonkman, J.M. Assessing the Importance of Nonlinearities in the Development of a Substructure Model for the Wind Turbine CAE Tool FAST. In *ASME 2013 32nd International Conference on Ocean, Offshore and Arctic Engineering*; American Society of Mechanical Engineers Digital Collection: New York, NY, USA, 2013; Volume 8.

9. Oyvind, N.S. Offshore Wind Turbine. Patent No: US 2011/0311360 A1, 10 February 2009.
10. Nielsen, F.G. Wind Turbine for Use Offshore. Patent No: US 7,456,515 B2, 25 November 2008.
11. Fyfe, A.J. Support Structure for An Offshore Wind Turbine. Patent No: US 2013/0183163 A1, 13 July 2013.
12. Li, F.; Niu, F.; Kang, Z.; Meiyang, Z.; Zhu, R. Jacket Platform of Offshore Wind Turbine. Patent No: CN103669312A, 26 March 2014.
13. Lee, J.K. Supporting Structure for Offshore Wind Power System. Patent No: KR20130076251A, 8 July 2003.
14. Kidu, K. Transition Pieces of Offshore Wind Turbines and Whole Structure of Wind Turbines Having it. Patent No: KR101613844B1, 7 July 2015.
15. Pipee, A.J. Support Structure for An Offshore Wind Turbine. Patent No: KR101786063B1, 27 July 2012.
16. Hyun, K.D.; Yun, J.-L.; Keun, L.S. Reliability Analysis Method for Offshore Wind Turbine Support Structure Recording Medium for the Same and Electronic Device Comprising the Same. Patent No: KR101562457B1, 12 October 2015.
17. Fischer, T.; Soe-Jensen, A. Monopile Foundation for Offshore Wind Turbine. Patent No: WO2009026933A1, 29 August 2008.
18. Park, G. One Body Type Jacket Support Structure for Offshore Wind Turbine. Patent No: KR101865511B1, 4 July 2017.
19. Kolios, A.; Di Maio, L.F.; Wang, L.; Cui, L.; Sheng, Q. Reliability assessment of point-absorber wave energy converters. *Ocean Eng.* **2018**, *163*, 40–50.
20. Leimeister, M.; Kolios, A. A review of reliability-based methods for risk analysis and their application in the offshore wind industry. *Renew. Sustain. Energy Rev.* **2018**, *91*, 1065–1076.
21. Wang, L.; Liu, X.; Renevier, N.; Stables, M.; Hall, G.M. Nonlinear aeroelastic modelling for wind turbine blades based on blade element momentum theory and geometrically exact beam theory. *Energy* **2014**, *76*, 487–501.
22. Petrini, F.; Manenti, S.; Gkoumas, K.; Bontempi, F. Structural Design and Analysis of Offshore Wind Turbines from a System Point of View. *Wind Eng.* **2010**, *34*, 85–107.
23. Wang, L.; Kolios, A.; Nishino, T.; Delafin, P.L.; Bird, T. Structural optimisation of vertical-axis wind turbine composite blades based on finite element analysis and genetic algorithm. *Compos. Struct.* **2016**, *153*, 123–138.
24. Gentils, T.; Wang, L.; Kolios, A. Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. *Appl. Energy* **2017**, *199*, 187–204.
25. Wang, L.; Quant, R.; Kolios, A. Fluid structure interaction modelling of horizontal-axis wind turbine blades based on CFD and FEA. *J. Wind Eng. Ind. Aerodyn.* **2016**, *158*, 11–25.
26. Achmus, M.; Abdel-Rahman, K. Finite Element Modelling of Horizontally Loaded Monopile Foundations for Offshore Wind Energy Converters in Germany. In Proceedings of the International Symposium on Frontiers in Off-shore Geotechnics (ISFOG), Perth, Australia, 19–21 September 2005.
27. Wang, L.; Kolios, A.; Delafin, P.-L.; Nishino, T.; Bird, T. Fluid structure interaction modelling of a novel 10MW vertical-Axis Wind Turbine Rotor Based on Computational Fluid Dynamics and Finite Element Analysis. In Proceedings of the EWEA 2015 Annual Event, Paris, France, 17–20 November 2015; Volume 44.
28. Jung, S.; Kim, S.R.; Patil, A.; Hung, L.C. Effect of monopile foundation modeling on the structural response of a 5-MW offshore wind turbine tower. *Ocean Eng.* **2015**, *109*, 479–488.
29. DNV GL AS. *Standard DNVGL-ST-0126—Support Structures for Wind Turbines*; DNV GL: Oslo, Norway, 2016; pp. 1–182.

30. Sørensen, J.D. Reliability-Based Calibration of Fatigue Safety Factors for Offshore Wind Turbines. In Proceedings of the Twenty-First International Offshore and Polar Engineering Conference, Maui, HI, USA, 19–24 June 2011.
31. Márquez-Domínguez, S.; Sørensen, J.D. Fatigue Reliability and Calibration of Fatigue Design Factors for Offshore Wind Turbines. *Energies* **2012**, *5*, 1816–1834.
32. Morató, A.; Sriramula, S.; Krishnan, N. Reliability Analysis of Offshore Wind Turbine Support Structures Using Kriging Models. In *Risk, Reliability and Safety: Innovating Theory and Practice*; Walls, L., Revie, M., Bedford, B., Eds.; Taylor & Francis Group: London, UK, 2017.
33. Wei, K.; Arwade, S.R.; Myers, A.T. Incremental wind-wave analysis of the structural capacity of offshore wind turbine support structures under extreme loading. *Eng. Struct.* **2014**, *79*, 58–69.
34. Kim, D.H.; Lee, S.G. Reliability analysis of offshore wind turbine support structures under extreme ocean environmental loads. *Renew. Energy* **2015**, *79*, 161–166.
35. Mardfekri, M.; Gardoni, P. Probabilistic demand models and fragility estimates for offshore wind turbine support structures. *Eng. Struct.* **2013**, *52*, 478–487.
36. Mardfekri, M.; Gardoni, P. Multi-hazard reliability assessment of offshore wind turbines. *Wind Energy* **2015**, *18*, 1433–1450.
37. Vahdatirad, M.J.; Griffiths, D.; Andersen, L.V.; Sørensen, J.D.; Fenton, G. Reliability analysis of a gravity-based foundation for wind turbines: A code-based design assessment. *Géotechnique* **2014**, *64*, 635–645.
38. Yeter, B.; Garbatov, Y.; Soares, C.G. Fatigue reliability of an offshore wind turbine supporting structure accounting for inspection and repair. In *Analysis and Design of Marine Structures*; Soares, G., Shenoi, E., Eds.; Taylor & Francis Group: London, UK, 2015; pp. 737–747.
39. Yeter, B.; Garbatov, Y.; Soares, C.G. Reliability of Offshore Wind Turbine Support Structures Subjected to Extreme Wave-Induced Loads and Defects. In Proceedings of the ASME 2016 35th International Conference on Ocean, Offshore and Arctic Engineering OMAE2016-54240, Busan, Korea, 30 June 2016; pp. 1–8.
40. Yeter, B.; Garbatov, Y.; Guedes Soares, C. System Reliability of a Jacket Offshore Wind Turbine Subjected to Fatigue. In Proceedings of the 5th International Conference on Marine Structures, MARSTRUCT, Lisbon, 8–10 May 2017; pp. 939–950.
41. Yeter, B.; Garbatov, Y.; Guedes Soares, C. Uncertainty analysis of soil-pile interactions of monopile offshore wind turbine support structures. *Appl. Ocean Res.* **2019**, *82*, 74–88.
42. Dong, W.; Moan, T.; Gao, Z. Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection. *Reliab. Eng. Syst. Saf.* **2012**, *106*, 11–27.
43. Muskulus, M.; Schafhirt, S. Reliability-Based Design of Wind Turbine Support Structures. In Proceedings of the Symposium on Reliability of Engineering System, Hangzhou, China, 2–5 November 2015.
44. Ciampoli, M.; Petrini, F. Performance-based design of offshore wind turbines. In *Earth and Space 2010: Engineering, Science, Construction, and Operations in Challenging Environments*; American Society of Civil Engineers: Reston, VA, USA, 2010.
45. Karadeniz, H. Review of Structural Reliability Methods with Applicability in Practice. *Civ. Eng.* **2006**, *4*, 880653.
46. Choi, S.-K.; Grandhi, R.; Canfield, R. *Reliability-based Structural Design*; Springer: Berlin/Heidelberg, Germany, 2006.
47. Bai, Y. *Marine Structural Design*, 1st ed.; Elsevier: Amsterdam, The Netherlands, 2003.
48. Ang, A.; Tang, W. Probability concepts in engineering planning and design. In *Decision, Risk, and Reliability*; John Wiley Sons: New York, NY, USA, 1984; Volume 2.
49. Kolios, A. A Multi-Configuration Approach to Reliability Based Structural Integrity Assessment for Ultimate Strength. Ph.D. Thesis, Cranfield University, Bedford, UK, 2010.

50. Hohenbichler, M.; Rackwitz, R. First-order concepts in structural reliability. *Struct. Saf.* **1983**, *1*, 177–188.
51. Der Kiureghian, A.; Lin, H.-Z.; Hwang, S.-J. Second Order Reliability Approximations. *J. Eng. Mech. Div ASCE* **1987**, *113*, 1208–1225.
52. Jiang, Z.; Hu, W.; Dong, W.; Gao, Z.; Ren, Z. Structural reliability analysis of wind turbines: A review. *Energies* **2017**, *10*, 1–25.
53. ANSYS DesignXplorer User's Guide. 2018. Available online: www.ansys.com. (Accessed on 1 April, 2018).
54. Reh, S.; Beley, J.D.; Mukherjee, S.; Khor, E.H. Probabilistic finite element analysis using ANSYS. *Struct. Saf.* **2006**, *28*, 17–43.
55. Melchers, R.; Andre, T. *Structural Reliability Analysis and Prediction*, 3rd ed.; Wiley: Hoboken, NJ, USA, 2018.
56. Melchers, R.E. *Structural Reliability: Analysis and Prediction*, 2nd ed.; Ellis Horwood: Chichester, UK, 2002.
57. Hammersley, J.M.; Handscomb, D.C. *Monte Carlo Methods*; Chapman & Hall: London, UK, 1964.
58. Mastumoto, M.; Nishimura, T. Mersenne twister: A 623-Dimensionally equidistributed uniform pseudorandom number generator. *ACM Trans Model. Comput. Simul.* **1998**, *8*, 3–30.
59. Kececioglu, D. *Reliability Engineering Handbook*; Prentice-Hall: Upper Saddle River, NJ, USA, 1991; Volume 2.
60. Ayyub, B.M.; Lai, K.-L. Structural Reliability Assessment Using Latin Hypercube Sampling. In *Structural Safety and Reliability, Proceedings of the 5th International Conference on Structural Safety and Reliability (ICOSSAR), San Francisco, CA, USA, 7–11 August 1989*; Ang, A.-S., Shinozuka, M., Schueeler, G., Eds.; American Society of Civil Engineers: San Francisco, CA, USA, 1989; pp. 1177–1184.
61. Florian, A. An efficient sampling scheme: Updated latin hypercube sampling. *Probab. Eng. Mech.* **1992**, *7*, 123–130.
62. Ang, A.-S.; Tang, W.H. *Probabilistic Concepts in Engineering Planning and Design. Basic Principles*; Wiley: New York, NY, USA, 1975.
63. Dahlquist, G.; Björck, A. *Numerical Methods*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1974.
64. Rubinstein, R.Y. *Simulation and the Monte Carlo Method*; John Wiley & Sons: New York, NY, USA, 1981.
65. Warner, R.F.; Kabaila, A.P. Monte Carlo study of structural safety. *J. Struct. Div. ASCE* **1968**, *94*, 2847–2859.
66. McKay, M.; Beckman, R.; Conover, W. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* **1979**, *21*, 239–245.
67. Melchers, R.E. *Structural Reliability: Analysis and Prediction*, 1st ed.; Ellis Horwood: Chichester, UK, 1999.
68. Olsson, A.; Sandberg, G.; Dahlblom, O. On Latin hypercube sampling for structural reliability analysis. *Struct. Saf.* **2003**, *25*, 47–68.
69. Huntington, D.E.; Lyrantzis, C.S. Improvements to and limitations of Latin hypercube sampling. *Prob. Eng. Mech.* **1998**, *13*, 245–253.
70. Hasofer, A.; Lind, N. An exact and invariant second moment code format. *J. Eng. Mech. Div ASCE* **1974**, *100*, 111–121.
71. DNV. *DNV-OS-J101 Design of Offshore Wind Turbine Structures*; DNV GL: Oslo, Norway, 2014; pp. 212–214.
72. IEC. *Wind Turbines—Part 3: Design Requirements for Offshore Wind Turbines*. IEC 61400-3, Geneva, Switzerland, 2009.

73. Veritas, N. *Environmental Conditions and Environmental Loads*; DNV GL: Oslo, Norway, 2000.
74. Minguez, L. *Fatigue and Fracture Mechanics of Offshore Wind Turbine Support Structures*. Ph.D. Thesis, Cranfield University, Bedford, UK, 2015.
75. Freebury, G.; Musial, W. Determining equivalent damage loading for full-scale wind turbine blade fatigue tests. In *Proceedings of the 2000 ASME Wind Energy Symposium*, Reno, NV, USA, 10–13 January 2000.
76. Chakrabarti, S.K. *Handbook of Offshore Engineering*; Elsevier: Amsterdam, The Netherlands, 2005; Volume 1.
77. Muskulus, M.; Schafhirt, S. Design Optimization of Wind Turbine Support Structures—A Review. *J. Ocean Wind Energy* **2310**, 1, 12–22.
78. Lee, Y.S.; Choi, B.L.; Lee, J.H.; Kim, S.Y.; Han, S. Reliability-based design optimization of monopile transition piece for offshore wind turbine system. *Renew. Energy* **2014**, 71, 729–741.
79. IEC. *IEC 61400-1: Wind Turbines Part 1: Design Requirements*; IEC: Geneva, Switzerland, 2005.
80. Fisher, T.; De Vries, W.; Schmidt, B. Upwind Design Basis (WP4 Offshore Foundations and Support Structures). 2010. Available online: <https://repository.tudelft.nl/islandora/object/uuid%3Aa176334d-6391-4821-8c5f-9c91b6b32a27> (accessed on 4th June 2019).
81. Schaumann, P.; Boker, C.; Bechtel, A.; Lochte-Holtgreven, S. Support structures of wind energy converters. In *Environmental Wind Engineering and Design of Wind Energy Structures*; Baniotopoulos, C., Borri, C., Stathopoulos, T., Eds.; Springer: Berlin/Heidelberg, Germany, 2011; pp. 191–253.
82. GL Rule for Regulation IV-Non Marine Technology, Part 2 Offshore Wind Energy. 1995. In *JacketSE: An Offshore Wind Turbine Jacket Sizing Tool Theory Manual and Sample Usage with Preliminary Validation*; National Renewable Energy Lab.(NREL): Golden, CO, USA, 2016.
83. Damiani, R. *JacketSE: An Offshore Wind Turbine Jacket Sizing Tool Theory Manual and Sample Usage with Preliminary Validation*; National Renewable Energy Lab.(NREL): Golden, CO, USA, 2016.
84. Jonkman, J.; Butterfield, S.; Musial, W.; Scott, G. *Definition of a 5-MW Reference Wind Turbine for Offshore System Development*; National Renewable Energy Lab.(NREL): Golden, CO, USA, 2009.
85. Drucker, D.; Prager, W. Soil mechanics and plastic analysis or limit design. *Q. Appl. Math.* **1952**, 10, 157–165.
86. ANSYS Inc. *Introduction to Contacts—ANSYS Mechanical Structural Nonlinearities*; ANSYS Inc.: Canonsburg, PA, USA, 2010.
87. ANSYS. ANSYS Help Documentation. 2018. Available online: www.ansys.com (accessed on 5th June 2019).
88. Kühn, M. *Dynamics and Design Optimization of Offshore Wind Energy Conversion Systems*; DUWIND, Delft University Wind Energy Research Institute: Delft, The Netherlands, 1999.
89. Zwick, D. *Simulation and Optimization in Offshore Wind Turbine Structural Analysis*. Ph.D. Thesis, Norwegian University: Trondheim, Norway, 2015.
90. BSI. *BS EN 1990 Eurocode: Basis of Structural Design*; British Standards Institute: London, UK, 2002.
91. (DNV) Det Norske Veritas. *Structural Reliability Analysis of Marine Structures*; Det Norske Veritas: Oslo, Norway, 1992.
92. Det Norske Veritas. Fatigue design of offshore steel structures. In *DNV Recommended Practice DNV-RP-C203*; Det Norske Veritas: Oslo, Norway, 2010; pp. 37–41.



© 2019 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

4 SENSITIVITY ANALYSIS OF DESIGN PARAMETERS FOR RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE JACKET SUPPORT STRUCTURES

Abdulahakim Adeoye Shittu, Ali Mehmanparast, Peyman Amirafshari, Phil Hart, Athanasios Kolios

Statement of contributions:

Abdulahakim A. Shittu conducted the literature review, developed, and validated the model, performed the simulations, generated all the results, drafted and critically revised the manuscript. A. Mehmanparast, P. Amirafshari, P. Hart, and A. Kolios provided supervision, reviewed and critically commented on the manuscript before submission.

Abstract

Offshore wind turbine (OWT) support structures are subjected to harsh environments which are defined by highly stochastic loads and complex soil-structure interaction, and thus the need for a probabilistic approach towards design. The study carried out herein presents the sensitivity analysis of these inherent stochastic variables imposed on a complex OWT support structure. The stochastic sensitivity analysis, recognized as an efficient way to perform the characterization of such complex systems, is used in this study. Also, the response of the structure to these design stochastic variables is studied using a non-intrusive structural reliability sensitivity assessment formulation which is a combination of stochastic parametric FEA, response surface modelling, and stochastic sensitivity analysis (SSA). The iterative FORM has been incorporated in the SSA algorithm for enhanced simulation towards achieving accurate approximation of the sensitivity assessment levels. The results from this study, reveals that the uncertainties in the design wind speed is a design driving factor and the hydrodynamic load effects are secondary to this, for the ultimate (ULS), and fatigue limit states (FLS) while their relative sensitivities on the serviceability limit state (SLS) cannot be clearly distinguished but are seen to have dominant impact. The uncertainties in the wind speed have a percentage influence of more than 90% on the reliability sensitivities than the hydrodynamic parameters for the ULS and FLS. Also, it was inferred that incorporating correlation between the design variables have a significant impact on the reliability of the structure in the ULS design. The SSA performed herein enables designers to focus on

the parameters with uncertainties having significant effects on the reliability sensitivities, and to assume deterministic values for those having little influence.

Keywords: stochastic sensitivity assessment; stochastic FEA modelling; non-intrusive formulations; iterative FORM; offshore wind structures.

4.1 Introduction

Research on the design of jacket structures are based on studies that took place 3-4 decades ago, and the new application to offshore wind, with serial production of units and increased operational loads, have re-established the issue of advanced methods of design to be very relevant in current research and practice. Stronger and more steady winds found offshore as well as the reduced need for land area are substantial advantages compared to onshore wind installations. In recent years, studies have mainly focussed predominantly on the use of monopiles for offshore wind turbine applications thereby making detailed studies on the use of jacket foundations an aspect open to further investigation [1–6].

With few exceptions, most of the existing offshore wind turbines have been installed on monopile foundations in shallow waters (depths<50m). However, monopiles become progressively uneconomical, basically due to modal requirements which forces the structural dimensions to grow beyond fabrication and installation capabilities currently available as the turbines become larger (>5MW) and as water depth increases beyond 35-50m [3,4,7]. Extensive studies on monopile foundations can be found in [8,9]. Structural space frames such as jackets, used extensively in the oil and gas industry, offer a lighter and yet stiff alternative to monopiles. In view of turbine system dynamics, coupled with the inherent highly stochastic loads, effective design of these structures is resource intensive. Therefore, although jacket foundations could go a long way in solving challenges in the offshore wind industry, research is still necessary to support their basic design and analysis [4,10] also considering factors such as the requirement for optimisation due to the serial production required and the nature of these unmanned structures [11].

Since modern structures require more complex and reliable designs, it becomes increasingly necessary to propose an accurate and efficient approach to assess uncertainties in material properties and operating environments. In recent years, reliability analysis as a form of uncertainty analysis has been shown to be a useful tool

in structure design because it can directly quantify the effect of uncertainty about input parameters on the structural performance [12–17]. In view of this, reliability-based design optimization is has seen increased interest [18]. In the reliability-based design optimization process, the probability of failure is limited to a target level in order to minimize the failure risk.

For reliability analysis, given an arbitrary limit-state function $Z = g_X(\mathbf{X})$, the probability of failure (POF), P_f , can be described as a multi-dimensional integral, which is given by

$$P_f \equiv Pr(g_X(\mathbf{X}) \leq 0) = \int \dots \int_{g_X(\mathbf{x}) \leq 0} f_X(\mathbf{x}) d\mathbf{x} \quad (4-1)$$

where $Pr(.)$ is a probability function, $\mathbf{X} = [X_1, \dots, X_n]^T$ is an n -dimensional random vector where the upper case X_i denotes it is a random variable and the lower case x_i denotes it is the realization of the random variable X_i , $f_X(\mathbf{x})$ is the joint probability density function (PDF) of the random variables $\mathbf{X}$.

Generally, since the convolution integral shown in Equation (4-1) is complicated, and of high dimensionality, both analytical and direct numerical methods are unable to solve it directly. Due to the difficulty in computing this probability function, over the past few decades, various methods have been developed. Out of all these methods, the first-order reliability method (FORM) is one of the most popular. FORM approximates the true limit state function at the most probable point (MPP) which is the point on the limit state surface nearest to the origin in the standard normal space. This process enables FORM to work with a good balance between efficiency and accuracy. Because of this good balance, it has become a basic method for reliability analysis [12,19–21].

One of the main steps in solving an optimization problem is to determine search direction based on function gradients referred to as sensitivity analysis. Derivative-based approaches, where parameter sensitivity is measured in terms of the change in model output with respect to an incremental change in the input, are most common in the literature due to their efficiency [22]. According to [22–24] other approaches include linear regression of Sobol's decomposition method, Monte Carlo simulations, Morris screening, and variance-based methods. Sensitivity analysis demonstrates changes in the quantity of reliability in terms of variations in design variables. Sensitivity analysis is also used to identify the most significant uncertain variables that have the highest

contribution to reliability. Furthermore, sensitivity analysis could be used to provide information for reliability-based design [25].

In general, the sensitivity analysis studies the relationship between information flowing in and out of the model. Sensitivity analysis in reliability refers to the study of how uncertainty in the model output can be decomposed into different sources of uncertainties in the model inputs and model uncertainty. The basic categorization of sensitivity analysis is: the deterministic sensitivity analysis and the stochastic sensitivity analysis [23]. Ideally, limit state analyses are performed using integrated structural models to capture the complex interactions between the Offshore Wind Turbine (OWT) structure and the environment. Despite uncertainties related to parameter estimation and mathematical representation of wind, wave, soil and structure, deterministic approaches are normally performed, by utilizing partial safety factors which account for load and resistance uncertainties. Probabilistic design approaches, on the other hand, allow more rigorous consideration of parameter uncertainties, particularly site-specific environmental inputs, at the expense of higher calculation times. In this regard, identification of the most important sources of uncertainties, i.e. by performing a stochastic sensitivity analysis of a complex nonlinear model becomes important [22].

Structural models to determine the response of support structures for OWT can be roughly classified into two groups, namely one-dimensional (1D) beam models and three-dimensional (3D) finite element analysis (FEA) models. In the 1D beam model, the structure is discretized into a series of elastic Euler or Timoshenko beam elements. It is computationally efficient and can be used to accurately model the global structural behaviour, such as for evaluating deflections and modal frequencies [26]. It, however, calculates local structural responses such as stress concentration effects with compromised precision [27]. In the 3D FEA model, the support structure is usually described by the application of brick or shell elements. In comparison to the 1D beam model, the 3D Finite Element Analysis Model (FEM) has capabilities of assuming detailed stress distributions and capturing structural responses within the structure accurately. The 3D FEM has been applied extensively to structural modelling of wind turbine foundations owing to its high fidelity [11,28–34]. Thus, in this study, the 3D FEA model is employed to evaluate the structural responses of the OWT jacket support structure.

Because OWT jacket foundations are embedded through piles into the soil system, it becomes essential to account for soil-structure interaction to capture their structural response adequately. A straightforward method of modelling the soil is by assuming equivalent springs having stiffness based on soil properties, and this approach is known as the p-y method. However, this method tends to underestimate the deflection and the modal frequency [35,36]. A reliable way of modelling the soil system is by assuming 3D FEA with brick elements such that accurate and reliable results can be obtained [11,37,38]. Due to its high efficacy, the 3D FEA with brick elements is adopted in this study to model the soil.

This work aims to carry out stochastic sensitivity assessment (SSA) for a typical OWT jacket type support structure considering various limit state and stochastic variables. A generic reliability assessment framework which combines parametric FEA modelling, response surface modelling and reliability analysis specifically for complex OWT jacket type support structures in the presence of highly stochastic variables has been previously developed by the authors and will stand as the basis of this study. The method adopted proposes a non-intrusive stochastic formulation which links the structural model to a reliability analysis algorithm through approximation modelling. A quadratic response surface modelling is adopted in order to map the response of the structure in the domain of stochastic variables. The benefit of this approach is that it allows for high fidelity computational tools to be employed for the analysis, hence extending its applicability to various specialist engineering problems through the advanced modelling techniques, and further permitting coupling with analytical reliability methods such as FORM/SORM in order to allow for low values of probability of failure to be calculated, thus allowing sensitivity assessment based on derivatives [11]. The variables considered in the sensitivity analysis include the wind speed (V), tilting (M_{Tilt}) and torsional moments (M_{Tors}) due to aerodynamics, significant wave height (H_s), Young's modulus (E_{Si}) of each soil strata, Rotor-Nacelle Assembly (RNA)/ Self weight (W_i), and the wave period (T).

The rest of the present paper is organised as follows: Section 4.2 introduces the design load analysis where the sources of loads, design load cases, and site specification are discussed; Section 4.3 discusses the parametric FEA built for the OWT highlighting the geometry, mesh, material, and boundary conditions used, as well as the validation of the FEA model; Section 4.4 highlights the implementation of the steps of the proposed

stochastic sensitivity analysis discussing the non-intrusive formulation and the SSA based on the iterative FORM; In section 4.5, results obtained from the study are discussed extensively; and finally, Section 4.6 draws the main conclusions of the work conducted.

4.2 Design load analysis

4.2.1 Sources of loads

OWTs are subjected to several load sources usually imposed by their environment. A list of loads to be accounted for in the design of OWT jacket support structures are set out in design standards, such as DNV-OS-J101 [39] and IEC 61400-3 [40]. Calculations and formulations of each load produced by the environment will in this study be based on DNV-RP-C205 [41]. The relevant loads imposed on OWT support structures can roughly be classified into six groups i.e. (1) aerodynamic Loads transferred from the rotor; (2) wind loads on the tower; (3) inertia Loads; (4) current load; (5) wave loads and (6) hydrostatic loads [29]. These loads are illustrated in **Figure 4-1**.

Gravitational and inertia loads are static and dynamic loads resulting from gravitational pull, the mass of the whole structure and equipment imposed on the structure under operation, and the forces acting on the structure as a result of operations [42]. The inertia loads, resulting from the weight of the support structure and RNA at the tower top, can significantly impact on the buckling and influence the eigenfrequencies of the OWT foundation [29].

Aerodynamic loads are dynamic and static loads occurring as a result of the interaction between the airflow, and the moving and stationary components of the wind turbine. The magnitude of load varies and depending on the air density, the mean wind speed and turbulence across the rotor plane, and the aerodynamic shapes of the components of the wind turbine and their interactive effects. These loads are determined by using aeroelastic load models [42]. The aerodynamic loads produced by the rotor pushes the tower at the top and are often decomposed into a load matrix defined in the referential axis of the wind turbine. The fatigue loads were evaluated by adopting the Damage Equivalent Load (DEL) method, which is explained in [43]. A thrust load in the same direction as the diagonal of the base of the jacket was imposed on the support structure and applied at the assumed RNA Centre of Mass (CM). This loading set-up is assumed to resemble a yaw error situation intentionally to produce an additional moment due to

torsion at the top of the tower. This was carried out in the presence of a horizontal offset for the RNA CM which led to a moment due to gravity at the top of the tower [10]. Wave load and rotor thrust vectors were applied in the same direction as the jacket base diagonal so that the maximum compression and tension effects are produced on the opposite legs [4,11].

Environmental loads are those caused by environmental phenomena, i.e., the set produced by wave force, current force and wind force. Wave loads are dynamic loads resulting from waves and their interaction with the OWT support structure. Le Mehaute's graph depicts the range of validity of each wave theory and can be employed to decide which theory is the most suitable for a given set of wave characteristics, such as wave period (T), wave height (H) and water depth (d) [42]. The regular wave theories are suitable for designs where a single wave method is employed, and this method is used extensively in the design of offshore structures. In this case, a regular wave of the appropriate period and height is adopted to represent an extreme wave. This approach provides a simple analysis in approximating extreme response of the offshore structure. On the other hand, the energy density spectrum is assumed in defining the random ocean wave. The spectrum describes the ocean wave energy content and its distribution over a random wave frequency range. Thus, the random wave design approach may be assumed as ideal for designing floating structures [44]. The Stokes third-order theory was found to be ideal in this study based on the wave profile data presented in **Table 4-1**.

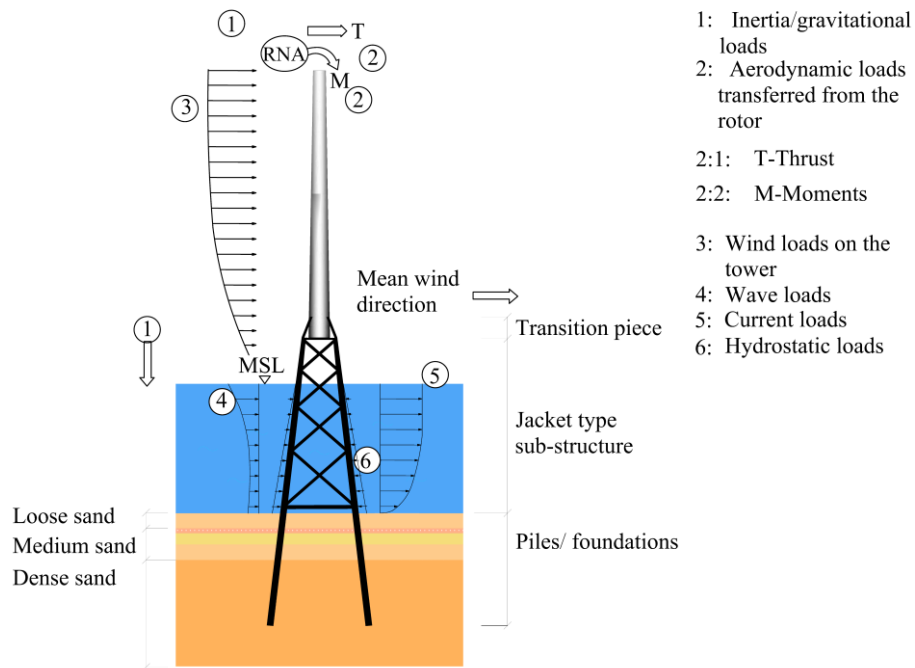


Figure 4-1. Representation of the loads on the support structure of the OWT and jacket geometry embedded in layered soil [11].

Table 4-1: Water levels and wave data of interest for the K-13 deep water site.

Parameter	Value
Lowest Astronomical Tide, LAT (m)	-1.06
Tidal range, Δz_{tide} (m)	2.22
Storm surge, Δz_{surge} (m)	2.13
Air gap, Δz_{air} (m)	1.5
Significant wave height, H_s (m)	9.4
Maximum 50-year wave height, $H_{50,max}$ (m)	17.48
Maximum wave period range, T_{50} (s)	10.8 – 14
Max. wave height above still water for deck height calculation, ξ_w (m)	11.36

Typically, bottom-fixed offshore structures are considered to be dominated by drag owing to the wavelength, water depth, structural shape and size; thus, the Morison's equation is employed. In Morison's equation, it is assumed that the total wave force exerted on a structure can be calculated by the linear superimposition of the drag and inertia forces. To evaluate the wave loads which acts on the structure using Morrison's equation, the member diameter, D , has to be less than one-fifth of the wavelength, λ , i.e.:

$$D \leq 0.2\lambda \quad (4-2)$$

Current and wave loads can be calculated using Morison's equation thus, for slender member such as components of jackets submerged in water [39]:

$$F = F_d + F_m = \frac{1}{2}\rho_w C_d D |u_x| u_x + \rho_w C_m \frac{\pi D^2}{4} a_x \quad (4-3)$$

where the drag force is the first term while the inertia force is the second term; ρ_w is the density of water; C_d and C_m are the piles' coefficients of drag and inertia, respectively and their corresponding values are 1.25 and 2.0 respectively [4]; D is the cylinder diameter; a_x and u_x are the horizontal wave-induced or current-induced acceleration and velocity of water, respectively which were derived from the regular wave theory.

Current loads can be described as dynamic loads emanating from the water flow from external sources, other than surface waves. Current can lead to drag loads being induced on the support structure. The current velocity $u_c(z)$ is assumed to follow a sub-surface current exponential profile from the seabed, d to the Mean Sea Level (MSL). The total current velocity of a submerged, stationary, tubular member, in the absence of vortex shedding, can be computed thus:

$$u_c(z) = u_{c,MSL} \left(\frac{d+z}{d} \right)^{1/7} \quad (4-4)$$

where, $u_{c,MSL}$ is the current velocity at MSL, d is the depth of water from MSL to the seabed. The wave-particle velocity and the current velocity are summed up in the Morison's equations drag term in Equation (4-3), assuming that the wave and current acts in the same direction.

The wind loads pushing the tower structure results from the drag and are a function of the average wind velocity $\bar{V}(z)$. Generally, the wind shear is described by a power law profile, and can be determined from the following equation:

$$\bar{V}(z) = \bar{V}_r \left(\frac{z}{Z_r} \right)^\alpha \quad (4-5)$$

where $\bar{V}_r$ represents the reference wind speed at the elevation of nacelle altitude Z_r , and α , which has a value of 0.115, is the roughness coefficient for the offshore site [29]. Wind loads exerted along the tower can be computed, thus:

$$F_{tower}(z) = \frac{1}{2} \rho_a C_{D,T} D(z) \bar{V}_r^2(z) \quad (4-6)$$

where $C_{D,T}$ which is taken as 1.0 is the coefficient of drag of the tower, $D(z)$ denotes the external diameter of the tapered tower at height z . Having calculated the wind load, the moment due to the effects of the wind load can then be determined.

Hydrostatic pressure, exerted on the submerged members of the jacket foundation, is a constant normal load and varies with the depth of water. The hydrostatic force can be calculated from:

$$F_h = \rho_w g h \quad (4-7)$$

Where F_h is the hydrostatic force, g is the acceleration due to gravity and h is the water depth.

4.2.2 Design load cases (DLCs) and site specifications

The DLCs should cover a set of design situations taking into consideration the most severe conditions that an OWT foundation is likely to be subjected to, combining extreme or standard external conditions with operational states of the wind turbine or other operational modes (such as installation, transportation, fault, or maintenance) [42]. Thirty-two (32) DLCs are set out consisting all modes of operation of an OWT in IEC61400-3 [40], for the structural design of OWTs, including start-up, standard operation, shut down and 50-year extreme conditions. These DLCs can be classified roughly into two main groups, namely, ultimate and fatigue. Typical load cases employed, basically, in the structural design for OWTs foundations are mainly by assuming the fatigue loads based on normal sea states while assuming the ultimate load based on a 50-year extreme condition. According to [38], the serviceability load cases can be determined as specified in [45]. For simplicity, both the ultimate and fatigue load cases are considered in this study:

4.2.2.1 Ultimate load case

The load derived from the 50-year return period is commonly assumed to be a critical ultimate load case for the extreme hydrodynamic loads experienced by OWT. In a previous study [46], it was revealed that the wind loading is a design driving factor for a typical OWT rather than the hydrodynamic loading. Hence, it is usually assumed that the

critical load case for ULS is defined by the parked turbine, under the 50-year EWM (extreme wind model) with 50-years RWH (reduced wave height) and ECM (extreme current model). The loading characteristics, as described above, corresponds to the IEC 61400-3 [40] DLC 6.1b and 2.1 GL regulation [47] respectively. Load safety factors for gravitational and other loads (such as environmental loads) are given as 1.1 and 1.35, respectively [48,49].

4.2.2.2 Fatigue load case

During the life of OWTs, a significant source of periodic loadings acts on the structure, due to the nature of rotor operation as well as hydrodynamic loading. Hence, there is a high risk of OWT foundations failing by fatigue [29,50]. A widely used fatigue DLC correlates to an operating state within the Normal Sea State (NSS) and Normal Turbulence Model (NTM) where the site is assumed to have no current and the wave height and the cross zero period are obtained via a probability density function of the site. DLC 1.2, as prescribed in the IEC standard [40], is generally regarded as the governing fatigue DLCs for OWT support structures, and therefore they are considered in this study as fatigue load cases [29,51]. According to the IEC standard [48,49], the safety factor for fatigue load is equivalent to 1.0.

4.2.2.3 Site specification

The information from a previous study for a deep water site located off the coast of the Netherlands designated as K-13 deep-water site [49] was adopted for this study as presented in **Table 4-1**.

4.3 OWT case study

Given the exorbitant cost of support structures and related Operation and Maintenance (O&M) activities, there is continued interest in increasing the size for offshore turbines. The OWT [4,10,52] is assumed to be a simple reference 10 MW turbine scaled from 5 MW (National Renewable Energy Laboratory) NREL reference turbine [53]. The main properties were calculated through basic mechanics considerations and scaling laws. The RNA is supported by an 88.4 m tapered tubular tower. Its basic characteristics are summarised in

Table 4-2, and further details can be found in [4,10].

Table 4-2: Main properties of the baseline 10 MW OWT model [4].

Item	Value
Rated power (MW)	10
Blade length (m)	87.70
Hub radius (m)	3.05
Rotor diameter (m)	181
Tip radius (m)	90.74
Rotor-nacelle assembly mass (kg)	1,072,000
Blade vertical clearance (m)	2
Precone (deg)	3
Shaft-tilt (deg)	-5
Overhang (m)	-9.10

4.3.1 Parametric FEA

The ANSYS software package is a well-established multi-purpose FEA software that is used to build a parametric Finite Element Analysis Model (FEM) of the OWT foundation and the soil system. The parametric FEM enhances the modelling of OWT structures with stochastic variables, such as material properties and environmental parameters. The parametric FEM represents the jacket support structure of the 10-MW OWT, where the main parameters are presented in **Table 4-3**. The wind and wave loads, which are environmental loads, are calculated manually and then applied to the structure in an uncoupled way, such that fluid-structure interactions are ignored. The geometry, material, mesh and boundary conditions used in the FEM are presented in the next subsections [11].

Table 4-3: Baseline 10 MW support structure parameters [4,10,49,52]. MSL – mean sea level; OD – outer diameter; WL – wall thickness; TP – transition piece; RNA – rotor-nacelle assembly; UL – ultimate limit; FL – fatigue limit.

Parameter	Value
Deck height above MSL (m)	16
Water depth (m)	50
Leg OD (m)	1.74
Leg WT (m)	0.030
Number of bays	4
Jacket batter	8.47

Height of TP (m)	7
Number of legs	4
Pile OD (m)	1.59
Pile WT (m)	0.037
Mud brace OD (m)	0.762
Mud brace WT (m)	0.017
x-brace OD (m)	0.61
x-brace WT (m)	0.016
RNA mass (kg)	1,072,000
Tower length (m)	88.4
Tower-top OD (m)	3.85
Tower-top thickness (m)	0.03
Tower-base OD (m)	7
Tower-base thickness (m)	0.055
Thrust associated with rated power UL case (kN)	1700
Maximum Rotor thrust taking into account dynamic amplification UL case (kN)	3400
Thrust FL case (kN)	203
Torsional moment UL case (kN-m)	7876
Torsional moment FL case (kN-m)	3483
Tilting moment UL case (kN-m)	38567
Tilting moment FL case (kN-m)	3687

4.3.1.1 Geometry

The jacket configuration is usually a space frame with four legs, inter-connected with bracings welded together which could have diameters up to 2m. The structural assembly comprises a transition piece which transfers the forces from the tower into the submerged jacket structure, which is anchored via piles or suction caissons, to the seabed at each leg. The jacket structure is of 66m vertical height, and the Transition Piece (TP) is 7 meters long which joins the jacket with the tower. The TP is assumed to be a deck reinforced by stringers which supports a central cylindrical shell supported by four tubular struts. The piles are embedded 42 m in the soil and are intended to be driven through the legs and thus feature a batter angle [4,10,11].

4.3.1.2 Mesh

The mesh generation is an essential step in the coupling of the model to be used for the FEA. The ANSYS software package provides a powerful and reliable structure mesh generator capable of developing a mesh which is consistent in all of the structure with minimal computational requirement.

In order to ensure accuracy of results, the mesh was optimized by performing a mesh sensitivity analysis. This is depicted in **Table 4-4**. From the mesh sensitivity study, the Equivalent (von-Mises) stress converged at the mesh size of 2m for the soil and 0.5m for the support structure corresponding to a total number of elements of 190,222. Hence, 2m and 0.5m are deemed as suitable mesh sizes for the soil and the support structure, respectively. The generated mesh for the FEA model is shown in **Figure 4-2** [11].

Table 4-4: Mesh sensitivity.

Soil element size (m)	Jacket structure element size (m)	Number of elements	Maximum von Mises stress (Pa)
8	2	8047	2.5297E+08
4	1	36,164	2.5328E+08
2	0.5	190,222	2.5346E+08
1	0.25	1,298,092	2.5353E+08

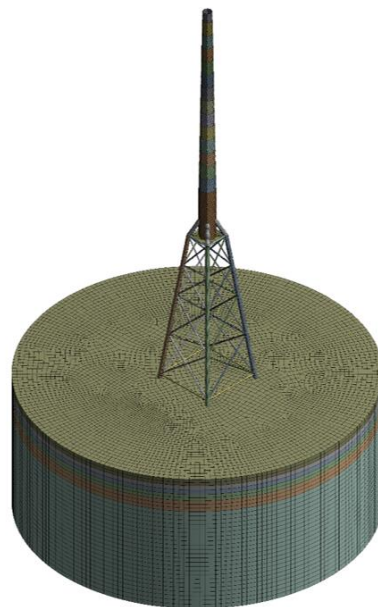


Figure 4-2. 3D display of meshing performed on the structural model [11].

4.3.1.3 Material

The jacket structure is made of S355 structural steel with a density of $8,500 \frac{\text{kg}}{(\text{m})^3}$ (increased by 8% to account for secondary steel appurtenances, coatings and welds that are not taken into account in the thickness data of the support structure), Young modulus of 210GPa, a Poisson's ratio of 0.3, and nominal yield strength of 355MPa. The tower and TP is made of structural steel of the same properties [4,29].

4.3.1.4 Soil profile

Apart from the OWT support structure, a crucial step in developing the detailed parametric model includes considering soil-structure interaction, which is a design factor of significant importance for the structural response of piles-jacket-tower assembly. A cylindrical shape having a diameter of 140m and height of 50m was assumed for the soil modelled in the FEA, having six different strata (see **Table 4-5**). The Drucker-Prager strength linear model is applied in modelling the soil material [54]. This model is applied in calculating the yield strength of each soil strata. According to the Drucker-Prager model, the yield strength of the soil, σ_{ys} , can be calculated from:

$$\sigma_{y,s} = \frac{6c \cos \phi}{\sqrt{3}(3 - \sin \phi)} \quad (4-8)$$

where ϕ denotes the internal friction angle, and c denotes the cohesion value. The coefficient of friction C_f between the soil and the pile is given by [37].

$$C_f = \tan\left(\frac{2}{3}\phi\right) \quad (4-9)$$

Table 4-5: K-13 Deep-water site's soil profile [4].

Depth seabed (m)	below	Unit weight (N/m^3)	Friction angle ($^\circ$)	Shear strength (N/m^2)	Young's Modulus (MPa)
0-3		10,000	36	60,000	30
3-5		10,000	33	60,000	30
5-7		10,000	26	60,000	50
7-10		10,000	37	60,000	50
10-15		10,000	35	60,000	50
15-50		10,000	37.5	60,000	80

4.3.1.5 Boundary conditions

The wind and wave loads are applied to the tower surface and the support structure surface submerged into the water, respectively. Additionally, the following three boundary conditions are also defined: 1) the bottom of the soil model is fixed against translation in all directions; 2) the soil model's lateral boundaries are fixed against lateral translation; (3) an augmented Lagrangian formulation-based frictional contact [55,56] is established between the soil and pile with suitable friction coefficients in order to enable soil-structure interaction. See **Figure 4-3**.

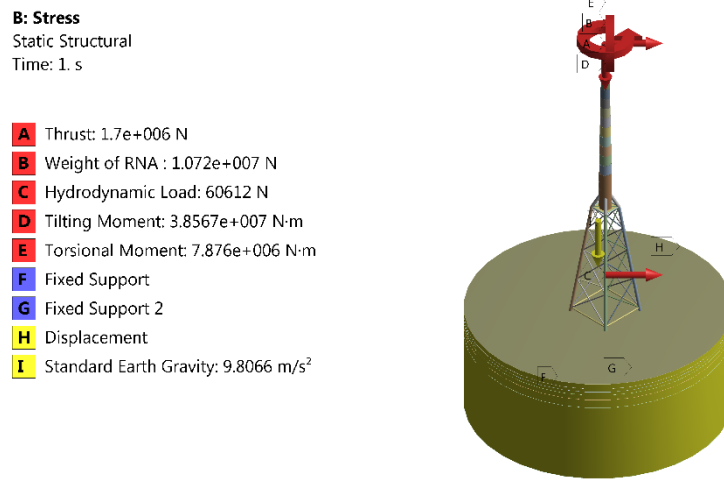


Figure 4-3. A 3D structural model with applied loads and BCs on a global scale [11].

4.3.2 Validation of the FEA model

4.3.2.1 Modal analysis

Taking into consideration the analysis of the natural/modal frequencies (Eigen-frequencies) accounting for self-weight of the entire structure, a comparison is made between the present FEA model and values found in the literature [4,10,52]. As can be observed in **Table 4-6**, from the first and second fore-aft and side-to-side modal frequencies gotten from the present FEA model, a good agreement with the values found in literature is achieved with the observed maximum percentage difference being 11.11% for the second side-side mode. Therefore, the present FEA model validation is achieved. See **Figure 4-4**.

Table 4-6: Comparison of the support structure mode frequencies with reference values.

Mode frequencies (Hz)	Present	Ref. [10,52]	%Difference
1 st side-to-side bending	0.21346	0.21320	0.12%
1 st fore-aft bending	0.22297	0.21629	2.99%
2 nd side-side bending	1.1602	1.0313	11.11%
2 nd fore-aft bending	1.5292	1.6561	-8.29%

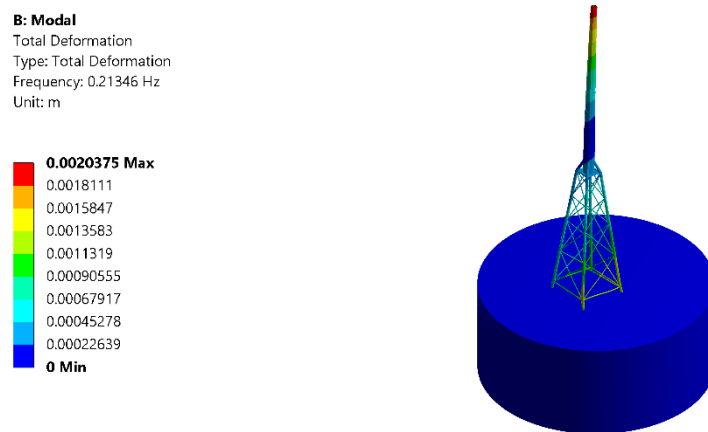


Figure 4-4. Display of the structural model's modal analysis results showing the first mode frequency [11].

4.3.2.2 Deflection in static analysis

This section of the validation aims to examine, in a static analysis, the deformation behaviour of the support structure. In the literature [4,10], the RNA weight and a 3.4 MN thrust load were applied on the tower top. The displacements at the RNA elevation and the base of the tower are compared with reference values, and results are presented in **Table 4-7**. Under the loaded condition, the deflections at the RNA and base of the tower measured with respect to the location of the RNA and centre of the base of the tower, respectively.

Table 4-7: Static deformation of the baseline 10 MW on the jacket.

Load case	Displacement at RNA			Displacement at the tower base		
Mass/ thrust	Present	Ref.	% Diff	Present	Ref. [10]	% Diff
			[10]			

RNA/ 3.4 MN	1.263 m	1.2688	-	1.6085	1.6639×10^{-1}	-
			0.46%	$\times 10^{-1}$		3.44%

As can be observed from **Table 4-7**, a good agreement is obtained when making a comparison between the present FEA model's results and the reference values reported in [10], for both deflections at the RNA and base of the tower, with an observed maximum difference of 3.44% for deflection at the base of the tower. Therefore, the validity of the present FEA model is further confirmed. See **Figure 4-5**.

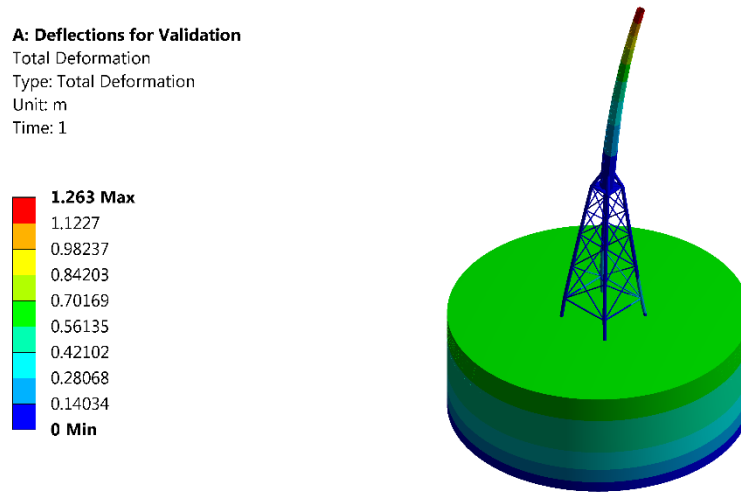


Figure 4-5. Display of results of total deformation showing the deflection at RNA level [11].

4.4 Implementation of the stochastic sensitivity analysis (SSA) on the OWT support structure

In this section, the structural reliability sensitivities of design variables for the OWT support structure is assessed considering five limit state, according to DNV-OS-J101 [37]. The fully parametric FEA model presented in Section 4.3.1 is employed in developing the FEA model taking into consideration the stochastic variables. The results are then post-processed using a non-intrusive formulation developed for the purpose of SRA and SSA in this study [11].

4.4.1 Limit state design criteria

As set-out in DNV-OS-J101, it is important to safeguard the structure against failure resulting from the violation of three limit state conditions for OWT support structures, i.e., (1) ULS (ultimate limit state), which involves designing for maximum loading-carrying

capacity (i.e. buckling and yielding stress); (2) FLS (fatigue limit state), which entails safeguarding against failure resulting from cyclic loads; and (3) SLS (serviceability limit state), which implies attaining tolerance criteria (i.e. vibrations and deflections) acceptable for standard use. Thus, in this study, the structural reliability sensitivity assessment of OWT support structures takes into consideration, five design criteria, i.e. stress (ULS), vibration (SLS), buckling (ULS), deformation (SLS) and fatigue (FLS).

4.4.1.1 Stress limit state

The ULS (ultimate limit state) defines the resistance of the structure against yielding. In terms of ultimate limit state, the maximum stress in the support structure $\sigma_{VM,max}$ should not exceed the allowable stress limits $\sigma_{VM,allow}$. The limit state function (LSF) for the von-Mises criterion can be expressed as Equation (4-10):

$$g_u(x) = \sigma_{VM,allow} - \sigma_{VM,max} \quad (4-10)$$

The allowable stress $\sigma_{VM,allow}$ can be expressed as:

$$\sigma_{VM,allow} = \frac{\sigma_y}{\gamma_m} \quad (4-11)$$

where σ_y is the yield strength, with a value of 355 MPa for steel S355; γ_m is the material safety factor, with a value of 1.1 as suggested in the DNV-OS-J101 standard [39]. Thus, the allowable stress $\sigma_{VM,allow}$ is 323 MPa.

4.4.1.2 Buckling limit state

The slenderness of the support structure coupled with the large RNA mass at the tower top, forces investigation of the risk of instability as a result of buckling. The ultimate limit state static analysis results are employed as pre-stress loads. The load multiplier L_m which is defined as the critical load divided by the present load applied, should exceed the permissible load multiplier, $L_{m,allow}$, in order to avoid failures. This design criterion is given as:

$$L_m \geq L_{m,allow} \quad (4-12)$$

According to the DNV standard [38], 1.4 is adopted as the $L_{m,allow}$ value, in this study. The LSF for buckling criteria can thus be expressed as:

$$g_b(x) = L_m - L_{m,allow} \quad (4-13)$$

4.4.1.3 Fatigue limit state

The fatigue limit state is a crucial phenomenon in OWT support structures as they are subjected to significant cyclic loads. OWT support structures normally have a long service period that may exceed 20 years. This, in conjunction with the inspection intervals, affects the reliability requirement of the jacket structural design. According to the S-N curve method, the number of loading cycles to failure, N , can be obtained by:

$$\log N = A - m \log \Delta S \quad (4-14)$$

where A and m are the intercept and the slope of the S-N curve on the log-log plot, respectively; ΔS is the stress range. The two parameters in Equation (4-14), i.e. intercept A and slope m are generally given by design standards, e.g. DNVGL-ST-0126. The LSF of fatigue reliability assessment based on the S-N curve method can be expressed as:

$$g_{f,SN} = \log N - \log N_t \quad (4-15)$$

where subscripts f and SN denote the fatigue limit state and S-N curve method respectively; N is the number of loading cycles to failure given by Equation (4-14), N_t is the number of loading cycles expected during the given design life. The number of cycles during the design life N_t may be determined as a function of rated rotor speed n_{rated} and availability η_a (98.5%) on the location chosen [29,57]. Therefore, considering the design life of 20 years, the number of cycles can be expressed as:

$$N_t = \eta_a \cdot n_{rated} \times (20[\text{year}] \times 365[\text{day/year}] \times 24[\text{hour/day}] \times 60[\text{min/hour}]) \quad (4-16)$$

The minimum fatigue safety ratio $f_{sr,min}$ must be greater than the allowable fatigue safety ratio $f_{sr,allow}$ which is equivalent to the product of one and the material PSF (Partial Safety Factor) $\gamma_{m,f}$ for fatigue:

$$f_{sr,min} \geq f_{sr,allow} \quad (4-17)$$

Since the material's PSF for Fatigue Limit State is 1.15 [38], $f_{sr,allow}$ is equivalent to 1.15. Hence, the LSF based on the fatigue safety ratio can be expressed as

$$g_{f,fsr} = f_{sr,allow} - f_{sr,min} \quad (4-18)$$

4.4.1.4 Deformation limit state

Excessive deflections influence the serviceability of OWT support structures and therefore, should be avoided. The allowable deflection d_{allow} must exceed the maximum deflection d_{max} to ensure overall structural stability. This can be expressed as:

$$d_{allow} > d_{max} \quad (4-19)$$

The LSF for deflection criteria can be expressed as:

$$g_d(x) = d_{allow} - d_{max} \quad (4-20)$$

The allowable deflection d_{allow} is given by the following empirical equation as suggested by DNV-OS-J101 [39]:

$$d_{allow} = \frac{L}{200} \quad (4-21)$$

Where L is the height of the jacket.

4.4.1.5 Vibration limit state

One of the critical concerns for offshore wind turbines on jacket support structures is the resonance phenomena. In order to design the structure against such phenomena, the first eigenfrequency f_{1st} of the OWT support structure must be separated sufficiently from rotor induced frequencies f_{1P} and blade-passing frequency f_{3P} . A soft-stiff structural design whereby the modal frequency lies between the rotor upper bound f_{1P} (f_{1PH}) and lower bound f_{3P} (f_{3PL}) frequencies are presently the most usual and cost-effective design for jacket. Therefore the resonance constraint could be expressed by [2,4,11,29]:

$$f_{1PH} \leq f_{1st} \leq f_{3PL} \quad (4-22)$$

$$0.133 \leq f_{1st} \leq 0.233 \quad (4-23)$$

The LSF for the resonance criterion at the rotor lower bound can thus be expressed as

$$g_r(x) = f_{1st} - f_{1PH} \quad (4-24)$$

While at the rotor upper bound,

$$g_r(x) = f_{3PL} - f_{1st} \quad (4-25)$$

The lower g-function value is chosen to be applied in the reliability assessment.

4.4.2 A non-intrusive formulation

The FEA model is used here to perform a series of FEA simulations on the structure with the help of design of experiments (DoE) module in ANSYS (in the ANSYS DesignXplorer© facility). From the simulations executed on the ANSYS DoE tool, the results are imported into a MATLAB code that has been developed for response surface modelling via the use of multivariate polynomial regression (MPR). In brief, the analysis starts from the definition of the system, associated limit state and determination of which variables will be considered as stochastic in the analysis. Next, a number of FEA simulations is executed by varying inputs and recording outputs related to limit states in order to map the response of the structure in the domain of stochastic variables. An appropriate method is then selected in order to approximate the response of the system and link output variables with global inputs. Finally, the SSA is carried out employing the iterative FORM algorithm. A flow chart of the non-intrusive formulation developed for this study is presented in **Figure 4-6**.

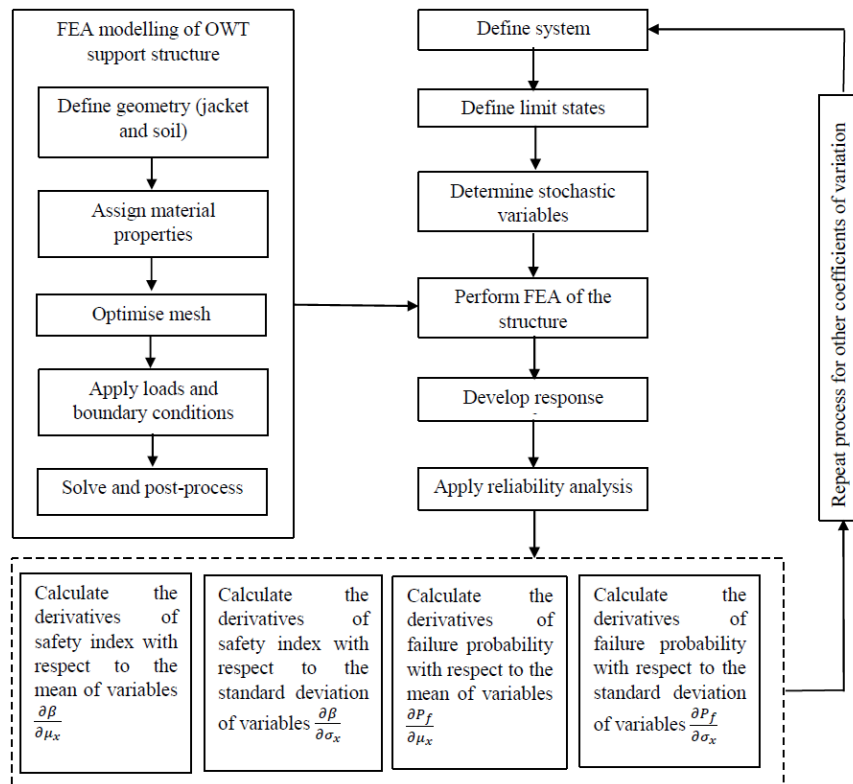


Figure 4-6. Flow chart of non-intrusive formulation with SSA.

4.4.2.1 Multivariate regression

Regression analysis is a statistical process for establishing the relationship between a dependent variable and one or more independent variables. Taking the Ultimate Limit State (ULS) stress constraint as an example, the dependent variable (i.e. maximum von-Mises stress, $\sigma_{VM,max}$) and independent variables (i.e. thrust load x_1 , tilting moment x_2 , torsional moment x_3 , total hydrodynamic load (wave) x_4 , soil 1 young's modulus x_5 , soil 2 young's modulus x_6 , soil 3 young's modulus x_7 and weight of RNA x_8) are assumed to have the following functional relationship:

$$\sigma_{VM,max} = [a_0, a_1, \dots, a_{16}] \begin{bmatrix} 1 \\ x_1 \\ x_1^2 \\ \cdot \\ \cdot \\ \cdot \\ x_8 \\ x_8^2 \end{bmatrix} \quad (4-26)$$

$(a_0, a_1, \dots, a_{16})$ in Equation (4-26) are $2n + 1$ regression coefficients for a quadratic regression. For other types of limit states, i.e. deformation, buckling, vibration and fatigue, expressions similar to Equation (4-26) can be derived. Multivariate regression can be used to obtain the regression coefficients for different limit states [58]. The response surfaces for every single component can be produced, but the results for the most critical will be presented here.

In this study, 300 stochastic FEA simulations were performed, obtaining 300 sample sets. The R-square values obtained in the multivariate polynomial regression (MPR) analysis performed in all cases were consistently higher than 0.95, which indicates the success of the MPR.

4.4.3 SSA

Consider the performance function of a component is $G(b, x)$, where b is the design variables, and x is the vector of random variables. When FORM is employed for reliability assessment, the probability of failure is calculated as follows [59]:

$$P_f = 1 - \Phi(\beta) \quad (4-27)$$

Where β is the reliability index (RI) and $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution. Thus, the sensitivity of failure probability with respect to design variable $\left(\frac{\partial P_f}{\partial b}\right)$ can be expressed as:

$$\frac{\partial P_f}{\partial b} = -\phi(\beta) \frac{\partial \beta}{\partial b} \quad (4-28)$$

Where $\frac{\partial \beta}{\partial b}$ is the derivative of the safety index with respect to design variable (b) and $\phi(\cdot)$ is the density function of standard normal distribution. One of the most crucial issues in the approximation of sensitivity derivatives is the type of distribution function governing the variables [60]. To address this issue, the input variables are transformed to the normal standard space using the change of variable using Rosenblatt transformation [60,61]. Then, the variables are entered into the algorithm as a vector of equivalent normal variables. This technique allows the algorithm to accommodate a wide range of probabilistic distribution functions. For this purpose, irrespective of the type of distribution function governing the random variables involved, the standard normal form of variables (U), which is widely applied in reliability analysis, is expressed as [62]:

$$U = \frac{x - \mu_x}{\sigma_x} = \{U_1, U_2, \dots, U_n\}^T \quad (4-29)$$

Where μ_x and σ_x are the mean and standard deviation of random variables, respectively. Hence, the performance function can be rewritten based on standard normal variables in the form of $G(b, U)$. According to [63] the derivative of β with respect to design variable (b), as a general case, can be expressed as:

$$\frac{\partial \beta}{\partial b} = \lambda \frac{\partial G}{\partial U} \frac{\partial U}{\partial b} \quad (4-30)$$

Where λ , the Lagrange multiplier, can be calculated as:

$$\lambda = -\frac{1}{\left|\frac{\partial G}{\partial U}\right|} \quad (4-31)$$

Meanwhile, two scenarios are considered here:

- The design variable is the mean of the random variables
- The design variable is the standard deviation of random variables

These two cases are examined separately in the next sub-sections.

4.4.3.1 Reliability sensitivity with respect to mean

Taking the mean of the random variables as the design variable, b , Equation (4-30) can be expressed as:

$$\frac{\partial \beta}{\partial \mu_x} = - \frac{1}{\left| \frac{\partial G}{\partial U} \right|} \frac{\partial G}{\partial U} \frac{\partial U}{\partial \mu_x} \quad (4-32)$$

The derivative $\frac{\partial U}{\partial \mu_x}$ can be calculated from Equation (4-29):

$$\frac{\partial U}{\partial \mu_x} = \frac{\partial}{\partial \mu_x} \left(\frac{x - \mu_x}{\sigma_x} \right) = - \frac{1}{\sigma_x} \quad (4-33)$$

Employing the chain rule, the derivative $\frac{\partial G}{\partial U}$ can be expanded as:

$$\frac{\partial G}{\partial U} = \frac{\partial G}{\partial x} \frac{\partial x}{\partial U} = \frac{\partial G}{\partial x} \sigma_x \quad (4-34)$$

Substituting Equations (4-33) and (4-34) into Equation (4-32), $\frac{\partial \beta}{\partial \mu_x}$ can be simplified as:

$$\frac{\partial \beta}{\partial \mu_x} = - \frac{\frac{\partial G}{\partial x} \sigma_x}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \left(- \frac{1}{\sigma_x} \right) = \frac{\frac{\partial G}{\partial x}}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \quad (4-35)$$

4.4.3.2 Reliability sensitivity with respect to standard deviation

In this section, taking standard deviation of random variables as design variable, b , Equation (4-30) is rewritten as:

$$\frac{\partial \beta}{\partial \sigma_x} = - \frac{1}{\left| \frac{\partial G}{\partial U} \right|} \frac{\partial G}{\partial U} \frac{\partial U}{\partial \sigma_x} \quad (4-36)$$

Using Equation (4-29), the derivative $\frac{\partial U}{\partial \sigma_x}$ is calculated as:

$$\frac{\partial U}{\partial \sigma_x} = - \frac{\partial}{\partial \sigma_x} \left(\frac{x - \mu_x}{\sigma_x} \right) = - \frac{x - \mu_x}{\sigma_x^2} \quad (4-37)$$

Substituting Equations (4-34) and (4-37) into Equation (4-36), $\frac{\partial \beta}{\partial \sigma_x}$ is obtained as:

$$\frac{\partial \beta}{\partial \sigma_x} = -\frac{\frac{\partial G}{\partial x} \sigma_x}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \times \left(-\frac{x - \mu_x}{\sigma_x^2} \right) = \frac{\frac{\partial G}{\partial x}}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \frac{x - \mu_x}{\sigma_x} \quad (4-38)$$

In furtherance of the calculation, a RI should be defined. By definition, RI is the minimum distance from the origin to the failure surface. Coordinates of the point on the failure surface at a distance shortest to the origin can be expressed as:

$$U^* = \beta \cos(\theta_u) \quad (4-39)$$

where $\cos(\theta_u)$ (or $\cos(\theta_x)$) denotes the direction cosine of the unit outward normal vector (also known as the sensitivity vector (α_x)) and is determined from [25,64]:

$$\cos(\theta_x) = \alpha_x = -\frac{\frac{\partial G}{\partial x} \sigma_x}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \quad (4-40)$$

Substituting Equation (4-40) into Equation (4-39), U^* is calculated as:

$$U^* = -\beta \frac{\frac{\partial G}{\partial x} \sigma_x}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \quad (4-41)$$

Now, if the term $\frac{(x-\mu_x)}{\sigma_x}$ in Equation (4-38) is replaced by U^* , Equation (4-42) is obtained:

$$\frac{\partial \beta}{\partial \sigma_x} = \frac{\frac{\partial G}{\partial x}}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \times \left(-\beta \frac{\frac{\partial G}{\partial x} \sigma_x}{\left| \frac{\partial G}{\partial x} \sigma_x \right|} \right) = \frac{\left(\frac{\partial G}{\partial x} \right)^2 \sigma_x}{\left| \frac{\partial G}{\partial x} \sigma_x \right|^2} \beta \quad (4-42)$$

Sensitivities of failure probability with respect to the mean and standard deviations of the variables involved can be calculated according to Equation (4-28).

The above is used in developing an algorithm coded in MATLAB, which is developed for the purpose of this study. Initially, in the stochastic parametric FEA model, the loads were applied to the structure in an uncoupled way ignoring fluid-structure interactions and the environmental parameters were used in evaluating the magnitude and distribution of the loads. In the present study, these parameters are reintroduced into the stochastic model and the equations incorporated in the LSF model of the FORM on implementation of the SSA.

The algorithm used in [18] employed the Advanced First Order Second Moment Method (AFOSM) which have a number of limitations such as not being suitable for highly nonlinear limit states. To address this problem, the iterative FORM algorithm (successfully validated against the literature [11]) has been incorporated into the SSA in this study. Better beta index, as well as sensitivity estimates, were obtained, which offers another solution to a drawback of the AFOSM.

4.4.4 Stochastic variables

The nine (9) stochastic variables considered in this study are presented in **Table 4-8**. The coefficient of variation (COV) of all stochastic variables was assumed to vary from 0.02 to 0.2 by step increase of 0.02 [65] except for the variables having Weibull distribution [11].

Table 4-8: Stochastic variables.

Description	Mean		Distribution types [11,33,65–68]
	Ultimate load case	Fatigue load case	
Wind speed, V (m/s)	55	20	Weibull
Tilting moment, M_{Tilt} (kN.m)	38,567	3687	Normal
Torsional moment, $M_{Torsion}$ (kN.m)	7876	3483	Normal
Wave height, H (m)	17.48	9.4	Weibull
Young's modulus of soil stratum 1, E_{s1} (MPa)		30	Normal
Young's modulus of soil stratum 2, E_{s2} (MPa)		50	
Young's modulus of soil stratum 3, E_{s3} (MPa)		80	
RNA Weight, W_{RNA} (kg)	1,072,000		Normal
Peak wave period, T (s)	10.8	14	Lognormal

4.4.5 FORM (First Order Reliability Method)

Having obtained the performance function from regression, the FORM is used to calculate the RI β . The FORM Hasofer and Lind algorithm is summarised below [11,69].

1. Define the performance function for different limit states. For example, in the ULS (stress constraint) case Equation (4-26) is substituted into Equation (4-10) which yields the following performance function:

$$g_u(x) = \sigma_{VM,allow} - [a_0, a_1, \dots, a_{18}] \begin{bmatrix} 1 \\ x_1 \\ x_1^2 \\ \cdot \\ \cdot \\ x_9 \\ x_9^2 \end{bmatrix} \quad (4-43)$$

2. Set the mean value point as an initial design point, i.e. $x_{i,k} = \mu_{x_i}$ $i = 1, 2, \dots, n$, and calculate the gradients $\nabla g(X_k)$ of the limit-state function at this design point. Here, $x_{i,k}$ refers to the i^{th} element in the vector X_k of the k^{th} iteration, and μ_{x_i} is the mean value of the i^{th} element;
3. Calculate the initial RI β using the mean-value method, i.e. $\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}}$ and its direction cosine α .

$$\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}} = \frac{g(\mu_X)}{\left[\sum_{i=1}^n \left(\frac{\partial g(\mu_X)}{\partial x_i} \right)^2 \cdot \sigma_{x_i}^2 \right]^{\frac{1}{2}}} \quad (4-44)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (4-45)$$

4. Compute a new design point X_k and U_k , function value, and gradients at this new design point.

$$x_{i,k} = \mu_{x_i} + \beta \sigma_{x_i} \alpha_i \quad (4-46)$$

$$u_{i,k} = \frac{x_{i,k} - \mu_{x_i}}{\sigma_{x_i}} \quad (4-47)$$

5. Compute the RI β and direction cosine α_i using Equations (4-46) and (4-47), respectively.

$$\beta = \frac{g(U^*) - \sum_{i=1}^n \frac{\partial g(U)}{\partial x_i} \sigma_{x_i} u_i^*}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(U^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (4-48)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (4-49)$$

Repeat steps 4) to 5) until convergence of the RI β is achieved.

4.5 Results and discussion

A key output of the SRA is a set of failure probabilities and reliability indices for the analysed limit states. In this section, SRA of the OWT support structure was performed, and the effect of the structural response on the RI as the CoV is varied is studied, and depicted in **Figure 4-7a-e**. It can be inferred that higher safety indices were recorded for the buckling and deformation limit states. For the buckling limit state convergence of the RI was not achieved for CoV values 0.02-0.06. The RI varied considerably for the vibration limit state, which is an indication that variability in the uncertainties has a drastic influence on the safety index. While for the fatigue and deformation limit states, the RI varied slightly and hence, an indication that variability in CoV has no drastic influence on the safety index. For all limit states considered the RI generally decreased with increase in the CoV, which implies negative correlation.

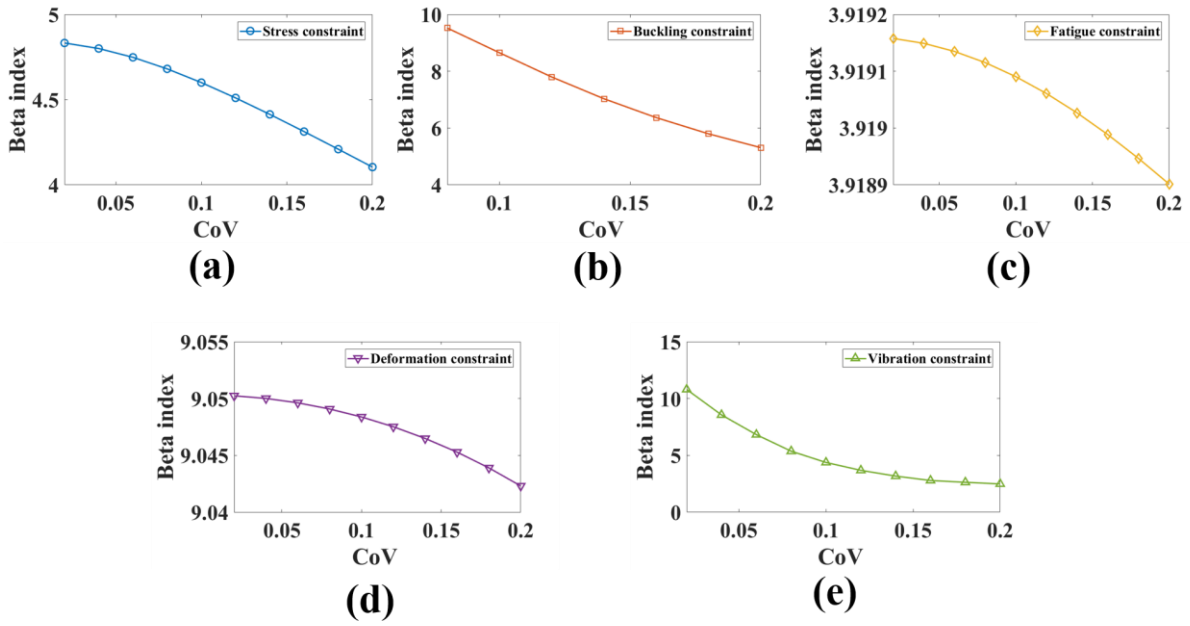


Figure 4-7: Variation of the reliability indices with CoV: (a) stress (b) buckling (c) fatigue (d) deformation (e) vibration limit state

The reliability sensitivities based on the hyper-plane under different variation coefficients are depicted in **Figure 4-8-Figure 4-12**. From the results in each Figure, it can be concluded that the reliability sensitivity of each random variable is sensitive to its distribution parameters and the sensitivities between variables are comparable. The reliability sensitivity is applied in determining the rate of change in the reliability or failure probability due to changes in the variables, such as means and standard deviations, of distributions. The dimensionless sensitivities were computed to investigate the degree of influence of the mean and standard deviation values for each stochastic variable on the reliability of the structure [18,25].

In **Figure 4-8a**, for the stress limit state, the means of the design variables: H , T , and E_{Soil3} showed a positive correlation with the RI i.e., the RI increased with the means of these parameters, so the structure tended to be more reliable. Meanwhile, the mean of variables: V , M_{Tilt} , $M_{Torsional}$, E_{Soil1} , E_{Soil2} , and W_{RNA} showed a negative correlation (due to the negative value of $\frac{\partial \beta}{\partial \mu}$); i.e., the RI decreased as the means of these parameters increased. For all limit states studied, the standard deviations of all the design variables: V , H , T , $M_{Torsional}$, E_{Soil1} , W_{RNA} , M_{Tilt} , E_{Soil2} , and E_{Soil3} showed negative correlation

with the RI; i.e., the RI decreased as the standard deviations of these parameters increased. For example, the stress limit state see **Figure 4-8b**.

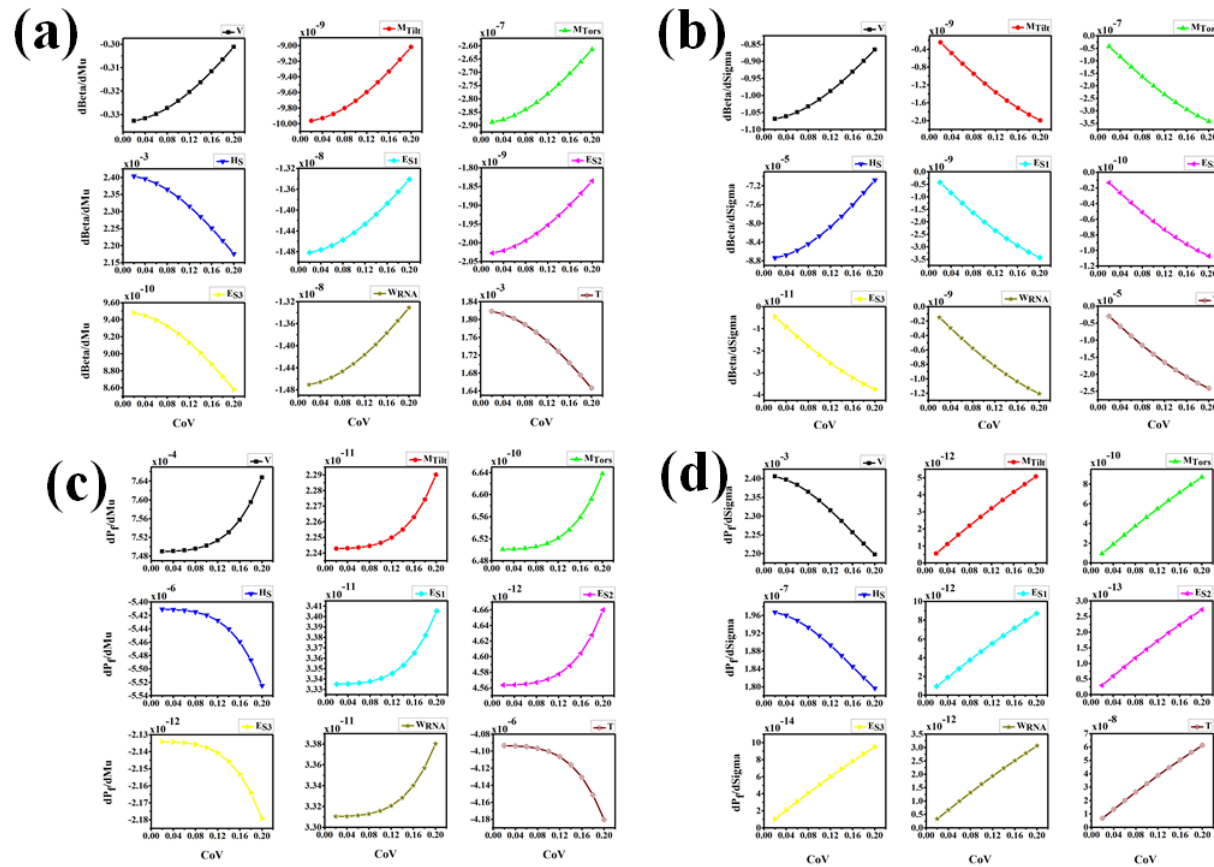


Figure 4-8. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c)POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the stress limit states and their variation with CoV.

In **Figure 4-9a**, for the buckling limit state, the means of the design variables: H , T , M_{Tilt} , E_{Soil1} , E_{Soil2} and E_{Soil3} showed a positive correlation with the RI. Meanwhile, the mean of variables: V , $M_{Torsional}$, and W_{RNA} showed a negative correlation. In the **Figure 4-10a**, for the fatigue limit state, the means of the design variables: H , and T showed a positive correlation with the RI. Meanwhile, the mean of variables: V , $M_{Torsional}$, E_{Soil1} , W_{RNA} , M_{Tilt} , E_{Soil3} and E_{Soil2} showed a negative correlation. In the **Figure 4-11a**, for the deformation limit state, the means of the design variables: H , T , E_{Soil1} , and E_{Soil3} showed a positive correlation with the RI i.e., the RI increased with the means of these parameters, so the structure tended to be more reliable. Meanwhile, the mean of variables: V , M_{Tilt} , $M_{Torsional}$, W_{RNA} , and E_{Soil2} showed a negative correlation. In the **Figure 4-12a**, for the vibration limit state, the means of the design variables: H , T , $M_{Torsional}$, E_{Soil1} , E_{Soil2} and E_{Soil3} showed a positive correlation with the RI i.e., the RI increased with the means of these parameters, so the structure tended to be more reliable. Meanwhile, the mean of variables: V , M_{Tilt} , and W_{RNA} showed a negative correlation; i.e., the RI decreased as the means of these parameters increased.

In addition from **Figure 4-8a**, it can be inferred that as the degree of uncertainties increases (i.e. as the value of CoV increases) the reliability sensitivity with respect to the mean increases for all the design variables considered (i.e. positive correlation) except for the variables H_s , E_{Soil3} and T which shows negative correlation. This assessment should not be confused with the one performed in the foregoing as here the reliability sensitivity is used, which is different from the RI. The assessment is also carried out for the PoF sensitivity as presented in **Figure 4-8c**, and as can be observed, a similar trend with that of the reliability sensitivity as discussed earlier is obtained. The same similarities can be depicted from **Figure 4-8b and d** for the reliability sensitivities with respect to the standard deviation.

In **Figure 4-8a and c**, considering the stress limit state, the order of magnitude of sensitivities with respect to change in mean values, from highest to the lowest are as follows: V , H , T , $M_{Torsional}$, E_{Soil1} , W_{RNA} , M_{Tilt} , E_{Soil2} , and E_{Soil3} . While in **Figure 4-8b and d**, which is with respect to change in standard deviation, are as follows: V , T , H , $M_{Torsional}$, E_{Soil1} , M_{Tilt} , W_{RNA} , E_{Soil2} , and E_{Soil3} . From **Figure 4-9 a and c**, considering the buckling limit state, the order of magnitude of sensitivities with respect to change in mean values, from highest to the lowest are as follows: V , H , T , W_{RNA} , $M_{Torsional}$, E_{Soil1} , E_{Soil3} , M_{Tilt} , and E_{Soil2} . While in **Figure 4-9b and d**, which is with respect to change in

standard deviation, are as follows: V , H , T , W_{RNA} , $M_{Torsional}$, E_{Soil1} , E_{Soil3} , M_{Tilt} , and E_{Soil2} . From **Figure 4-10a and c** considering the fatigue limit state, the order of magnitude of sensitivities with respect to change in mean values, are as follows: V , H , T , W_{RNA} , M_{Tilt} , $M_{Torsional}$, E_{Soil2} , E_{Soil1} , and E_{Soil3} . While for **Figure 4-10b and d**, which is with respect to change in standard deviation, are as follows: V , T , W_{RNA} , H , M_{Tilt} , $M_{Torsional}$, E_{Soil2} , E_{Soil3} , and E_{Soil1} . From the foregoing, it can be inferred that the reliability is more sensitive to variable V , the wind speed, than to the other variables in the system considering the stress and buckling (ULS), as well as the fatigue limit state (FLS). As can be observed, for the ULS and FLS, the wave height and period are, in addition to the wind speed, the main driving factors. In other words, the hydrodynamics load effects are only secondary compared to the wind load effect. Therefore, in reliability-based design for the ULS and FLS, we need to pay more attention to V than other variables.

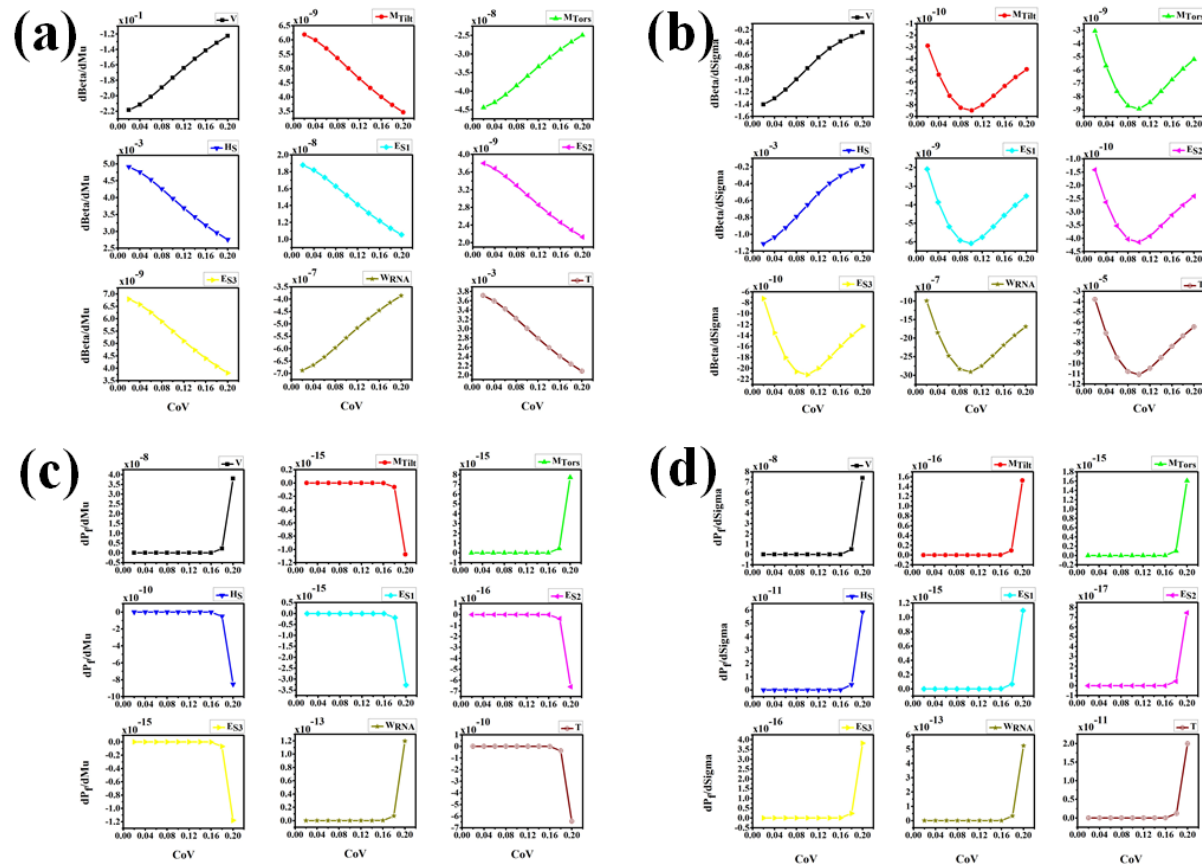


Figure 4-9. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c) POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the buckling limit state and their variation with CoV.

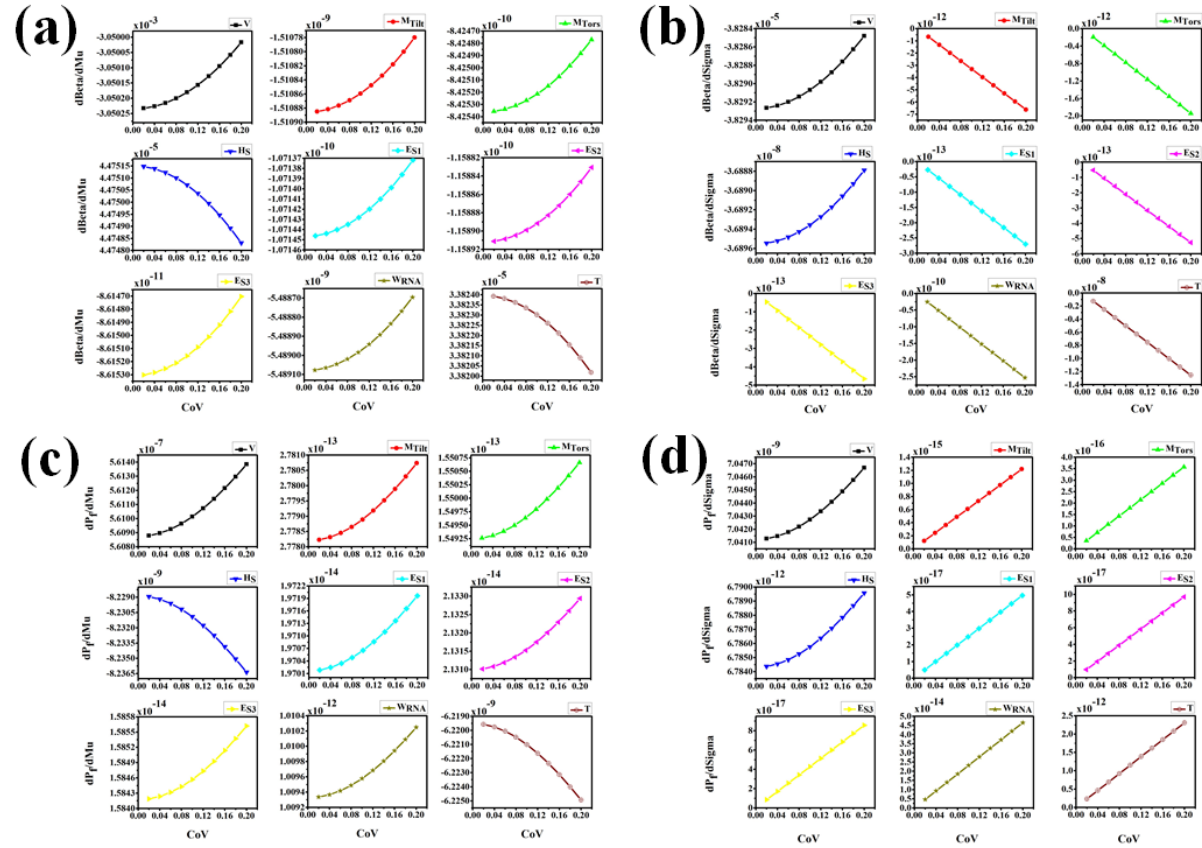


Figure 4-10. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c)POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ)for the fatigue limit state and their variation with CoV.

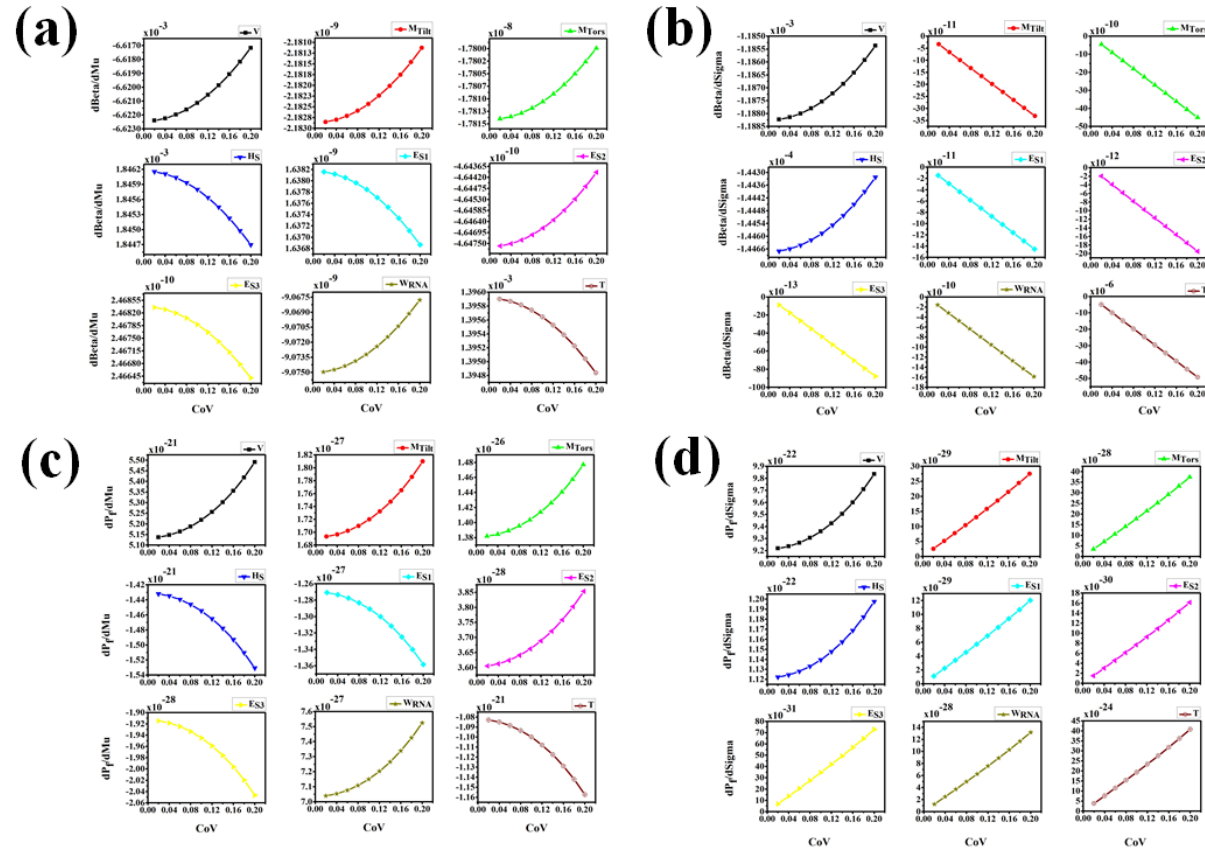


Figure 4-11. Sensitivities of: (a) beta index to parameter means (μ) (b)POF to parameter standard deviations (σ) (c)POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the deformation limit state and their variation with CoV.

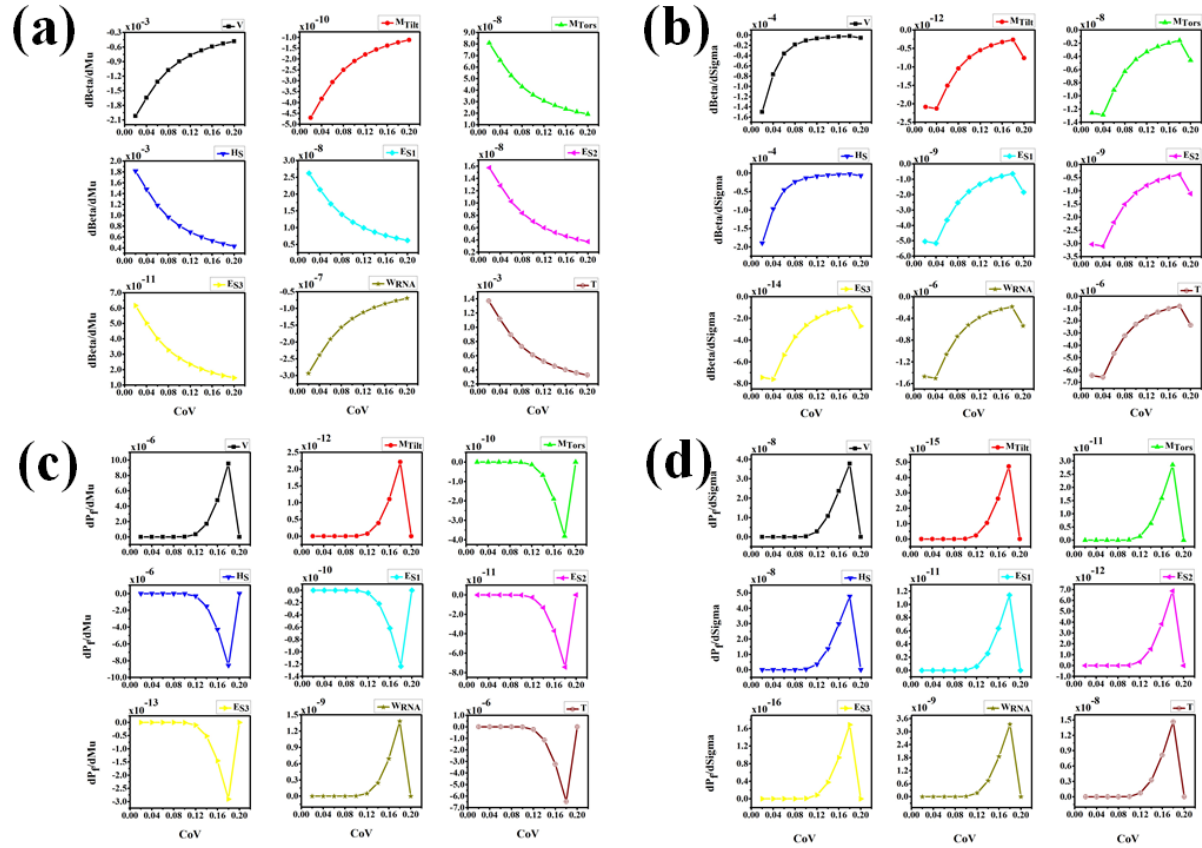


Figure 4-12. Sensitivities of: (a) beta index to the parameter means (μ) (b)POF to parameter standard deviations (σ) (c)POF to parameter means (μ) to parameter standard deviations (σ) and (d) POF to parameter standard deviations (σ) for the vibration limit state and their variation with CoV.

Furthermore, in **Figure 4-11a and c**, for the deformation limit state, the order of magnitude of sensitivities with respect to the change in mean values are as follows: V , H , T , M_{Tors} , W_{RNA} , M_{Tilt} , E_{Soil1} , E_{Soil2} , and E_{Soil3} . While from **Figure 4-11b and d**, which is with respect to change in deviation are as follows: T , V , H , M_{Tors} , W_{RNA} , M_{Tilt} , E_{Soil1} , E_{Soil2} , and E_{Soil3} . From **Figure 4-12a and c**, considering the vibration limit state, the order of magnitude of sensitivities with respect to change in mean values, are as follows: V , H , T , W_{Self} , $M_{Torsional}$, E_{Soil1} , E_{Soil2} , M_{Tilt} , and E_{Soil3} . While in **Figure 4-12b and d**, which is with respect to change in deviation, are as follows: H , V , T , W_{Self} , $M_{Torsional}$, E_{Soil1} , E_{Soil2} , M_{Tilt} , and E_{Soil3} . From the foregoing, it can be inferred that there are inconsistencies in the order of magnitude of the reliability sensitivities to design variables for the different cases (i.e. in $\frac{\partial \beta}{\partial \mu}$, and $\frac{\partial \beta}{\partial \sigma}$) considering each limit states. Hence, the design variable with the highest impact cannot be clearly distinguished from the rest. However, V , T , and H which are hydrodynamic and wind parameters are dominant, and are therefore considered as the key design variables in reliability based design optimisation of the system considering the SLS criteria.

The percentage influence of each design variables on the reliability corresponding to the limit states considered is presented in **Table 4-9-Table 4-13**.

Table 4-9: Percentage (%) influence of design parameters on reliability corresponding to the stress limit state.

Variables	$\frac{d\beta}{d\mu}$	$\frac{d\beta}{d\sigma}$	$\frac{dP_f}{d\mu}$	$\frac{dP_f}{d\sigma}$
V	9.87E+01	1.00E+02	9.87E+01	1.00E+02
M_{Tilt}	2.96E-06	8.51E-07	2.96E-06	1.26E-06
M_{Tors}	8.57E-05	1.46E-04	8.57E-05	2.16E-04
H_s	7.13E-01	8.17E-03	7.13E-01	4.91E-03
E_{S1}	4.40E-06	1.46E-06	4.40E-06	2.16E-06
E_{S2}	6.01E-07	4.56E-08	6.02E-07	6.75E-08
E_{S3}	2.81E-07	1.60E-08	2.81E-07	2.36E-08
W_{RNA}	4.36E-06	5.14E-07	4.36E-06	7.60E-07
T	5.39E-01	1.03E-02	5.43E-01	1.52E-02

Table 4-10: Percentage (%) influence of design parameters on reliability corresponding to the buckling limit state.

Variables	$\frac{d\beta}{d\mu}$	$\frac{d\beta}{d\sigma}$	$\frac{dP_f}{d\mu}$	$\frac{dP_f}{d\sigma}$
-----------	-----------------------	--------------------------	---------------------	------------------------

V	9.62E+01	9.99E+01	9.62E+01	9.99E+01
M_{Tilt}	2.72E-06	5.20E-09	2.72E-06	2.05E-07
M_{Tors}	1.96E-05	5.48E-08	1.96E-05	2.16E-06
H_s	2.16E+00	7.91E-02	2.16E+00	7.91E-02
E_{S1}	8.28E-06	3.73E-08	8.28E-06	1.47E-06
E_{S2}	1.67E-06	2.54E-09	1.67E-06	1.00E-07
E_{S3}	2.99E-06	1.30E-08	2.99E-06	5.12E-07
W_{RNA}	3.03E-04	1.78E-05	3.03E-04	7.03E-04
T	1.64E+00	6.80E-04	1.64E+00	2.68E-02

Table 4-11: Percentage (%) influence of design parameters on reliability corresponding to the fatigue limits state.

Variables	$\frac{d\beta}{d\mu}$	$\frac{d\beta}{d\sigma}$	$\frac{dP_f}{d\mu}$	$\frac{dP_f}{d\sigma}$
V	9.69E+01	4.06E+01	9.75E+01	7.20E+01
M_{Tilt}	4.70E-05	3.07E-02	4.84E-05	1.44E-02
M_{Tors}	2.63E-05	9.00E-03	2.70E-05	4.23E-03
H_s	1.42E+00	3.91E-02	1.43E+00	6.94E-02
E_{S1}	3.34E-06	1.25E-03	3.43E-06	5.87E-04
E_{S2}	3.61E-06	2.44E-03	3.71E-06	1.15E-03
E_{S3}	2.68E-06	2.16E-03	2.76E-06	1.01E-03
W_{RNA}	1.71E-04	1.17E+00	1.76E-04	5.50E-01
T	1.68E+00	5.82E+01	1.03E+00	2.73E+01

Table 4-12: Percentage (%) influence of design parameters on reliability corresponding to the deformation limit state.

Variables	$\frac{d\beta}{d\mu}$	$\frac{d\beta}{d\sigma}$	$\frac{dP_f}{d\mu}$	$\frac{dP_f}{d\sigma}$
V	6.75E+01	6.01E+00	6.71E+01	5.80E+01
M_{Tilt}	2.22E-05	6.29E-04	2.21E-05	2.35E-04
M_{Tors}	1.81E-04	8.55E-03	1.81E-04	3.20E-03
H_s	1.88E+01	7.32E-01	1.87E+01	7.07E+00
E_{S1}	1.67E-05	2.75E-04	1.66E-05	1.03E-04
E_{S2}	4.73E-06	3.69E-05	4.71E-06	1.38E-05
E_{S3}	2.51E-06	1.67E-05	2.50E-06	6.23E-06
W_{RNA}	9.25E-05	3.01E-03	9.20E-05	1.13E-03

T	1.37E+01	9.32E+01	1.42E+01	3.49E+01
-----	----------	----------	----------	----------

Table 4-13: Percentage (%) influence of design parameters on reliability corresponding to the vibration limit state.

Variables	$\frac{d\beta}{d\mu}$	$\frac{d\beta}{d\sigma}$	$\frac{dP_f}{d\mu}$	$\frac{dP_f}{d\sigma}$
V	3.88E+01	4.30E+01	3.88E+01	3.68E+01
M_{Tilt}	9.02E-06	6.96E-07	9.02E-06	4.37E-06
M_{Tors}	1.55E-03	4.21E-03	1.55E-03	2.64E-02
H_s	3.49E+01	5.44E+01	3.49E+01	4.65E+01
E_{S1}	5.03E-04	1.68E-03	5.03E-04	1.06E-02
E_{S2}	3.02E-04	1.01E-03	3.02E-04	6.36E-03
E_{S3}	1.18E-06	2.48E-08	1.18E-06	1.56E-07
W_{Self}	5.62E-03	4.91E-01	5.62E-03	3.08E+00
T	2.63E+01	2.15E+00	2.63E+01	1.35E+01

The sensitivity analyses can be used to improve estimated reliability by identifying the variables that their CoV have the highest influence on estimated reliability. The estimated reliability is improved by reducing the epistemic uncertainty of those variables through, i.e. collecting more data to enable choosing appropriate probability distribution which better estimates the variables, and in turn lead to a reduction in the values of standard deviation or CoV. In other words, it is important to collect appropriate information for wind variation across the site. This should account for the performance of each unit (including factors such as wake effects) as this can significantly alter performance and reliability across the wind farm. For instance, from **Figure 4-9** and **Figure 4-12**, the POF sensitivities recorded a spike in values as the CoV tend towards higher magnitudes. These behaviours show that the offshore structure studied herein is highly nonlinear, a typical characteristic of complex structures. This further supports the claim that emphases should be laid on acquiring highly accurate data on such structures in order to reduce the inherent uncertainties.

Additionally, a case study is performed to investigate the effects of correlation between the design stochastic variables on the reliability indices of the different limit states considered. The variables considered correlated are the wind speed, tilting moment and torsional moment, and the significant wave height and wave period. The calculated reliability indices for the different limit states as they vary with the variation in percentage correlation (0-90%) is depicted in **Figure 4-13 a-e**. As can be observed, as the correlation between the wind parameters as well as between the hydrodynamic parameters increases the reliability indices calculated

decreases. Also, the RI is sensitive to the percentage correlation, and the ULS is calculated to be the highest. Therefore, during design for the ULS, the correlation between the different variables should be taken into account.

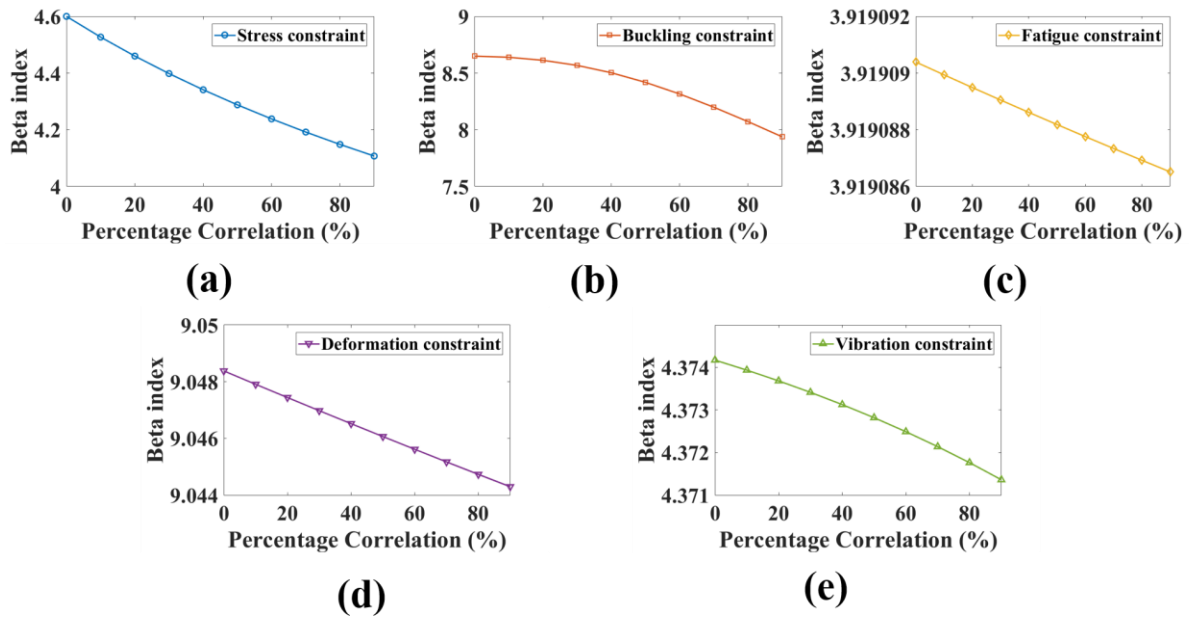


Figure 4-13. Variation of reliability indices with change in percentage correlation for: (a) the stress (b) buckling (c) fatigue (d) deformation (e) vibration limit states.

4.6 Conclusion

This paper presented a methodology for the sensitivity assessment of the inherent stochastic variables often imposed on typical complex OWT support structures due to harsh environments. Sensitivity refers to the most critical variables that can radically impact on the reliability performance of the structure. The reliability of the structure can be improved by reducing the uncertainties by virtue of statistical parameters for the design variables having an insignificant impact on the reliability. The proposed method was used to investigate the influence of several stochastic variables on the reliability of the structure. This proposed non-intrusive method involves a sequence of steps which involves incorporating responses obtained from parametric FEA with the iterative FORM-based SSA via multivariate quadratic polynomial regression for the approximation of more reliable levels of sensitivities with respect to the various design variables. The SSA adopts an approach which determines the search direction based on function gradients. For the ULS, the influence of the most influencing variable, the wind speed, V on the reliability is between 94 and 98% higher than the second most influencing variable, the wave height, H_s considering sensitivities with respect to the

mean, and 99% considering sensitivities with respect to standard deviation. For the FLS, the influence of the most, V is 95% higher than the second, T considering sensitivities to the mean, and 45% considering sensitivities to the standard deviations. While for the SLS, the influence of the most, V is between 4% and 49% higher than the second hydrodynamic effects considering sensitivities to the mean, and the most hydrodynamic effects higher than V with between 33% and 11% considering sensitivities to standard deviation. In this study, it is revealed that the key design variables to be considered for reliability-based design optimization (RBDO) are the wind speed, significant wave height and peak wave period for all design limit states studied. Moreover, it was concluded that the influence of weight, torsional moments resulting from aerodynamic loads as well as that of soil-structure interactions of the first soil strata is not insignificant for all the considered limit states. The influence of the other design variables considered stochastic in this study: the significance of second and third soil strata, as well as the tilting moment, can be considered negligible. Also, the study ascertained how important the correlation between design variables are, to the reliability of the OWT support structure.

Acknowledgements

Author Abdulhakim A. Shittu would like to acknowledge the Petroleum Technology Development Fund (PTDF), Nigeria, for doctoral study scholarship, award number: PTDF/ED/PHD/SAA/1142/17.

References

1. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative study of structural reliability assessment methods for offshore wind turbine jacket support structures. *Applied Sciences* (Switzerland). 2020; 10(3). Available at: DOI:10.3390/app10030860
2. Zwick D. *Simulation and Optimization in Offshore Wind Turbine Structural Analysis*. NTNU-Trondheim Norwegian University of Science and Technology; 2015.
3. Kolios AJ., Rodriguez-Tsouroukdissian A., Salonitis K. Multi-criteria decision analysis of offshore wind turbines support structures under stochastic inputs. *Ships and Offshore Structures*. Taylor & Francis; 2016; 11(1): 38–49. Available at: DOI:10.1080/17445302.2014.961295
4. Damiani R., Song H. A Jacket Sizing Tool for Offshore Wind Turbines within the Systems Engineering Initiative. *Offshore Technology Conference*. 2013; : 27. Available at: DOI:10.4043/24140-MS
5. Coccon MN., Song J., Ok SY., Galvanetto U. A new approach to system reliability analysis of offshore structures using dominant failure modes identified by selective searching technique. *KSCE Journal of Civil Engineering*. 2017; 21(6): 2360–2372. Available at: DOI:10.1007/s12205-016-1192-z
6. Shittu AA., Mehmanparast A., Shafiee M., Kolios A., Hart P., Pilario KE. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting Corrosion-Fatigue: A Damage Tolerance Modelling Approach. *Wind Energy*. 2020; Accepted.
7. Martin H., Spano G., Küster JF., Collu M., Kolios AJ. Application and extension of the TOPSIS method for the assessment of floating offshore wind turbine support structures. *Ships and Offshore Structures*. 2013; 8(5): 477–487. Available at: DOI:10.1080/17445302.2012.718957

8. Wang X., Zeng X., Yang X., Li J. Feasibility study of offshore wind turbines with hybrid monopile foundation based on centrifuge modeling. *Applied Energy*. January 2018; 209: 127–139. Available at: DOI:10.1016/j.apenergy.2017.10.107
9. Wang X., Zeng X., Yang X., Li J. Seismic response of offshore wind turbine with hybrid monopile foundation based on centrifuge modelling. *Applied Energy*. February 2019; 235: 1335–1350. Available at: DOI:10.1016/j.apenergy.2018.11.057
10. Damiani RR., Song H., Robertson AN., Jonkman JM. Assessing the Importance of Nonlinearities in the Development of a Substructure Model for the Wind Turbine CAE Tool FAST. Volume 8: Ocean Renewable Energy. 2013; 8(March): V008T09A093. Available at: DOI:10.1115/OMAE2013-11434
11. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Applied Sciences*. 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860
12. Huang X., Li Y., Zhang Y., Zhang X. A new direct second-order reliability analysis method. *Applied Mathematical Modelling*. Elsevier Inc.; 2018; 55: 68–80. Available at: DOI:10.1016/j.apm.2017.10.026
13. Kang F., Xu Q., Li J. Slope reliability analysis using surrogate models via new support vector machines with swarm intelligence. *Applied Mathematical Modelling*. Elsevier Inc.; 1 June 2016; 40(11–12): 6105–6120. Available at: DOI:10.1016/j.apm.2016.01.050
14. Zhang L., Lu Z., Wang P. Efficient structural reliability analysis method based on advanced Kriging model. *Applied Mathematical Modelling*. Elsevier Inc.; 2015; 39(2): 781–793. Available at: DOI:10.1016/j.apm.2014.07.008
15. Zhao H., Li S., Ru Z. Adaptive reliability analysis based on a support vector machine and its application to rock engineering. *Applied Mathematical Modelling*. Elsevier Inc.; 1 April 2017; 44: 508–522. Available at: DOI:10.1016/j.apm.2017.02.020
16. Kolios A., Di Maio LF., Wang L., Cui L., Sheng Q. Reliability assessment of point-absorber wave energy converters. *Ocean Engineering*. Elsevier Ltd; 2018; 163(October 2017): 40–50. Available at: DOI:10.1016/j.oceaneng.2018.05.048
17. Leimeister M., Kolios A. A review of reliability-based methods for risk analysis and their application in the offshore wind industry. *Renewable and Sustainable Energy Reviews*. Elsevier Ltd; 2018; 91(July 2017): 1065–1076. Available at: DOI:10.1016/j.rser.2018.04.004
18. Far MS., Huang H. Simplified algorithm for reliability sensitivity analysis of structures: A spreadsheet implementation. *PLoS ONE*. 2019; 14(3): 1–22. Available at: DOI:10.1371/journal.pone.0213199
19. Breitung K. Asymptotic approximations for multi-normal integrals. *J. Engrg. Mech. Div ASCE*. 1984; 110(3): 357–366.
20. Lu Z., Song J., Song S., Yue Z., Wang J. Reliability sensitivity by method of moments. *Applied Mathematical Modelling*. October 2010; 34(10): 2860–2871. Available at: DOI:10.1016/j.apm.2009.12.020
21. Perićaro GA., Santos SR., Ribeiro AA., Matioli LC. HLRFBFGS optimization algorithm for structural reliability. *Applied Mathematical Modelling*. Elsevier Inc.; 2015; 39(7): 2025–2035. Available at: DOI:10.1016/j.apm.2014.10.024
22. Velarde J., Kramhøft C., Sørensen JD. Global sensitivity analysis of offshore wind turbine foundation fatigue loads. *Renewable Energy*. Elsevier Ltd; 2019; 140: 177–189. Available at: DOI:10.1016/j.renene.2019.03.055
23. Kala Z. Sensitivity analysis of steel plane frames with initial imperfections. *Engineering Structures*. Elsevier Ltd; 2011; 33(8): 2342–2349. Available at: DOI:10.1016/j.engstruct.2011.04.007
24. Teixeira R., O'Connor A., Nogal M. Probabilistic sensitivity analysis of offshore wind turbines using a transformed Kullback-Leibler divergence. *Structural Safety*. Elsevier B.V.; 1 November 2019; 81. Available at: DOI:10.1016/j.strusafe.2019.03.007
25. Xiao NC., Huang HZ., Wang Z., Pang Y., He L. Reliability sensitivity analysis for structural systems in interval probability form. *Structural and Multidisciplinary Optimization*. 2011; 44(5): 691–705. Available at: DOI:10.1007/s00158-011-0652-9

26. Wang L., Liu X., Renevier N., Stables M., Hall GM. Nonlinear aeroelastic modelling for wind turbine blades based on blade element momentum theory and geometrically exact beam theory. *Energy*. Elsevier Ltd; 2014; 76: 487–501. Available at: DOI:10.1016/j.energy.2014.08.046
27. Petrini F., Manenti S., Gkoumas K., Bontempi F. Structural Design and Analysis of Offshore Wind Turbines from a System Point of View. *Wind Engineering*. 2010; 34(1): 85–107. Available at: DOI:10.1260/0309-524X.34.1.85
28. Wang L., Kolios A., Nishino T., Delafin PL., Bird T. Structural optimisation of vertical-axis wind turbine composite blades based on finite element analysis and genetic algorithm. *Composite Structures*. Elsevier Ltd; 2016; 153(January 2015): 123–138. Available at: DOI:10.1016/j.compstruct.2016.06.003
29. Gentils T., Wang L., Kolios A. Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. *Applied Energy*. Elsevier Ltd; 2017; 199: 187–204. Available at: DOI:10.1016/j.apenergy.2017.05.009
30. Wang L., Quant R., Kolios A. Fluid structure interaction modelling of horizontal-axis wind turbine blades based on CFD and FEA. *Journal of Wind Engineering and Industrial Aerodynamics*. Elsevier; 2016; 158: 11–25. Available at: DOI:10.1016/j.jweia.2016.09.006
31. Achmus M., Abdel-Rahman K. Finite element modelling of horizontally loaded monopile foundations for offshore wind energy converters in Germany. *Frontiers in Offshore Geotechnics*. 2005; (August 2005). Available at: DOI:10.1201/NOE0415390637.ch38
32. Wang L., Kolios A., Delafin P-L., Nishino T., Bird T. Fluid structure interaction modelling of a novel 10MW vertical-axis wind turbine rotor based on computational fluid dynamics and finite element analysis. *European Wind Energy Association Annual Conference and Exhibition 2015, EWEA 2015 - Scientific Proceedings*. 2015; 44(0).
33. Wang L., Kolios A. A generic framework for reliability assessment of offshore wind turbine monopiles considering soil-solid interaction and harsh marine environments. *5th International Conference on Marine Structures, MARSTRUCT*. Lisbon; 2017. Available at: DOI:10.1201/9781315157368-105
34. Kolios A., Wang L. Advanced reliability assessment of offshore wind turbine monopiles by combining reliability analysis method and SHM / CM technology. 2018; : 1412–1419.
35. Hyldal SP. Soil-structure interaction for non- slender , large-diameter offshore. 2012;
36. Hald T., Mørch C., Jensen L., Bakmar CL., Ahle K. Revisiting monopile design using py curves. Results from full scale measurements on Horns Rev. *Proceedings of European Offshore Wind 2009 Conference*. 2009.
37. Jung S., Kim SR., Patil A., Hung LC. Effect of monopile foundation modeling on the structural response of a 5-MW offshore wind turbine tower. *Ocean Engineering*. Elsevier; 2015; 109: 479–488. Available at: DOI:10.1016/j.oceaneng.2015.09.033
38. DNV GL AS. DNVGL-ST-0126 : Support structures for wind turbines. DNV GL - Standard Høvik, Norway: Det Norske Veritas; 2016 p. 182 pp. Available at: DOI:10.1016/j.jbiomech.2014.11.025
39. DNV. DNV-OS-J101 Design of Offshore Wind Turbine Structures. May. 2014; (May): 212–214.
40. IEC. Wind Turbines - Part 3: Design Requirements for Offshore Wind Turbines. IEC 61400-3. Geneva, Switzerland; 2009.
41. Det Norske Veritas. Environmental conditions and environmental loads. DNV RP C205. 2000;
42. Minguez L. Fatigue and fracture mechanics of offshore wind turbine support structures. Cranfield university; 2015.
43. Freebury G., Musial W. Determining equivalent damage loading for full-scale wind turbine blade fatigue tests. 2000 ASME Wind Energy Symposium. 2000; (February). Available at: DOI:10.2514/6.2000-50
44. Chakrabarti SK. Handbook of Offshore Engineering. Handbook of Offshore Engineering. 2005. 1127–1143 p. Available at: DOI:10.1016/B978-0-08-044381-2.50022-9
45. DNV GL AS. DNVGL-ST-0437: Loads and site conditions for wind turbines. DNV GL - Standard. Høvik, Norway: Det Norske Veritas; 2016. p. 108. Available at: <http://www.dnvgl.com>
46. Schaumann P., Boker C., Bechtel A., Lochte-Holtgreven S. Support structures of wind energy converters. In: Baniotopoulos C, Borri C, Stathopoulos T (eds.) *Environmental Wind Engineering and Design of Wind Energy Structures*. Springer; 2011. pp. 191–253.

47. GL. Rule for regulation IV-Non marine technology, Part 2 Offshore wind energy. Hamburg; 1995.
48. IEC. IEC 61400-1: Wind Turbines Part 1: Design Requirements. 2005;
49. Fisher T., De Vries W., Schmidt B. Upwind Design Basis (WP4 Offshore foundations and support structures). project upwind contract No. 019945 (SES6); 2010. Available at: DOI:10.1016/S0140-6736(02)81074-1
50. Muskulus M., Schafhirt S. Design Optimization of Wind Turbine Support Structures—A Review. *Journal of Ocean and Wind Energy*. 2310; 1(1): 12–22. Available at: DOI:10.13140/RG.2.1.5125.5766
51. Lee YS., Choi BL., Lee JH., Kim SY., Han S. Reliability-based design optimization of monopile transition piece for offshore wind turbine system. *Renewable Energy*. Elsevier Ltd; 2014; 71: 729–741. Available at: DOI:10.1016/j.renene.2014.06.017
52. Damiani R. JacketSE: An Offshore Wind Turbine Jacket Sizing Tool Theory Manual and Sample Usage with Preliminary Validation. 2016; (NREL/TP-5000-65417): 50.
53. Jonkman J., Butterfield S., Musial W., Scott G. Definition of a 5-MW Reference Wind Turbine for Offshore System Development. 2009; (February). Available at: DOI:10.2172/947422
54. Drucker D., Prager W. Soil mechanics and plastic analysis or limit design. *Quarterly of Applied Mathematics*. 1952; 10(2): 157–165.
55. ANSYS Inc. Introduction to contacts - ANSYS mechanical structural nonlinearities. 2010; (December).
56. ANSYS. ANSYS help documentation. 2018;
57. Kühn M. Dynamics and Design Optimization of Offshore Wind Energy Conversion Systems. Sciences-New York. 1999.
58. Kolios A. A multi-configuration approach to reliability based structural integrity assessment for ultimate strength. Cranfield University; 2010.
59. Haldar A., Mahadevan S. Probability, Reliability, and Statistical Methods in Engineering Design. Wiley; 1999.
60. Melchers RE. Structural reliability analysis and prediction. John Wiley & Sons; 1999.
61. Ditlevsen O., Madsen HO. Structural reliability methods. Wiley New York; 1996.
62. Nowak AS., Collins KR. Reliability of Structures. Second Edi. CRC Press; 2012.
63. Kwak BM., Tae Won Lee. Sensitivity analysis for reliability-based optimization using an AFOSM method. *Computers and Structures*. 1987; 27(3): 399–406. Available at: DOI:10.1016/0045-7949(87)90064-2
64. Guo J., Du X. Reliability sensitivity analysis with random and interval variables. *International Journal for Numerical methods in Engineering*. 2009; 78(1585–1617): 1102–1119. Available at: DOI:10.1002/nme.2543
65. (DNV) Det Norske Veritas. Structural Reliability Analysis of Marine Structures. DNV CN 30-6. 1992;
66. Horn JT., Leira BJ. Fatigue reliability assessment of offshore wind turbines with stochastic availability. *Reliability Engineering and System Safety*. Elsevier Ltd; 1 November 2019; 191. Available at: DOI:10.1016/j.ress.2019.106550
67. Teixeira R., O'Connor A., Nogal M. Probabilistic sensitivity analysis of offshore wind turbines using a transformed Kullback-Leibler divergence. *Structural Safety*. Elsevier; 2019; 81(March): 101860. Available at: DOI:10.1016/j.strusafe.2019.03.007
68. BSI. BS EN 1990 Eurocode: Basis of Structural Design. British standard institute. 2002;
69. Hasofer A., Lind N. An exact and invariant second moment code format. *J. Engrg. Mech. Div ASCE*. 1974; 100(1): 111–121.

5 STRUCTURAL RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE SUPPORT STRUCTURES SUBJECTED TO PITTING CORROSION-FATIGUE: A DAMAGE TOLERANCE MODELLING APPROACH

Abdulhakim Adeoye Shittu, Ali Mehmanparast, Mahmood Shafiee, Athanasios Kolios, Phil Hart, and Karl Pilario.

Published: Wind Energy, 2020, 23(11), Pages: 2004-2026

Statement of contributions:

Abdulhakim A. Shittu conducted the literature review, developed, and validated the model, performed the simulations, generated all the results, drafted and critically revised the manuscript. K. Pilario assisted in the MATLAB simulations and reviewed the manuscript. A. Mehmanparast, M. Shafiee, P. Hart, and A. Kolios provided supervision, reviewed and critically commented on the manuscript before submission.

Abstract: The structural integrity of Offshore Wind Turbine (OWT) support structures is affected by one of the most severe damage mechanisms known as pitting corrosion-fatigue. In this study, the structural reliability of such structures subjected to pitting corrosion-fatigue is assessed using a damage tolerance modelling approach. A probabilistic model that ascertains the reliability of the structure is presented, incorporating the randomness in cyclic load and corrosive environment as well as uncertainties in shape factor, pit size, and aspect ratio. A non-intrusive formulation is proposed consisting of a sequence of steps. First, a stochastic parametric Finite Element Analysis (FEA) is performed using SMART[®] crack growth and Design Xplorer[®] facilities within the software package ANSYS. Secondly, the results obtained from the FEA are processed using an Artificial Neural Network (ANN) response surface modelling technique. Finally, the First Order Reliability Method (FORM) is used to calculate the reliability indices of components. The results reveal that for the inherent stochastic conditions, the structure becomes unsafe after the 18th year, before the attainment of the design life of 20 years. The FEA results are in very good agreement with results obtained from analysis steps outlined in design standard BS 7910 and other references designated as ‘theoretical analysis methods’ in this study. The results predict, for the case study, that the pit growth life is approximately 56% of the total pitting corrosion fatigue life. Sensitivity analysis results show that the aspect ratio of pits at critical size plays a significant role on the reliability of the structure.

Keywords: pitting corrosion fatigue; reliability index; non-intrusive formulations, structural reliability analysis, offshore wind structures, artificial neural network

5.1 Introduction

Renewable energy technologies are now widely deployed in many parts of the world, including Europe, China, USA, etc. [1]. Wind energy is a technically and economically feasible option to partially address the global issues related to the energy crisis and climate change. The majority of wind energy is harnessed by onshore wind farms [2], despite regular local opposition due to visual and sound impacts. A solution is to deploy wind turbines at sea thus minimising sound and visual impact, with additional capacity factor benefits obtained from the improved wind domain due to unobstructed fetch. This has led to the increasing development of offshore wind industry, especially in Europe where the offshore wind energy capacity is expected to reach 64.8 GW by 2030 [1,3–7].

Most of the existing offshore wind turbines use monopile foundations and are installed in water depths less than 50 m. However, for larger turbines in deeper waters, monopiles become very large and increasingly uneconomical due to the difficulty of fabricating and installing such systems, as well as the consideration of modal requirements. More information on monopile foundations can be found in [8,9]. To address these issues, space frame structures such as jackets are used which have lighter weight and are stiffer than monopiles. Space frames can be cheaper in deep-water circumstances, and hence they can contribute to the offshore wind industry's goal on the reduction of Levelized Cost of Energy (LCoE). However, designing these structures effectively is resource-intensive, especially when designing to withstand the wide set of dynamic loading mechanisms. Thus, research is still required to improve the design and analysis of jacket type support structures [10,11], with due consideration of the requirement for manufacturing optimisation if ever these structures are to be mass-produced.

OWTs are subject to more significant dynamic structural responses than conventional jacket platforms utilised on the oil and gas industry as a result of the effects of wind load and turbine behaviours. The fatigue load levels as well as the number of cycles to be accounted for are especially of note. The fatigue damage contribution for the multi-planar welded tubular joint from wind load effects can be high (exceeding 60% of the total) and the number of hot spot stress cycles associated with wind and wave loads in a year can exceed 7×10^7 . Hence, the fatigue performance of members is a design driving criterion for numerous structural details of OWT foundations [6,12].

Structural design and analysis have initially been based on deterministic methods. However, it is potentially advantageous that probabilistic based methods could be employed due to the uncertainties in loads, strengths and structural modelling. As a fundamental design driver, a structure is expected to perform satisfactorily within a design life. This means for OWTs that it must fulfil specific functional requirements and does not become unsafe over, generally, at least 25 years [13]. Several studies [1,3,12,14–18] have already applied the structural reliability methodology for the safety assessment of offshore structures. However, most reliability methods assume that the system is time-invariant. In practical OWT instances, due to the degradation brought by corrosion and fatigue, as well as fluctuating loads in time, the system becomes time-variant.

Models used to determine the response of support structures for OWTs can be either one-dimensional (1-D) beam models or three-dimensional (3-D) finite element analysis (FEA) models. The 3-D FEA models are generally more advantageous since they are able to investigate detailed stress distributions and capture structural responses more accurately. Because of their high fidelity, 3-D FEA models have been extensively applied to model wind turbine structures [1,3,19–23] and this study therefore adopts the FEA approach to simulate the responses of OWT jacket support structures.

Since OWT jacket foundations are anchored via piles to the soil system, it is crucial to account for soil-structure interaction to adequately capture the response of the structure. A straightforward method to perform soil modelling is to assume equivalent springs to represent soil based stiffness, which is known as the p-y method [24]. However, in this method, the deflection as well as the modal frequency are underestimated. A more reliable way of carrying out soil modelling is to define 3-D FEA brick elements to achieve precision and reliability in the results [25,26]. Considering its efficacy, 3-D finite element analysis with brick elements is adopted to model the soil in this study.

A most severe form of localized corrosion is pitting corrosion, characterized by the evolution of pits that penetrate the metal, leading to local mass loss. It is considered one of the most crucial degradation mechanisms as cracks are seen to initiate and propagate in structures from these corrosion pits under sustained fatigue loading [27]. According to the literature [28,29], the analysis of the effect of corrosion on the structural reliability of jacket type offshore structures is a subject open to investigation. There have been very few detailed studies for failures in offshore structures due to pitting characteristics. Cyclic loads of variable amplitude resulting from wind speed variations and wave motion fluctuations referred to as stochastic

loads coupled with environments containing chloride jeopardize the structural capability of OWT structures [29].

To address the above challenges, this study aims to: (a) develop a corrosion fatigue model based on pit and crack growth; (b) predict the nucleation/development and growth to critical size of the corrosion pits using data obtained from the literature; (c) predict pit to crack transition and crack propagation using the sequential steps of a high capability tool applying fracture mechanics functions and afterwards building stochastic parametric FEA model; (d) apply surrogate/meta model methods via ANN Response Surface Method (RSM) to post-process the data in order to aid in expressing the limit state/performance function in terms of important stochastic variables; and (e) perform structural reliability assessment that employs the generated limit state function (LSF) using widely recognized numerical reliability assessment techniques such as First Order Reliability Method (FORM) and Monte-Carlo simulation (MCS).

ANNs are established to be universal function approximators and have found applications in Structural Reliability Assessment (SRA) by several researchers [30–35]. The neural structure of the brain has been employed in creating mathematical models defining ANNs. ANNs establish a functional relationship between two spaces of data during a learning process, and replicate that connection during a recall process. The multi-layer feed-forward network is the most widely used ANN architecture [35]. According to [36], ANNs can approximate highly non-linear functions accurately over the entire domain with very high fidelity. Several studies [32,34] have also been carried out, proving the precision and efficiency of the response surface method based on ANN in comparison with the conventional response surface methods for reliability assessment. According to [35], ANN-based reliability assessment methods are robust and efficient alternatives compared to conventional reliability analysis methods for complex structures, especially those requiring training set selection techniques which are advanced.

In [37], a comprehensive mechanics-based probabilistic model for pitting corrosion-fatigue life prediction for aluminium alloys by including all stages was presented where an analytical FORM and MCS were implemented with the proposed model. An extensive review which focuses on the recent developments in the methodologies used for predicting pitting corrosion-fatigue lifetime especially pit-to-crack transition was presented in [29]. In [38], the pitting corrosion-fatigue behaviour of a medium strength structural steel shaft was studied in seawater. Emphasis was placed on the study of corrosion pit formation and the development of cracks from pits. A model which included the stages of pitting and the pit-to-crack transition

was developed in order to predict the fatigue life by quantifying the pitting and crack propagation throughout the fatigue loading. There are several classical pitting corrosion-fatigue models some of which are included in [38–45]. Recent works on the structural reliability with respect to fracture where a new methodology for the statistical inference of the Equivalent Initial Flaw Size Distribution (EIFSD) using Dual Boundary Element Method was proposed has been presented in [46,47]. To the best of the authors' knowledge, the work presented herein, in this study, is the first of its kind where the SRA of a steel OWT support structure subjected to pitting corrosion-fatigue is performed by applying a new approach to damage tolerance modelling methodology. In this study, in order to accurately predict the pit-to-crack transition behaviour, a stochastic parametric FEA model was built and incorporated with FORM for approximating time-variant reliability levels of the structure via ANN. The novelty of this paper is in the application of the reliability analysis together with a stochastic approach where the short and long crack models are combined to determine the damage tolerance design of offshore wind turbine structure. Apart from accounting for the uncertainties involved in modelling pitting corrosion-fatigue mechanisms, this study incorporates the responses of the structure to environmental loads such as due to wind, wave, and current as well as due to soil-structure interaction.

The stochastic expansion consists of the intrusive and non-intrusive formulations. An intrusive formulation is the one whereby the representation of uncertainty is expressed explicitly within the analysis of the system. Practically, this refers to methods that use Karhunen-Leove expansion (K-L) and Polynomial Chaos Expansion (PCE) to directly modify the stiffness matrix of a finite element analysis procedure, such as SSFEM (Spectral Stochastic FEM) and Stochastic Galerkin FEM. On the other hand, non-intrusive formulations, such as Stochastic Response Surface Methods [6,17,48], represent uncertainties in a non-explicit way and treat the analysis code as a “black box” without requiring access to the source code. Surrogate models, also referred to as meta-models or response surface models (e.g. based on the ANN, Kriging, support vector machines, etc.) are used for time-consuming implicit limit state functions (i.e. which will require the use of finite element analysis) such as obtained in complex frame type structures as adopted herein. In this study, a non-intrusive SRA formulation is proposed for the probabilistic evaluation of the structure considering pitting corrosion-fatigue mechanism in the application of the damage tolerance model method. It involves the combination of high capability tools: SMART fracture[®] and DesignXplorer[®] as packaged in ANSYS, with FORM through ANN in the non-intrusive formulation.

This paper is organised as follows. Section 5.2 presents the theoretical background where the SMART crack growth analysis package in ANSYS workbench as well as the fracture mechanics analysis of planar flaws and corrosion fatigue modelling are discussed. Section 5.3 discusses the methodology adopted in the present study, where global elements to be considered when designing a typical OWT support structure are presented, an OWT support structure subjected to pitting corrosion fatigue at critical joint is reviewed and then the implementation method of SRA taking into account stochastic variables is discussed. Section 5.4 presents the results obtained from the analysis and a comprehensive discussion is provided on the mesh optimisation, validation of the FEA based fracture mechanics model results, pitting corrosion-fatigue SRA results and global sensitivity analysis results; and finally Section 5.5 presents the conclusions drawn from the present study.

5.2 Research background

5.2.1 SMART[®] crack growth analysis

Fracture simulation has relied on two models: traditional cohesive zone modelling (CZM) and, more recently, the eXtended Finite Element Method (XFEM). CZM is commonly applied to the simulation of de-bonding between two surfaces attached adhesively. CZM is ideal for simulating composites, but it is generally not suitable for simulating the crack growth in the bulk of a material [49].

The XFEM is better for internal crack calculations. Introduced into ANSYS toolkit, XFEM eliminates the need for re-meshing crack tip regions. Instead, it defines an extended finite element enrichment area around the crack tip and in regions where it is plausible that the crack tip might grow. XFEM splits the special volume elements in the enrichment zone from the centre of the element. In this way, it creates a finer mesh by splitting existing cells instead of re-meshing. However, the enrichment regions in XFEM are very computationally expensive and as the enrichment area increases, the simulation slows down. Hence, XFEM is not easy to scale up to large projects which led to the development of the SMART[®] crack growth tool.

SMART[®] stands for Separating Morphing and Adaptive Re-meshing Technology which relies on the Unstructured Mesh Method (UMM) process. SMART[®] updates the mesh from crack-geometry changes due to crack growth automatically at each solution step. It is a new feature introduced in ANSYS R19. Instead of using the enrichment technique, it uses a localized re-mesh function as the crack grows. Unlike the XFEM, SMART[®] can be scaled up for larger projects because re-meshing is limited to a small area around the crack tip at each iteration. An advantage is that in this technique there is no need to develop new elements, and standard

elements already included in mechanical, i.e. the conventional solid 187, 186, etc. can still be used. The software also enables engineers to enter alternative crack growth laws as these emerge from new research about the particular material being modelled.

The following important characteristics of the SMART[®] crack-growth method pertain to its use: (1) It only applies to 3-D Mode 1 dominant crack growth. (2) It only supports linear elastic isotropic materials (3) It is being developed for the solid 187 (quadratic tetrahedral element) only. This is because the tetrahedral element can model any geometry, unlike the hex element, where there could be difficulty in some cases. It currently ignores the large-deflection and finite-rotation effects, crack tip plasticity effects, and crack-tip closure or compression effects. The fracture criteria for static crack growth includes critical stress-intensity factor K_I and J-integral J . The fatigue crack growth is based on Paris' law [50].

5.2.2 Fracture mechanics analysis of planar flaws

In BS 7910 [51], two methods both based on fracture mechanics crack analysis under fatigue loading which include a general procedure and a simplified procedure associated with S-N curves have been outlined for the assessment of planar flaws. The methods evaluate the fatigue life by the integration of the crack growth law. The general procedure allows accurate expressions for cyclic stress intensity factor to be used as well as specific data for fatigue crack growth. The quality category procedure implies the use of fracture mechanics calculation results which have been already conducted and depicted graphically.

It is common in a fracture mechanics assessment to employ conservative estimates of the various parameters required. However, an alternative approach is to employ reliability methods to account for the parameter uncertainties. In the fracture mechanics approach, an assumption is made that a flaw can be considered as a crack with a sharp tip which propagates according to the law associated with crack growth rate, da/dN , and stress intensity factor range, ΔK , for the flaw containing material. The crack growth law is generated experimentally. It is normally observed that the overall relationship between da/dN and ΔK is a sigmoid curve in a $\log(da/dN)$ versus $\log(\Delta K)$ plot. It is reasonable to assume a linear relationship (i.e. the Paris' law) at the central portion of the plot; or for greater accuracy, the data is represented by two or more straight lines. The rate of growth rate falls rapidly at low values of ΔK such that there is insignificant crack growth below a threshold stress intensity factor range, ΔK_0 . When the maximum stress intensity factor K_{max} , at high values of ΔK , approaches the critical stress intensity factor for static load failure, K_c , there is a rapid acceleration in the rate of crack growth. However, it is usually assumed that the central portion is applicable for all ΔK values (from ΔK_0 up to failure). The Paris' law equation is given by the following equation [50,51]:

$$\frac{da}{dN} = C(\Delta K)^m \quad (5-1)$$

where C and m are material coefficients and also depend on environmental effects. For $\Delta K < \Delta K_0$, da/dN is assumed to be zero. The stress intensity factor range, ΔK , is a function of geometry factor, Y , stress range, $\Delta\sigma$, and instantaneous crack size, a , and is calculated from the following equation:

$$\Delta K = Y(\Delta\sigma)\sqrt{(\pi a)} \quad (5-2)$$

The overall life is calculated by substituting Eq. (5-2) into Eq. (5-1) and integrating the following equation:

$$\int_{a_i}^{a_f} \frac{da}{Y^m(\pi a)^{m/2}} = C(\Delta\sigma)^m N \quad (5-3)$$

The acceptability of a crack of initial size a_i then depends on whether the calculated cyclic life, N , is greater or less than the required life. If the initial crack size a_i and final crack size a_f are known, the number of cycles to failure can be obtained through integrating Eq. (5-3):

$$N_f = \frac{2}{C\Delta\sigma^m Y^m \pi^{\frac{m}{2}} (2-m)} \left[a_f^{1-\frac{m}{2}} - a_i^{1-\frac{m}{2}} \right] \quad (5-4)$$

Based on the assessment procedures for tubular joints in offshore structures (see BS 7910), the stress analysis and fatigue assessment can be performed as follows.

In the stress analysis, it is important to acquire the forces and moments in the members of the assessed regions under critical loading conditions, as a result of the structural analysis of the entire frame. These include the axial force, in-plane and out-of-plane bending moments. Both ranges of maximum as well as fatigue load are required. The current literature identifies two types of stress analysis: global and local. In order to evaluate the stress spectrum associated with the wave loading at the location of a flaw, the global FEA of the entire structure is conducted. A histogram of the wave height against the number of occurrences is constructed using the wave exceedance curve. The global structural analysis is used to determine the stress range corresponding to each wave height. The latter gives the loading at the nominal brace as a result of the fatigue action as well as loading from storm waves. Hence, stress ranges corresponding to the axial, in-plane bending and out-of-plane bending brace ($\Delta\sigma_{AX}$, $\Delta\sigma_{IPB}$ and $\Delta\sigma_{OPB}$ respectively) are calculated for each wave height.

On the other hand, local stress analysis aims to find the stress range variation around the periphery of the joint as well as the evaluation of the stress range histograms for at least eight equally spaced positions, including the saddle and crown locations. Note that bending loads and nominal brace axial resulting from the chord reaction generates stress ranges at the local joint. The tubular walls local deformation leads to the development of high secondary bending stresses. This results in through-thickness stress gradients and high-stress concentrations at the intersection of the brace/chord.

In this paper, the global and local structural analysis methods are adopted from reference [51], as part of the theoretical analysis. For the fatigue assessment, the damage variation at the periphery of the joint should be evaluated, and the stress range histogram for the maximum damage in the selected crack region. The application of the stress range histogram is then performed on a block by block basis.

Corrosion pits at different locations of a joint and interaction between the pits necessarily results in variation of localized stress near a crack and then have critical effect on calculation of the crack size. According to [51] multiple flaws in close proximity can lead to an interaction and to more severe effects than single flaws alone. Also according to the same standard, it is not necessary to apply flaw interaction criteria for fatigue assessment. However, if there is any uncertainty as to whether flaws are separate they should be combined or specific calculations carried out. The effective dimension after interaction as prescribed in [51] is $a = \max. \{a_1, a_2\}$ where a_i is the depth of a coplanar surface flaw which has been adopted in this study.

5.2.3 Modelling of corrosion fatigue

The process of corrosion fatigue is synergistic, occurring as a result of electrochemical, microstructural and mechanical loading interactions. The process includes pit formation, pit growth, crack nucleation from pits and crack propagation. The proportions of the time spent/cycles in each of these systems are dependent on the material/ environment system, stress magnitude and applied load frequency. The modelling approach for corrosion fatigue process found in several studies [26, 37–40] is simplified into the three main regimes: pit growth N_{pit} , small crack growth N_s and long crack growth N_l . The total life due to fatigue (N) can be expressed as the summation of each of the individual stages [38]. Thus,

$$N = N_{pit} + N_s + N_l \quad (5-5)$$

5.2.3.1 Assumptions

The following assumptions are made for this study [38,40,51]:

- 1) The failure cracks nucleated in the largest corrosion pits.
- 2) The corrosion-fatigue process is composed of two stages: crack initiation composed of pit nucleation and pit growth and corrosion-fatigue crack propagation.
- 3) There is a critical pit size for the transition from crack pit initiation to crack growth
- 4) Both the pitting growth and fatigue crack nucleation from pits control the corrosion-fatigue initiation life.
- 5) The critical pit is assumed as a semi-circular surface crack (hemispherical pits)

5.2.3.2 Corrosion pit growth law (N_{pit})

According to several studies [29,38,40], it is common to apply two methods in determining the pit growth depth, as follows;

(a) Exponential relation to t (Exponential law)

In [42,43] it was revealed that for a given corrosion pit, the depth a_p at time t can be defined by the following equation:

$$a_p = A. \left(\frac{t}{t_f} \right)^B \quad (5-6)$$

where t_f represents the time which corresponds to the number of cycles to failure, and A and B are respectively coefficient and exponent. Assuming a constant test frequency f (Hz), then $t = \frac{N}{f}$, and a_p can be defined by:

$$a_p = A. \left(\frac{N_{pit}}{N_f} \right)^B \quad (5-7)$$

The parameters A and B which are pit growth-dependent can be determined by interpolating the test data (for more see [44]).

(b) Faraday's law

The application of the Faraday's law has been in defining the pit growth law, which has been validated against experimental results [39,42,43]. The corrosion pit depth a_p in a material is proportional to the cube root of t , and is expressed by the following equation [38]:

$$a_p = \left(\frac{3M \cdot I_p}{2\pi \cdot n \cdot F \cdot \rho} \right)^{\frac{1}{3}} (t)^{\frac{1}{3}} \quad (5-8)$$

where I_p denotes the pit current (mA) which can be obtained from reference [52]; M refers to the material's atomic mass (kg/mol); ρ represents density (kg/m^3); F denotes Faraday's constant (C/mol), and n represents the number of released electrons during the metal corrosion. The pit current I_p can be calculated from:

$$I_p = I_{po} \cdot \exp\left(-\frac{\Delta H}{RT}\right) \quad (5-9)$$

where I_{po} denotes the pit current coefficient (C/s); H denotes the activation energy (enthalpy change, J/mol); R denotes the universal gas constant (J/mol K), and T denotes the absolute temperature (K). For the surface of a component consisting of hemispherical pits assumed similar to an infinite plate containing the 2D semi-circular surface flaw, the stress intensity factor range ΔK can be determined for a pitted surface from the following equation [40]:

$$\Delta K = \left(\frac{2.2}{\pi} \right) K_t \cdot \Delta \sigma \cdot \sqrt{\pi \cdot a_{pc}} \quad (5-10)$$

$$a_{pc} = \pi \left(\frac{\Delta K_{th}}{4.4 K_t \cdot \sigma_a} \right)^2 \quad (5-11)$$

$$N_{pit} = \left(\frac{a_{pc}}{A} \right)^{1/B} \cdot \left(\frac{10^{9.19}}{e^{0.036 \sigma_a}} \right) \quad (5-12)$$

where a_{pc} represents the critical pit size necessary for pit to crack transition (μm); K_t represents the stress concentration factor (SCF) which is derived from the curves in reference [53]. The number of cycles to crack initiation N_{pit} can be determined by substituting Eq. (5-11) and the stress and fatigue life relationship (i.e. seawater environment S-N data) into Eq. (5-7).

5.2.3.3 Corrosion fatigue 'small crack' life (N_s)

It has proven troublesome to establish an explicit formula describing the growth of short cracks, despite the high amount of research that has been conducted in this area, particularly for corrosive environments. According to some authors, the following empirical formula which is similar in form to the Paris' law can be employed [42,45], which has been validated with test data [38].

$$\frac{da}{dN_s} = C_s(\Delta K)^{m_s} \quad (5-13)$$

C_s and m_s can be determined by fitting the experimental data [29,38]. The notional concept of stress intensity factor can be employed, when a suitable parameter for describing the growth of small cracks under corrosion fatigue conditions is unavailable. Solving Eq. (5-13) within the limits a_{pc} to a_{tr} , the consumed number of cycles during the stage of small crack growth can be calculated from the following equation:

$$N_s = \int_{a_{pc}}^{a_{tr}} \frac{1}{C_s(\Delta K)^{m_s}} da \quad (5-14)$$

where a_{tr} denotes the crack length for small to long crack transition.

5.2.3.4 Corrosion fatigue long crack life (N_l)

The stage for long crack growth life can be ascertained using the Paris' law. Therefore,

$$\frac{da}{dN_l} = C_l(\Delta K)^{m_l} \quad (5-15)$$

where C_l and m_l can be determined from the experimental data [38,54]. Solving Eq. (5-15) using the limits a_{tr} to a_f (where a_f is computed from K_{IC}), the long crack growth life stage can be determined from:

$$N_l = \int_{a_{tr}}^{a_f} \frac{1}{C_l(\Delta K)^{m_l}} da \quad (5-16)$$

5.2.3.5 Kitagawa-Takahashi (K-T) diagram in air and artificial seawater

According to the Linear Elastic Fracture Mechanics (LEFM) approach, for crack propagation to take place the defect must be at threshold size. Hence, crack depths below this critical size will not grow on smooth surfaces. However, LEFM does not apply in cases where defects are small as a result of localised plasticity connected with such cracks. A Kitagawa-Takahashi (K-T) diagram which associates the threshold ΔK_{th} and the fatigue limit to the fatigue crack size has been established, to take into account the two approaches of pre-existing cracks (LEFM) and nominally defect-free samples (S-N curves).

According to several studies, it was revealed that short crack growth rate exceeds the corresponding long crack growth rate (for an 'equivalent' ΔK value) and that below the threshold ΔK_{th} short cracks growth occurs. Hence, taking short cracks into consideration, where a_0 is assumed to represent the length of crack below which the fatigue limit ceases to

be independent on crack size, Eq. (5-17), then the fatigue stress range variation can be defined as a function of crack size, Eq. (5-18).

$$a_0 = \left(\frac{1}{\pi}\right) \left(\frac{\Delta K_{th}}{Y\Delta\sigma_e}\right)^2 \quad (5-17)$$

$$\Delta K_{th} = Y\Delta\sigma_e \sqrt{\pi(a + a_0)} \quad (5-18)$$

where Y represents the shape factor and $\Delta\sigma_e$ represents the fatigue limit range (two times of the fatigue limit). **Figure 5-1** depicts a comparison of the K-T diagrams in air and artificial seawater, according to reference [38]. The A–B region, is defined as the microstructural short crack (MSC) regime while B–C as the physically small crack regime (PSC).

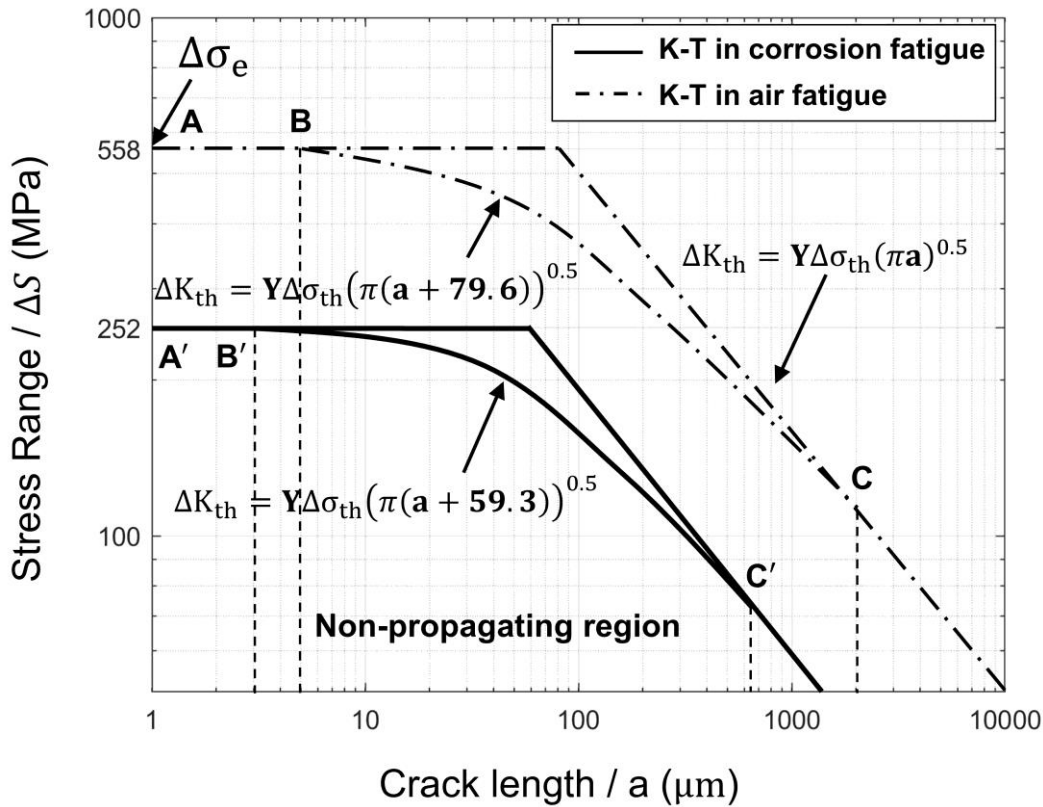


Figure 5-1. The K-T diagrams for air and artificial seawater environments. Source: Li and Akid [38]

5.3 Methodology

5.3.1 Design considerations for OWT support structures

5.3.1.1 Parametric modelling of OWT jacket support structures: Geometry, materials, structural components and soil profile

The reference case used for this analysis consists of a baseline 10MW NREL wind turbine, connected to an 88.4m tower, a transition piece and is sustained by a jacket foundation. The jacket is 66m vertical height, and the piles are embedded 42m into the soil and submerged 50m into the ocean. The piles are to be driven through the legs and thus feature a batter angle. The Transition Piece (TP) is 7m in length and joins together the jacket and the tower [10,11]. The OWT support structure was modelled using ANSYS, which is a widely used Finite Element Analysis (FEA) software [6] (see **Table 5-1** and **Figure 5-3** (a)).

The jacket, TP, piles and tower are made of steel S355 with a density of 8500 kg/m^3 , Young's modulus of 210 GPa, and a Poisson's ratio of 0.3 [10,11]. Aside from the OWT support structure, the soil-structure interaction is also an important design factor of the structural response model of the pile-jacket-tower assembly. Although the soil-structure interaction aspect is often neglected in OWT support structures modelling [55], it is included in this study for improved accuracy of the results. For this study, the soil profile is modelled as six layers of sand, corresponding to that of a deepwater site located off the coast of Netherlands designated as the K-13 deep-water site. **Table 5-2** gives the soil profile parameters used in the simulations, which are based on site measurements. A cylindrical shape ($D=140\text{m}$, $H=50\text{m}$) is assumed with six different strata to model the soil system in ANSYS (see **Table 5-2**). The Drucker-Prager Strength Linear model is adopted to model the soil material [56]. This model is employed in calculating each soil strata yield stress. The soil's yield strength, σ_{ys} , based on the Drucker-Prager model, can be expressed as:

Table 5-1. Baseline 10 MW support structure parameters [6, 9, 10, 48, 49]

Parameter	Value
Deck height above MSL (m)	16
Water depth (m)	50
Leg OD (m)	1.74
Leg wall thickness (m)	0.030
Number of bays	4
Jacket batter	8.47
Height of TP (m)	7
Number of legs	4
Pile OD (m)	1.59

Pile wall thickness (m)	0.037
Mud brace OD (m)	0.762
Mud brace wall thickness (m)	0.017
x-brace outer diameter (m)	0.61
x-brace wall thickness (m)	0.016
RNA mass (kg)	1,072,000
Tower length (m)	88.4
Tower-top OD (m)	3.85
Tower-top thickness (m)	0.03
Tower-base OD (m)	7
Tower-base thickness (m)	0.055
Thrust associated with rated power ultimate load (UL) case (kN)	1700
Maximum rotor thrust taking into account dynamic amplification UL case (kN)	3400
Thrust fatigue load (FL) case (kN)	203
Torsional moment UL case (kN-m)	7876
Torsional moment FL case (kN-m)	3483
Tilting moment UL case (kN-m)	38567
Tilting moment FL case (kN-m)	3687

Abbreviations: MSL, mean sea level; OD, outside diameter; RNA, rotor nacelle assembly; TP, transition piece.

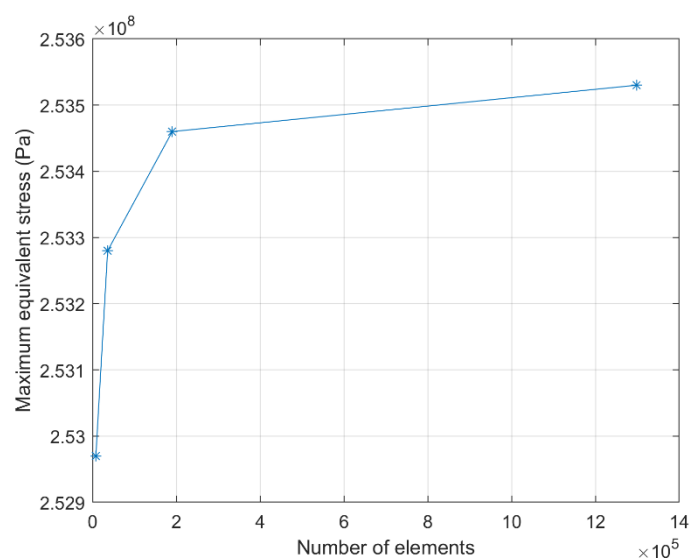


Figure 5-2: Mesh convergence test [6]

Table 5-2. K-13 deep-water site's soil profile [6,10]

Depth below seabed (m)	Unit weight N/m^3	Friction angle ($^\circ$)	Shear strength (N/m^2)	Young's modulus (MPa)
0-3	10,000	36	60,000	30
3-5	10,000	33	60,000	30
5-7	10,000	26	60,000	50

7-10	10,000	37	60,000	50
10-15	10,000	35	60,000	50
15-50	10,000	37.5	60,000	80

$$\sigma_{y,s} = \frac{6c \cos \phi}{\sqrt{3}(3 - \sin \phi)} \quad (5-19)$$

Here, ϕ denotes the internal friction angle and c denotes the cohesion value. Between the soil and the pile, the associated coefficient of friction C_f can be expressed as [25].

$$C_f = \tan\left(\frac{2}{3}\phi\right) \quad (5-20)$$

5.3.1.2 Mesh sensitivity analysis

A mesh sensitivity analysis was performed in order to optimize the element size and thus enhance the accuracy of results. The results are presented in **Table 5-3** and **Figure 5-2**. Based on the mesh sensitivity analysis, convergence of the Von-Mises (equivalent) stress was achieved at the soil element size of 2m and support structure element size at 0.5m, corresponding to a number of mesh totalling 190,222.

Table 5-3. Mesh sensitivity [6]

Soil element size (m)	Jacket structure element size (m)	Number of elements	Maximum Von-Mises stress (Pa)
8	2	8047	2.5297E+08
4	1	36,164	2.5328E+08
2	0.5	190,222	2.5346E+08
1	0.25	1,298,092	2.5353E+08

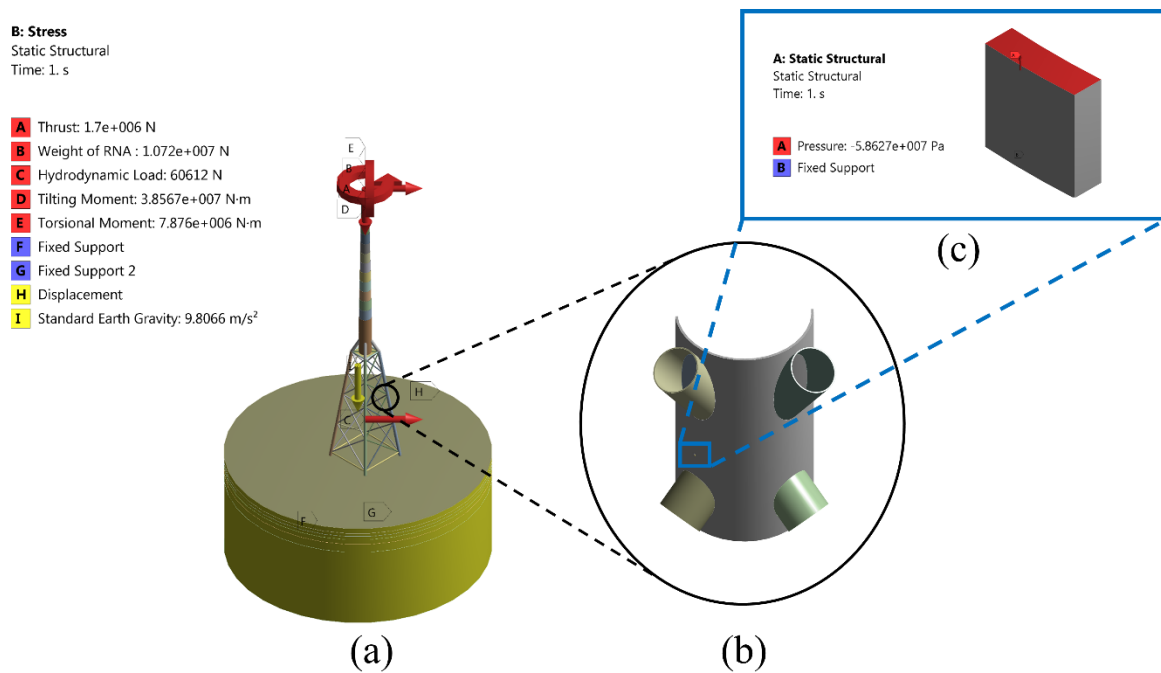


Figure 5-3. The 3D structural model: (a) with applied loads and boundary conditions on a global scale [6]; (b) half of the critical joint of the support sub-structure showing hemispherical pit; (c) curved plate with applied stress and BC in ANSYS.

5.3.1.3 Validation

This model has been validated by comparing the results of the modal analysis deflection in static analysis for the support structure against data from the reference OWT. Results of the modal analysis and deflection can be seen in **Table 5-4** and **Table 5-5**, respectively, where it can be appreciated that the first eigen-frequency of the model is within the range that typically represents the 3P frequency of the rotor. Moreover, the eigen-frequency is 0.21346, which represents 0.12% of the relative difference from the one obtained in references [11,57]. Also, the deflection at the RNA elevation and tower base are 1.236 m and 1.6085×10^{-1} , which represents -0.46% and -3.44% of the relative difference from the one obtained in reference [11]. These differences are considered to be acceptable.

5.3.1.4 Calculation of loads on OWT support structures

In this study, the environmental conditions of the design approach are defined as the normal operating conditions for the Fatigue Limit State (FLS) (see Section 5.3.3.1). Wave, wind, and current loads are calculated manually and then incorporated in the parametric FEA model.

Table 5-4. Comparison of the support structure mode frequencies with reference values [6]

Mode frequencies (Hz)	Present	References [11,57]	% Difference
1 st side-to-side bending	0.21346	0.21320	0.12%
1 st fore-aft bending	0.22297	0.21629	2.99%
2 nd side-side bending	1.1602	1.0313	11.11%
2 nd fore-aft bending	1.5292	1.6561	-8.29%

Table 5-5. Static deformation of the baseline 10 MW wind turbine jacket [6]

Load case	Displacement at RNA			Displacement at the tower base		
Mass/ Thrust	Present	Ref. [11]	% Diff	Present	Ref. [11]	% Diff
RNA/ 3.4 MN	1.263 m	1.2688	- 0.46%	1.6085×10^{-1}	1.6639×10^{-1}	- 3.44%

The normal wind climate conditions considered in this study are assumed to be cyclic structural loading conditions. These are calculated according to IEC 61400-1 [58], as follows:

$$V(h) = V_{ref} \frac{\ln\left(\frac{h}{z_0}\right)}{\ln\left(\frac{h_{ref}}{z_0}\right)} \quad (5-21)$$

where z_0 is the roughness coefficient (see [59]). After generating the wind speed profile, the horizontal force acting on the tower, TP and nacelle, can be calculated as:

$$F_x = \frac{1}{2} C_D \rho_e (V_{max})^2 A \cos \alpha \quad (5-22)$$

where C_D is the cylindrical drag coefficient (for the tower and TP) and plate drag coefficient (for the nacelle), A is the area being pushed by the wind, and α is the inclination angle of the wind with the horizontal axis. Blades are not accounted for in this study.

For the calculation the wave forces, Morrison's equation is used. The equation is composed of two terms, namely: the inertia, as identified by the inertia coefficient C_m , and the drag, as identified by the drag coefficient C_d [60]. Morrison's equation is given by:

$$F = F_d + F_m = \frac{1}{2} \rho_w C_d D |u_x| u_x + \rho_w C_m \frac{\pi D^2}{4} \frac{dU}{dt} \quad (5-23)$$

where U is the undisturbed fluid velocity, $\frac{dU}{dt}$ is the acceleration of the fluid, ρ_w is the water density, and D is the diameter of the cylinder. From the wave profile data depicted in **Table 5-6**, Stokes third-order wave theory can be used to model wave characteristics and behaviours. Stokes Wave theory is the most widely employed method applied in the offshore structural analysis because of its precision in predicting the wave kinematic properties.

Environmental loads, including tidal currents and wind-driven currents, do not pose significant hazards to integrity of structures in shallow-water. However, they can contribute to other significant excitations such as those generated by the wind and waves. The current speed ($v(z)$) can be used to represent the tidal current profile at distance z , from still water level. The current speed varies exponentially from the current at the level of still water v_0 through the distance to the topwater column z . This is given by:

$$v(z) = v_0 \left(\frac{h+z}{h} \right)^{\frac{1}{7}} \text{ for } z \geq 0 \quad (5-24)$$

where h is the depth of water. The extreme tidal current occurs approximately at mean water level, with zero tidal currents at high and low tide. Once the tidal current profile is determined, a constant over depth current will be assumed. Wind-driven currents are as a result of shear forces imposed on the water surface due to wind and are, hence, likely to have the same orientation in a similar direction with the wind. The sea surface wind-driven current can be approximated according to IEC61400-3, as:

$$U_{wind} \approx 0.01 U_{1h,10m \text{ in}} \quad (5-25)$$

where $U_{1h,10min}$ is the hourly mean at 10m height.

Table 5-6. Water levels and wave data of interest for the K-13 deepwater site [6]

Parameter	Value
Lowest Astronomical Tide, LAT (m)	-1.06
Tidal range, Δz_{tide} (m)	2.22
Storm surge, Δz_{surge} (m)	2.13
Air gap, Δz_{air} (m)	1.5
Significant wave height, H_s (m)	9.4
Maximum 50-year wave height, $H_{50,max}$ (m)	17.48
Maximum wave period range, T_{50} (s)	10.8 – 14
Max. wave height above still water for deck height calculation, ξ_w (m)	11.36

Hydrostatic pressure is the pressure of the water column the submerged jacket parts are subjected to. This can be evaluated by using a control volume analysis of an infinitesimally small cube of fluid by making a simplified assumption having constant gravity as well as density through depth. Therefore,

$$p(z) - p(z_0) = \frac{1}{A} \int_{z_0}^z dz' \iint^{\rho} (z')g(z')dA = \int_{z_0}^z dz' \rho(z')g(z') = \rho gh \quad (5-26)$$

where $p(z)$ is the pressure at a given height z , $p(z_0)$ is the pressure at z_0 , which is the top of the water column, Therefore, $p(z_0) = P_{atm}$, ρ is the water density (kg/m^3), g is the gravity (m/s^2), $h = (z - z_0)$ is the height of the liquid column between the test volume and the zero reference point of the pressure.

The nacelle and rotor are modelled in the FEA as concentrated or distributed masses. This means that the hub and blades are not part of the parametric model. According to [55], it is not necessary to model the blades since, apart from the added mass applied to the top of the tower, the impact of the parked and feathered blades on the eigen-frequency of OWTs is not significant. The Rotor Nacelle Assembly (RNA) mass is 1072 tons.

The structural integrity of the support structure is checked according to DNV-OS-J101, which is the most widely used standard in the design of OWTs. According to this standard, four limit states have to be considered in the design: Ultimate Limit States (ULS), FLS, Accidental Limit State (ALS) and Serviceability Limit State (SLS). This study focuses on FLS because according to several studies fatigue is the design driving criteria for offshore structural members [3,12]. For a detailed description of the ULS and FLS, the readers may refer to [3, 6, 18, 50].

5.3.2 OWT support structure subjected to pitting corrosion-fatigue

5.3.2.1 FEA model applying experimental procedure for validation

The material sample used is carbon steel material with maximum tensile strength of 610MPa, yield strength of 375MPa and elongation of 18% [38]. A dog-bone shaped sample is modelled in ANSYS environment employing the 4-point rotating bending fatigue test. The sample is pre-pitted in the centre section of the gauge length with the pit having diameter and depth of 0.9mm and 0.1mm respectively, and a pit aspect ratio of around 0.11. In-air and corrosion-fatigue tests were conducted under load control at $R = -1$. Further details of the experimental data

which was used and results to be compared for validation can be found in [38]. Details of the rotating bending test set-up as adapted for this study can be found in [61].

5.3.2.2 Parametric FEA

The jacket configuration, the sources of loads and a parametric FEA model of the three-dimensional space frame, tower and pile assembly (as shown in **Figure 5-3 (a)**) have been presented in this section. The present study is a continuation of the analysis been carried out in [6]. An ANN architecture is used in obtaining an expression to relate the input parameters with the output maximum stress range, which will be used later in this study. The parametric FEA, which will be used in this study, is presented in followings:

From the parametric FEA model explained earlier in this subsection, the critical joint is assessed by subjecting it to pitting corrosion and the result is shown in **Figure 5-3 (b)**. Since the pit size is very small, $223\mu m$, a model of a curved plate containing the crack is considered around the vicinity of the crack, in order to limit computational time/cost to practical levels.

The FEA model built in the [6] is used to find the equivalent stress at the vicinity of the pit, and the result is applied to the plate (see **Figure 5-3 (c)**). The Equivalent stress acting on the plate as modelled is then found to be 58.63 MPa.

A crucial step in assessment of the model to be applied for FEA is the mesh generation. The ANSYS software package provides a powerful and reliable structure mesh generator capable of developing a mesh which is consistent in all of the structure with the minimal computational requirement.

5.3.3 Structural Reliability Assessment (SRA) of the OWT support structure

In this section, the structural reliability of the OWT support structure subjected to pitting corrosion fatigue is assessed based on the damage tolerance approach considering FLS according to DNV-OS-J101 [59]. The SRA is carried out in two phases; the pit growth regime and the pit to crack transition regimes. Eq. (5-11) is used to determine the critical pit depth necessary for pit-to-crack transition, establishing $a_{pc} = 223\mu m$. This is also confirmed using the T-K diagram in **Figure 5-1** herein and from reference [38]. Then, Eq. (5-7) is used to calculate the time in years for the crack to reach critical size, establishing $t = 9 \text{ years}$.

The fully parametric FEA model presented in section 5.3 is used to perform FEA modelling taking into account of stochastic variables. The results are then post-processed using a non-intrusive formulation as developed in this study.

5.3.3.1 Fatigue limit state

OWT jackets are subjected to significant cyclic loads induced by wind and wave, and therefore their design is generally dominated by FLS. The FLS can be assessed by using two types of methods, i.e. S-N curve method and Fracture mechanics method. According to the S-N curve method the number of loading cycles to failure, N , can be obtained by [6]

$$\log N = A - m \log \Delta S \quad (5-27)$$

where A and m are the intercept and the slope of the S-N curve on the log-log plot, respectively, and ΔS is the stress range. The two parameters in Eq. (5-27), i.e. intercept A and slope m are generally given by design standards, e.g. DNVGL-ST-0126. The performance function of fatigue reliability assessment based on the S-N curve method can be expressed as [1,62]:

$$g_{f,SN} = \log N - \log N_t \quad (5-28)$$

where subscripts f and SN denote the FLS and S-N curve method respectively; N is the number of loading cycles to failure as given by Eq. (5-27), N_t is the number of loading cycles expected during the given design life. N_t can be estimated based on rated rotor speed n_{rated} and availability η_a (98.5%) on the selected location [20,63]. Thus, considering a lifetime requirement of 20 years, the number of cycles is equal to:

$$N_t = \eta_a \cdot n_{rated} \times (20[\text{year}] \times 365[\text{day/year}] \times 24[\text{hour/day}] \times 60[\text{min/hour}]) \quad (5-29)$$

Compared to the S-N curve method, the fracture mechanics method is more detailed and involves evaluating crack growth. The performance function for fatigue reliability analysis based on LEFM is given by:

$$g_{f,FM} = \int_{a_0}^{a_c} \frac{1}{Y(a)^m (\sqrt{\pi a})^m} da - C \Delta S^m (N(t) - N_0) \quad (5-30)$$

where subscript f and FM denote the fatigue limit state and fracture mechanics method, respectively; a_0 is the initial crack depth (or the crack depth at time t_0); a_c is the critical crack depth; $Y(a)$ is the geometry correction factor, which is a function of crack depth a ; m and C are material constants; $N(t)$ is the total number of stress cycles in the time period $[t_0, t]$; and N_0 is the initial number of stress cycles.

5.3.3.2 Stochastic variables and FEA

The stochastic variables considered in this study are presented in **Table 5-7**, **Table 5-8** and **Table 5-9** for the two crack propagation regimes. Two stochastic variables were considered for the pit growth regime and five variables considered for the crack propagation regimes, for each of the two cases. The coefficient of variation (COV) of all stochastic variables was assumed to be 0.05, except for inputs to the first ANN which were assumed to be 0.1 [37,64,65]. Eight stochastic variables were considered for the first ANN, including thrust force, tilting moment, torsional moment, weight of RNA, hydrodynamic load, and three young modulus at three soil strata. The total hydrodynamic load is considered differently, based on its dependence on the wave height, wave period and current speed. To find the peak hydrodynamic force acting on the system, a Weibull distribution is applied to the significant wave height and the current speed, while the lognormal distribution is applied to the wave period [3, 59, 60]. The distribution is then fitted into a Weibull-equivalent distribution. In the presence of observed data, distribution fitting algorithms (such as Akaike Information Criterion, Bayesian Information Criterion and Kolmogorov-Smirnov) are often employed to determine the shape coefficients of the most appropriate statistical distributions [16].

Table 5-7. Stochastic variables for the pit growth regime.

Description	Distribution types	References
Critical pit depth	Lognormal	[37]
Applied stress range	Weibull	[80]

Table 5-8. Stochastic variables for the crack propagation regimes for the SMART[®] crack growth analysis case.

Description	Distribution types	References
Young's modulus of steel ²	Normal	[16]
The major radius of semi-elliptical corrosion pit ²	Lognormal	[37]
The minor radius of semi-elliptical corrosion pit ²	Lognormal	[37]
Applied stress range ²	Weibull	[80]
Young's modulus of soils ¹	Normal	[3,6,64,66]
Thrust force ¹	Normal	[3,6,64,66]
RNA weight ¹	Normal	[3,12]
Tilting moment ¹	Normal	[3,12]
Torsional moment ¹	Normal	[3,12]
Material constant, C	Lognormal	[37]
Small crack length	Lognormal	[37]
Thickness/ final crack depth	Lognormal	[37]

¹Inputs to the first ANN architecture

Table 5-9. Stochastic variables for the crack propagation regimes for the theoretical analysis case.

Description	Distribution types	References
Pit depth	Lognormal	[37]
Small crack length	Lognormal	[37,80]
Thickness/ final crack depth	Lognormal	[37,80]
Equivalent stress range	Weibull	[37,80]
Material constant, C	Lognormal	[37,80]
Geometry/ shape factor	Normal	[37,80]

For the second regime, after defining the stochastic variables, stochastic FEA modelling of the OWT foundation was performed using the FEA model built earlier, as discussed in Section 5.3.2.2 with the aid of the Design of Experiments (DoE) tool in ANSYS. This allows the designation of the various input variables as stochastic, possessing distributions of different types. DoE enhances the design points variation with the output parameters, which are the stress intensity factor range and crack extension.

5.3.3.3 SRA using theoretical methods

Having defined the stochastic parameters, for the two methods, in **Table 5-7**, **Table 5-8** and **Table 5-9** the performance function is determined by substituting the pit growth regime, small crack regime life and long crack regime life into the FLS Equation, i.e. substituting Eq. (5-12), Eq. (5-14) and Eq. (5-16) into Eq. (5-30). The resulting performance function can be expressed by Eq. (5-31). Subsequently, the FORM is employed in predicting the time-variant reliability index.

$$g_{f,FM} = \int_{a_{pc}}^{a_{tr}} \frac{1}{Y(a)^{m_s}(\sqrt{\pi a})^{m_s}} da + \int_{a_{tr}}^{a_f} \frac{1}{Y(a)^{m_l}(\sqrt{\pi a})^{m_l}} da \quad (5-31)$$

$$- C_s \Delta S^{m_s} N(t_s) - C_l \Delta S^{m_l} (N(t_{pit} + t_l) - N_{pit})$$

5.3.3.4 Non-intrusive formulation

A flow chart of the non-intrusive formulation developed for this study is presented in **Figure 5-4**. The FEA model built earlier is employed to perform a number of FEA simulations on the plate by adopting the use of the ANSYS DoE package. The DoE used in this study is the Latin hypercube sampling design method [46,47]. Further information on the theoretical background on the ANSYS DesignXplorer can be found in [6,67,68]. Having executed the simulations on the DoE tool packaged in ANSYS, the results are imported into a developed MATLAB

algorithm that has been coded for ANN-based Response Surface Modelling (RSM), which is presented in later in this section. In summary, the sequential steps start from defining the system, the corresponding limit state and selection of the parameters to be designated stochastic in the analysis. Next, a series of FEA simulations are executed by changing inputs and recording outputs corresponding to the FLS to map the structural response over the domains of stochastic variables. A suitable method is then employed to estimate the system response and express the output parameters in terms of global inputs. Finally, the reliability index is computed using FORM and MCS. In this instance, the iterative FORM algorithm will be used and compared with MCS for validation of the results. The FORM is widely used because it offers a good balance between accuracy and efficiency for realistic problems. A limitation of the direct simulation method is in its requirement for prohibitively large amount of simulations to estimate the very low values of probability of failure characterised by complex engineering systems such as offshore structures [6,46,47].

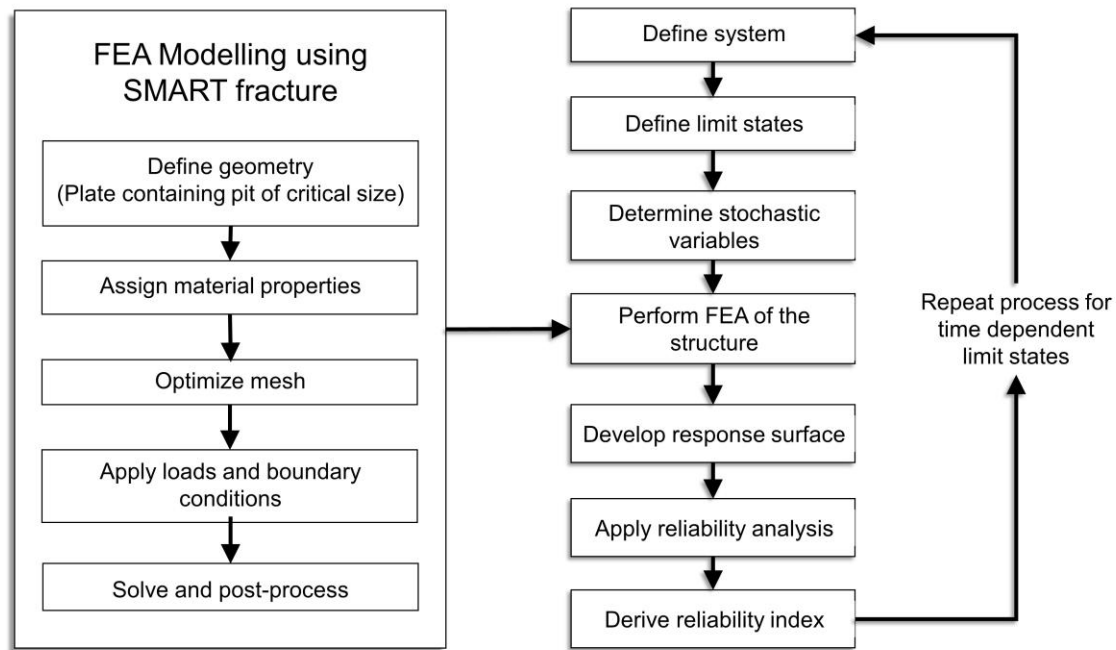


Figure 5-4. Flow chart of non-intrusive formulation

Two ANNs were trained to relate various stochastic variables for predicting the performance function. The first ANN, named ANN-1, uses Young's modulus of soils, thrust force, RNA weight, hydrodynamic loads, and tilting and torsional moments to predict the applied stress range to the structure. The second ANN, named ANN-2, uses Young's modulus of the steel structure, the major and minor radii of corrosion pit, and the applied stress range (supplied by ANN-1) to predict the stress intensity factor range, ΔK , and the crack extension, Δa . The latter

target variables are then used to compute the LSF. The readers may refer to **Table 5-8** for a summary of the variables involved.

Note that it is possible to use a single ANN that takes the eight stochastic variables as input for predicting the two desired target variables, instead of 2 separated ANNs. However, having an intermediate predictor for the applied stress range is more advantageous because of the added interpretability of results. The ANNs were trained with data generated from 300 stochastic FEA simulations in ANSYS. The training data set for ANN-1 consists of 300 instances of the eight stochastic variables and one target variable, while that for ANN-2 consists of 300 instances of the four stochastic variables and the two target variables. Both ANN architectures consist of 1 hidden layer with ten hidden neurons. The symmetric sigmoid activation function was used in each neuron. The ANNs were trained with 70% of the generated data, validated by the other 15%, and tested by the rest. Neural network training was performed using stochastic gradient descent with Bayesian regularization, which were used to obtain the weight values in the ANNs.

The results for training these ANNs are summarized in **Table 5-10**, showing high accuracy during both training and testing. This means that the trained ANNs are reliable predictors of the target variables for subsequent structural reliability analysis.

Table 5-10. Training results for the ANNs used in the study

Neural network	Training accuracy ^a	Testing accuracy	Accuracy for all data
ANN-1	99.90%	99.71%	99.87%
ANN-2	99.61%	99.58%	99.60%

^a Accuracies are given as R^2 -values.

Having obtained the performance function from the ANN, the FORM is used to calculate the reliability index β . The procedure for Hasofer and Lind's algorithm is summarised below [69]:

1. Define the performance function for the FLS. This is achieved by substituting the equation expressing the output parameter in terms of the four stochastic input parameters generated via ANN as described earlier in this section into Eq. (5-2). The solution obtained is then substituted into the FLS in Eq. (5-31) which yields the required performance function.

2. Set the mean value point as an initial design point, i.e. $x_{i,k} = \mu_{x_i}$ for $i = 1, 2, \dots, n$, and calculate the gradients $\nabla g(X_k)$ of the LSF at this design point. Here, $x_{i,k}$ refers to the i^{th} element in the vector X_k of the k^{th} iteration, and μ_{x_i} is the mean value of the i^{th} element;
3. Calculate the initial reliability index β using the mean-value method, i.e. $\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}}$ and its direction cosine α using the following equations:

$$\beta = \frac{\mu_{\tilde{g}}}{\sigma_{\tilde{g}}} = \frac{g(\mu_X)}{\left[\sum_{i=1}^n \left(\frac{\partial g(\mu_X)}{\partial x_i} \right)^2 \cdot \sigma_{x_i}^2 \right]^{\frac{1}{2}}} \quad (5-32)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (5-33)$$

4. Compute a new design point X_k and U_k , function value, and gradients at this new design point.

$$x_{i,k} = \mu_{x_i} + \beta \sigma_{x_i} \alpha_i \quad (5-34)$$

$$u_{i,k} = \frac{x_{i,k} - \mu_{x_i}}{\sigma_{x_i}} \quad (5-35)$$

5. Compute the reliability index β and direction cosine α_i using Eqs. (5-36) and (5-37), respectively.

$$\beta = \frac{g(U^*) - \sum_{i=1}^n \frac{\partial g(U)}{\partial x_i} \sigma_{x_i} u_i^*}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(U^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (5-36)$$

$$\alpha_i = - \frac{\left(\frac{\partial g(X^*)}{\partial x_i} \right) \cdot \sigma_{x_i}}{\sqrt{\sum_{i=1}^n \left(\frac{\partial g(X^*)}{\partial x_i} \sigma_{x_i} \right)^2}} \quad (5-37)$$

Repeat steps 4 to 5 until convergence of the reliability index β is achieved.

5.4 Results and discussion

5.4.1 Mesh sensitivity analysis

The numerical results of fatigue analysis using finite element simulations are affected by the element size [70]. This study aims to explore the influence of various mesh sizes on fatigue life prediction. Based on the numerical results, the mesh size used is $15\mu m$ within the pit depth vicinity (crack front) and $1000\mu m$ for the rest of the curved plate (15, 1000). In this section, two more element size configurations (10, 1000) and (20, 1000) are investigated for surface pit $223\mu m$ at different applied loads to study the effect of the mesh size. The curves of the fatigue life predictions from the three different element sizes are plotted in **Figure 5-5 (a)** and **(b)** for the two applied loads. Both figures reveal that the three curves obtained from different mesh sizes have a similar pattern of fatigue crack growth. Also, it can be observed that as the element size increases, the range of crack growth rate captured is wider. However, as the element size decreases a more closely spaced variation of the points is captured as against the widely dispersed captured for larger element sizes. This implies that more solution sub-steps is required when the element size is smaller to have the same range of crack growth rate captured by the larger element size. Also, as long as the mesh size is taken in a reasonable range, the mesh size does not affect the fatigue behaviour. Hence, fatigue behaviour can be determined solely by fatigue crack growth rate. In both Figures, the curves overlap as they are in very close proximity which indicates that the element size configuration of (15, 1000) is capable of simulating the fatigue behaviours of the structure with surface corrosion pits considered in this study (in view of the element size chosen to be intermediate, trading off between capturing more points and computational cost).

5.4.2 Validation of the FEA tool against experimental data

In this section, comparison of the fatigue crack growth rate have been made between the SMART© analysis results and experimental test data found in [38] as the test set-up have been presented in section 5.3.2.1. As depicted in **Figure 5-6**, there is a wide scatter in the fatigue crack growth rate in the threshold region for both the results predicted by the experiment and the FEA SMART© analysis tool. However, along the Paris' region, i.e. after the threshold region, the test data points are seen to be dispersed around the best fit line of the experimental data such that it aligns in and can be represented by a straight line [54,71–76]. From the foregoing, it can be inferred that there is reasonable agreement between the test results and the FEA SMART© analysis results predicted. Hence, it can be concluded that the SMART© FEA results are acceptable due to the slight variation in results predicted by the simulation in comparison with the experimental data at the Paris' region. The transition region

between the short and long crack was not predicted so well by the fatigue crack growth models. One way to address this problem is by introducing effective initial flaw size (EIFS), which is an alternative solution to the K-T diagram [46].

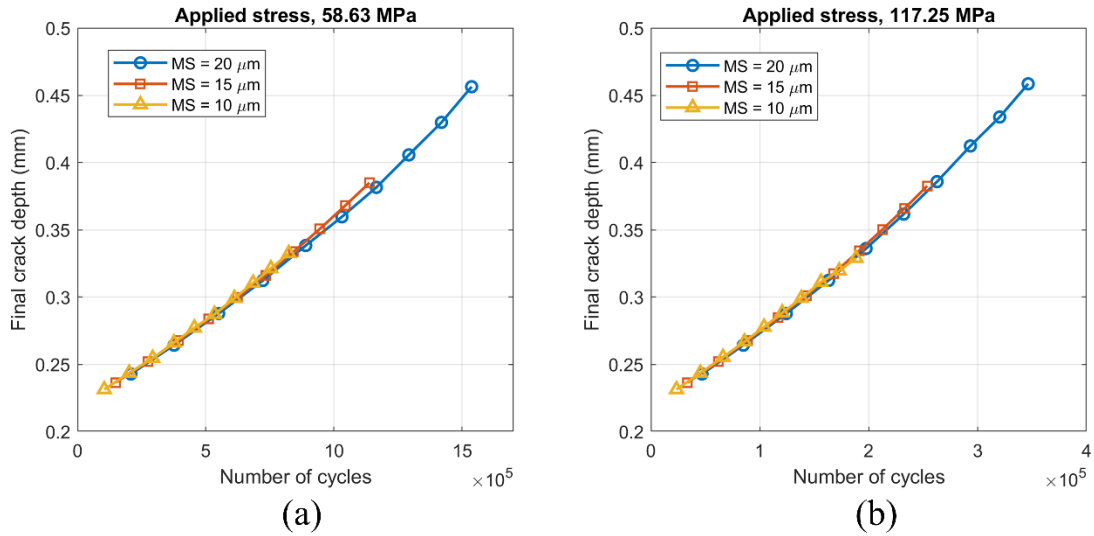


Figure 5-5. Curves of fatigue life prediction obtained from different element sizes for applied stress: (a) $\sigma = 58.63\text{MPa}$; (b) $\sigma = 117.25\text{MPa}$.

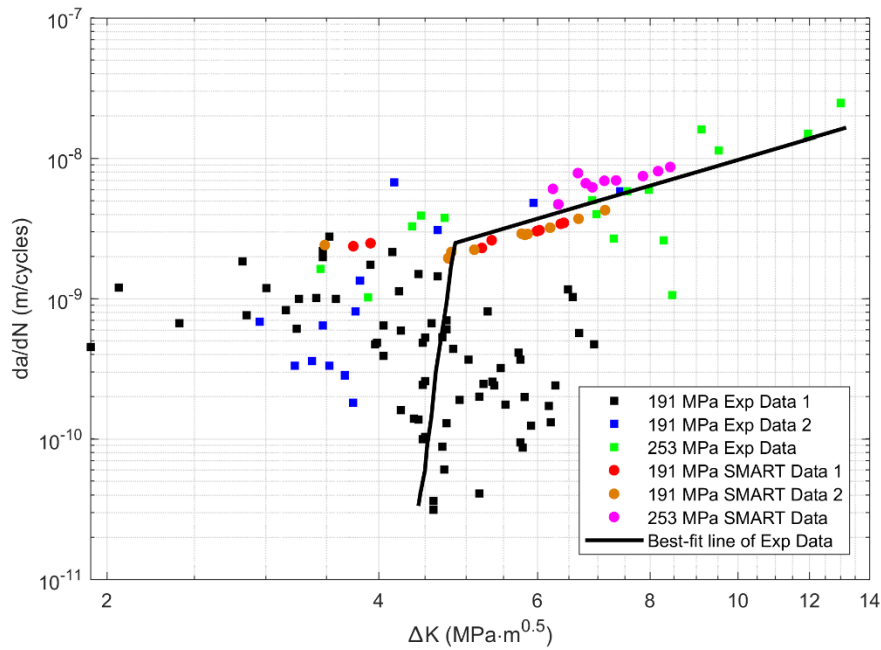


Figure 5-6. Comparison between experimental data according to [38] against the FEA tool adopting the same test set-up.

5.4.3 Validation of the FEA model

In this subsection, fatigue assessment is provided by a theoretical analysis, i.e. according to the literature [36, 37, 47, 64, 65] and procedures given in design standard BS7910 [51] for

offshore structures with tubular joints, as described in section 5.2.2. Based on the current SMART[®] analysis results, comparisons of the fatigue crack growth rate and cycle number for allowable crack growth have been made for validation.

5.4.3.1 Comparison of fatigue crack growth rate

Comparisons of fatigue crack growth rate with ΔK obtained from SMART[®] and theoretical analysis are presented in **Figure 5-7 (a)** and **(b)** for two surface crack geometries. For both pit sizes considered, the fatigue crack growth rate curve obtained by the SMART[®] analysis is close to that obtained from theoretical analysis with most of the fatigue crack growth rate of SMART[®] analysis points overlapping with the theoretical curve. In summary, the comparisons of fatigue crack growth rates indicate that the results obtained by SMART[®] are acceptable.

5.4.3.2 Comparison of fatigue life

In this section, comparisons of fatigue life predictions obtained from SMART[®] analysis and theoretical for two different crack sizes are presented. In **Figure 5-8 (a)** and **(b)**, it is observed that the results obtained using the two methods are very similar. From **Figure 5-8 (a)**, it can be said that the SMART[®] analysis is slightly more conservative than the theoretical analysis results while **Figure 5-8 (b)** indicates otherwise. Thus, it could be explained for surface cracks, predicting the fatigue crack growth by using the theoretical method considers only the crack height's variation, while in the current SMART[®] model the full 3-D crack is taken into account. Thus as the crack propagates, the SMART[®] approach takes account of the changes in the shape factor, whereas in the theoretical analysis this value remains constant. Hence, with SMART[®] the cycle number can be reduced at a certain crack extensions, in comparison to the theoretical results which show a larger value of the rate of fatigue crack growth for longer crack sizes. These results suggest that the SMART[®] analysis may be more reliable when compared to the theoretical analysis. It can be concluded that the fatigue crack growth behaviour of the structure with a hemispherical surface crack (corrosion pit) can be accurately predicted by the SMART[®] analysis tool inbuilt in ANSYS.

5.4.4 Validation of the FORM

Comparison of the probability of failure (POF) results obtained from the FORM and MCS is presented in **Table 5-11**. This was performed using a simple case assuming only the long crack growth regime life in the g-function. As can be observed, the difference in the values of POF predicted by the FORM and MCS remains consistently not more than 5%. Hence the agreement of the two methods can be considered sufficient. Also, as can be observed the values predicted by the FORM are more accurate for very low POF.

5.4.5 Corrosion-fatigue SRA results

Time-variant corrosion-fatigue reliability assessment was carried out employing the modelling approach presented in section 5.2.3. The results are presented in **Figure 5-9**. From the time-variant corrosion fatigue reliability index curve, it can be observed that the structure failed just after the 18th year as the reliability index β falls below the defined threshold of $\beta = 3.71$ as specified by DNV [1,3,16,64]. From **Figure 5-9**, it can be observed that the structural reliability prediction produced following the theoretical method gave conservative results compared to that produced using the non-intrusive formulation at the start of the through life of the structure (i.e. from year 2 to year 8) but towards the end of the design life the results may be overly optimistic. Apart from the FEA SMART model accounting for 3D effects, this variation could be attributed to the difference in the input stochastic variables between the two methods, i.e. the non-intrusive method incorporates the effects of the response of the structure to wind and hydrodynamic loads as well as soil-structure interaction. From Section 5.2.3 the life for the pit growth regime was calculated to be nine years which is almost equal to the crack propagation regimes. It can therefore be concluded that the structure's life is dominated by the pitting corrosion process. Therefore to mitigate against the effects of corrosion fatigue, factors promoting the pitting corrosion process should be eliminated in order to increase the time to failure of the structure.

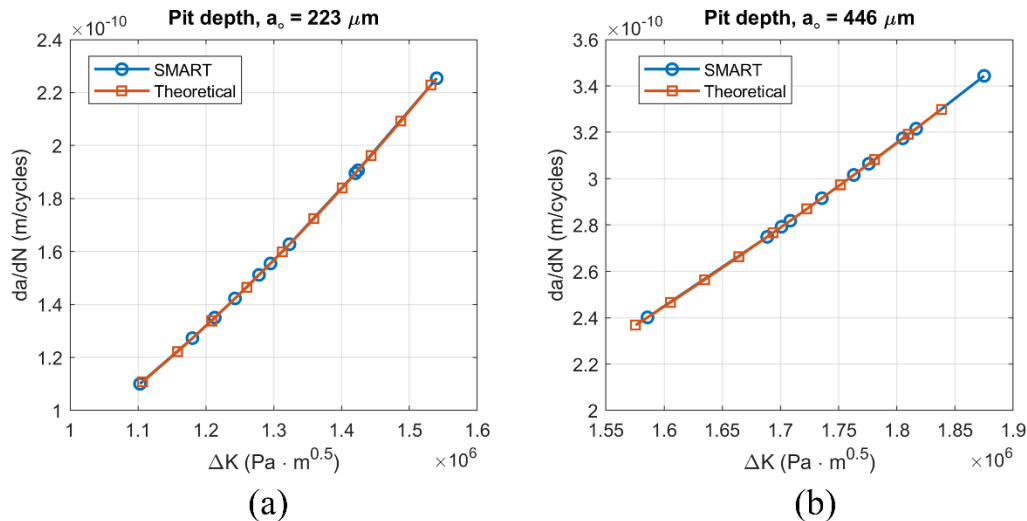


Figure 5-7. Fatigue crack growth rate with ΔK obtained from SMART® and theoretical analysis respectively for: (a) $a_0 = 223\mu\text{m}$; (b) $a_0 = 446\mu\text{m}$.

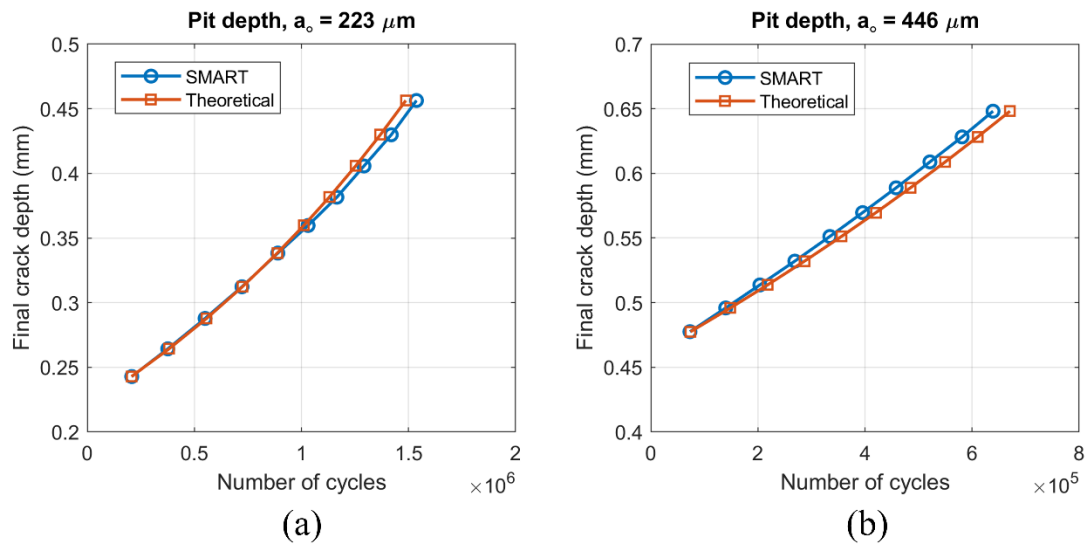


Figure 5-8. Crack heights versus the number of cycles obtained from SMART® and Theoretical analysis respectively: (a) $a_0 = 223\mu\text{m}$; (b) $a_0 = 446\mu\text{m}$.

The life of the structure can be increased by extending the pit growth regime, i.e. the time taken before critical pit depth is reached thus initiating the pit-to-crack transition. This can be achieved by reducing the pit current coefficient I_{po} . Practical ways of implementing this could be via the use of cathodic protection, protective coating, and/or improved scheduled inspection, maintenance and repair.

5.4.6 Global sensitivity analysis

The results of a sensitivity analysis performed on the SRA using the stochastic parametric FEA is depicted in **Figure 5-10**. This depicts the most critical parameters that can radically change the response and reliability performance of the structure. It can be observed that the magnitude of the RNA weight is the most significant and is negatively correlated. The magnitude of thrust force and the torsional moments are significant and have a positive correlation. The hydrodynamic load is negatively correlated and has little impact in comparison to the other parameters. The young's modulus of the soil system has very little or no impact, as do the tilting moment and steel young's modulus. While the other parameters major and minor radius of the pit are negatively correlated with little impact but inversely compared to the applied stress. From the analysis, it was revealed that a variation in the value of the aspect ratio of the corrosion pit at critical size (as long as size of axes are not more than the original value) leads to a corresponding variation in the reliability of the structure. Therefore, aspect ratio of pits at critical size plays a key role in the reliability of a structure.

Table 5-11. Probability of failure results as predicted by the FORM and MCS

Time (years)	POF using FORM	POF using MCS	Percentage difference (%)
10	5.29E-11	0	Undefined
12	4.96E-02	0.046982	5
14	8.35E-01	0.835043	0.03
16	9.94E-01	0.996683	0.24
18	0.999917672	0.999958	4
20	0.999999999996536	1	3.46E-10

Abbreviations: FORM, first-order reliability method; MCS, Monte Carlo simulation; POF, Probability of failure

Probability of failure

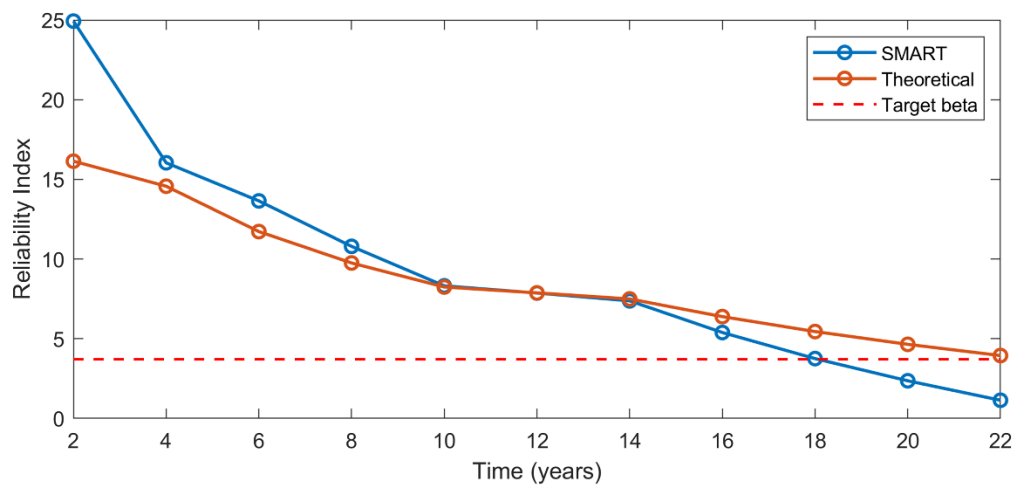


Figure 5-9. Corrosion fatigue reliability assessment

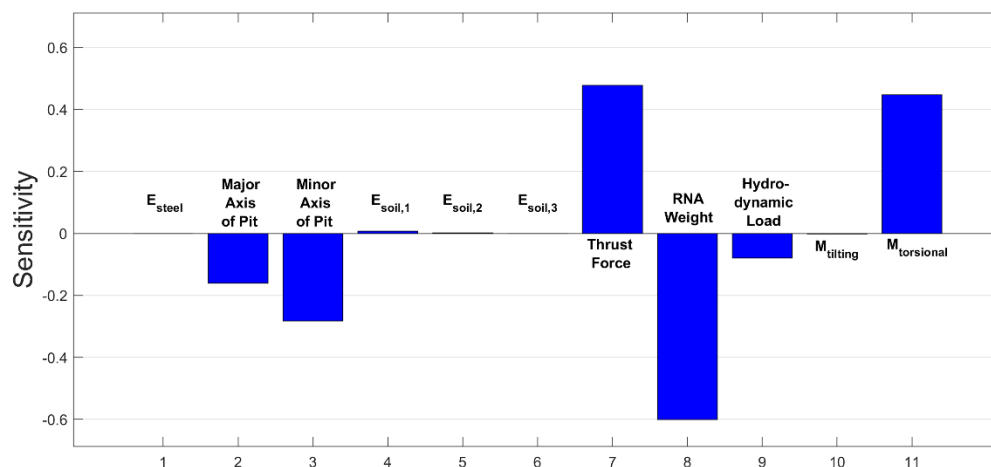


Figure 5-10. Global sensitivity analysis

5.5 Conclusions

In this study, a structural reliability assessment (SRA) of an offshore wind turbine (OWT) support structure subjected to pitting corrosion-fatigue was performed by employing the damage tolerance model approach. The reliability assessment for the corrosion pit growth regime was performed using empirical equations from classical corrosion mechanism methodologies, while the SRA for crack propagation regimes which includes the pit to small crack transition and the small crack to long crack transition regimes was performed using a stochastic parametric FEA model. A number of structural responses corresponding to varying input stochastic parameters were predicted using high capability tools: the SMART[®] crack growth analysis in combination with the Design Xplorer[®] as packaged in ANSYS workbench. Then these results were post-processed using an Artificial Neural Network (ANN) surrogate modelling method to evaluate the limit-state function (LSF). Afterwards, the reliability index is predicted via the widely used numerical reliability techniques of FORM and MCS. The following conclusions can be drawn from the present study:

- The conducted time-variant corrosion fatigue reliability assessment method presented in this work revealed that the modelled structure is not safe after the 18th year of operation as the reliability index falls below the target reliability set at 3.71. This result is believed to be more accurate than the theoretical study, which gives 22 years.
- The structural reliability prediction produced following the theoretical method gave conservative results compared to that produced using the non-intrusive formulation during the beginning of the through life, but reversed to give potentially overly optimistic results towards the end of the design life.
- The time-variant SRA carried out shows that the pitting corrosion growth regime dominates the life of the structure by 56%. The pit growth regime can be prolonged by reducing the pit current coefficient I_{po} .
- From the sensitivity analysis carried out, it was observed that a variation in the aspect ratio of the critical corrosion pit leads to a corresponding change in the structural reliability.
- The stochastic parametric FEA carried out in this study addresses the issue of randomness in the values of the shape factor, compared with the traditional methods which apply deterministic values.
- It was shown that the FEA predicts the pit accurately to small crack and small to long crack transition regimes as prescribed in classical corrosion fatigue mechanism methodology.

- The SMART© fracture FEA tool was validated against experimental data as there was agreement in the fatigue crack growth rate predicted using the same test set-up.
- Both the crack growth rate and fatigue life curves computed from the parametric FEA model show reasonable agreement with that computed using the theoretical analysis. It can be concluded that the validity of the FEA model used herein is confirmed.
- Good agreement is achieved when comparing the probability of failure calculated for the FORM and the MCS, which implies that the numerical reliability technique employed in this study is valid.

Acknowledgement

The Author Abdulhakim Shittu will like to acknowledge the Petroleum Technology Development Fund (PTDF) Nigeria for financial support. K.E.S. Pilario also acknowledges the support from the Faculty Development Fund of the Engineering Research and Development for Technology (ERDT) program of the Department of Science and Technology (DOST), Republic of the Philippines.

References

1. Kolios A., Wang L. Advanced reliability assessment of offshore wind turbine monopiles by combining reliability analysis method and SHM / CM technology. 2018; : 1412–1419.
2. IRENA. Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects. (A Global Energy Transformation paper) International Renewable Energy Agency. Abu Dhabi; 2019.
3. Wang L., Kolios A. A generic framework for reliability assessment of offshore wind turbine monopiles considering soil-solid interaction and harsh marine environments. 5th International Conference on Marine Structures, MARSTRUCT. Lisbon; 2017. pp. 931–938. Available at: DOI:10.1201/9781315157368-105
4. EWEA. Offshore Wind in Europe - Walking the tightrope to success. European Wind Energy Association. 2015;
5. Ioannou A., Angus A., Brennan F. A lifecycle techno-economic model of offshore wind energy for different entry and exit instances. Applied Energy. July 2018; 221: 406–424. Available at: DOI:10.1016/j.apenergy.2018.03.143
6. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. Applied Sciences. MDPI AG; 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860 (Accessed: 15 June 2020)
7. Ziegler L., Cosack N., Kolios A., Muskulus M. Structural monitoring for lifetime extension of offshore wind monopiles: Verification of strain-based load extrapolation algorithm. Marine Structures. 2019; 66(March): 154–163. Available at: DOI:10.1016/j.marstruc.2019.04.003

8. Wang X., Zeng X., Yang X., Li J. Feasibility study of offshore wind turbines with hybrid monopile foundation based on centrifuge modeling. *Applied Energy*. January 2018; 209: 127–139. Available at: DOI:10.1016/j.apenergy.2017.10.107
9. Wang X., Zeng X., Yang X., Li J. Seismic response of offshore wind turbine with hybrid monopile foundation based on centrifuge modelling. *Applied Energy*. February 2019; 235: 1335–1350. Available at: DOI:10.1016/j.apenergy.2018.11.057
10. Damiani R., Song H. A Jacket Sizing Tool for Offshore Wind Turbines within the Systems Engineering Initiative. Offshore Technology Conference, OTC 24140. Houston, Texas, USA; 2013. Available at: DOI:10.4043/24140-MS
11. Damiani RR., Song H., Robertson AN., Jonkman JM. Assessing the Importance of Nonlinearities in the Development of a Substructure Model for the Wind Turbine CAE Tool FAST. Volume 8: Ocean Renewable Energy. 2013; 8(March): V008T09A093. Available at: DOI:10.1115/OMAE2013-11434
12. Dong W., Moan T., Gao Z. Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection. *Reliability Engineering and System Safety*. Elsevier; 2012; 106: 11–27. Available at: DOI:10.1016/j.ress.2012.06.011
13. Silva JE., Garbatov Y., Guedes Soares C. Reliability assessment of a steel plate subjected to distributed and localized corrosion wastage. *Engineering Structures*. Elsevier Ltd; 2014; 59: 13–20. Available at: DOI:10.1016/j.engstruct.2013.10.018
14. Kim DH., Lee SG. Reliability analysis of offshore wind turbine support structures under extreme ocean environmental loads. *Renewable Energy*. Elsevier Ltd; 2015; 79(1): 161–166. Available at: DOI:10.1016/j.renene.2014.11.052
15. Gholizad A., Golafshani AA., Akrami V. Structural reliability of offshore platforms considering fatigue damage and different failure scenarios. *Ocean Engineering*. Elsevier; 2012; 46: 1–8. Available at: DOI:10.1016/j.oceaneng.2012.01.033
16. Kolios A., Di Maio LF., Wang L., Cui L., Sheng Q. Reliability assessment of point-absorber wave energy converters. *Ocean Engineering*. Elsevier Ltd; 2018; 163(October 2017): 40–50. Available at: DOI:10.1016/j.oceaneng.2018.05.048
17. Kolios A. A multi-configuration approach to reliability based structural integrity assessment for ultimate strength. Cranfield University; 2010.
18. Jiang Z., Hu W., Dong W., Gao Z., Ren Z. Structural reliability analysis of wind turbines: A review. *Energies*. 2017; 10(12): 1–25. Available at: DOI:10.3390/en10122099
19. Wang L., Kolios A., Nishino T., Delafin PL., Bird T. Structural optimisation of vertical-axis wind turbine composite blades based on finite element analysis and genetic algorithm. *Composite Structures*. Elsevier Ltd; 2016; 153(January 2015): 123–138. Available at: DOI:10.1016/j.compstruct.2016.06.003
20. Gentils T., Wang L., Kolios A. Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. *Applied Energy*. Elsevier Ltd; 2017; 199: 187–204. Available at: DOI:10.1016/j.apenergy.2017.05.009
21. Wang L., Quant R., Kolios A. Fluid structure interaction modelling of horizontal-axis wind turbine blades based on CFD and FEA. *Journal of Wind Engineering and Industrial Aerodynamics*. Elsevier; 2016; 158: 11–25. Available at: DOI:10.1016/j.jweia.2016.09.006
22. Achmus M., Abdel-Rahman K. Finite element modelling of horizontally loaded monopile foundations for offshore wind energy converters in Germany. *Frontiers in Offshore Geotechnics*. 2005; (August 2005). Available at: DOI:10.1201/NOE0415390637.ch38

23. Wang L., Kolios A., Delafin P-L., Nishino T., Bird T. Fluid structure interaction modelling of a novel 10MW vertical-axis wind turbine rotor based on computational fluid dynamics and finite element analysis. European Wind Energy Association Annual Conference and Exhibition, EWEA 2015 - Scientific Proceedings; Paris, France; 17 November 2015 through 20 November 2015; Code 125825; 44(0).
24. Yeter B., Garbatov Y., Guedes Soares C. Uncertainty analysis of soil-pile interactions of monopile offshore wind turbine support structures. *Applied Ocean Research*. Elsevier; 2019; 82(November 2018): 74–88. Available at: DOI:10.1016/j.apor.2018.10.014
25. Jung S., Kim SR., Patil A., Hung LC. Effect of monopile foundation modeling on the structural response of a 5-MW offshore wind turbine tower. *Ocean Engineering*. Elsevier; 2015; 109: 479–488. Available at: DOI:10.1016/j.oceaneng.2015.09.033
26. DNV GL AS. DNVGL-ST-0126 : Support structures for wind turbines. DNV GL - Standard Høvik, Norway: Det Norske Veritas; 2016 p. 182 pp. Available at: DOI:10.1016/j.jbiomech.2014.11.025
27. Kolios A., Srikanth S., Salonitis K. Numerical simulation of material strength deterioration due to pitting corrosion. *Procedia CIRP*. Elsevier B.V.; 2014; 13: 230–236. Available at: DOI:10.1016/j.procir.2014.04.040
28. Bhandari J., Khan F., Abbassi R., Garaniya V., Ojeda R. Modelling of pitting corrosion in marine and offshore steel structures - A technical review. *Journal of Loss Prevention in the Process Industries*. Elsevier Ltd; 2015; 37: 39–62. Available at: DOI:10.1016/j.jlp.2015.06.008
29. Larrosa NO., Akid R., Ainsworth RA. Corrosion-fatigue: a review of damage tolerance models. *International Materials Reviews*. Taylor & Francis; 2018; 63(5): 283–308. Available at: DOI:10.1080/09506608.2017.1375644
30. McCulloch WS., Pitts W. A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*. Kluwer Academic Publishers; December 1943; 5(4): 115–133. Available at: DOI:10.1007/BF02478259 (Accessed: 24 June 2019)
31. Hornik K., Stinchcombe M., White H. Multilayer feedforward networks are universal approximators. *Neural Networks*. Pergamon; 1 January 1989; 2(5): 359–366. Available at: DOI:10.1016/0893-6080(89)90020-8 (Accessed: 24 June 2019)
32. Bucher C., Most T. A comparison of approximate response functions in structural reliability analysis. *Probabilistic Engineering Mechanics*. 2008; 23(2–3): 154–163. Available at: DOI:10.1016/j.probengmech.2007.12.022
33. Hosni Elhewy A., Mesbahi E., Pu Y. Reliability analysis of structures using neural network method. *Probabilistic Engineering Mechanics*. Elsevier; 1 January 2006; 21(1): 44–53. Available at: DOI:10.1016/J.PROBENGMECH.2005.07.002 (Accessed: 26 June 2019)
34. Gomes HM., Awruch AM. Comparison of response surface and neural network with other methods for structural reliability analysis. *Structural Safety*. Elsevier; 1 January 2004; 26(1): 49–67. Available at: DOI:10.1016/S0167-4730(03)00022-5 (Accessed: 26 June 2019)
35. Chojaczyk AA., Teixeira AP., Neves LC., Cardoso JB., Guedes Soares C. Review and application of Artificial Neural Networks models in reliability analysis of steel structures. *Structural Safety*. Elsevier Ltd; 2015; 52(PA): 78–89. Available at: DOI:10.1016/j.strusafe.2014.09.002
36. Cardoso JB., de Almeida JR., Dias JM., Coelho PG. Structural reliability analysis using Monte Carlo simulation and neural networks. *Advances in Engineering Software*. Elsevier; 1 June 2008; 39(6): 505–513. Available at: DOI:10.1016/J.ADVENGSOFT.2007.03.015 (Accessed: 26 June 2019)
37. Shi P., Mahadevan S. Damage tolerance approach for probabilistic pitting corrosion fatigue life prediction. *Engineering Fracture Mechanics*. 2001; 68(13): 1493–1507. Available at: DOI:10.1016/S0013-7944(01)00041-8

38. Li SX., Akid R. Corrosion fatigue life prediction of a steel shaft material in seawater. *Engineering Failure Analysis*. Elsevier Ltd; 2013; 34: 324–334. Available at: DOI:10.1016/j.engfailanal.2013.08.004
39. Kondo Y. Prediction of Fatigue Crack Initiation Life Based on Pit Growth. *CORROSION*. 13 January 1989; 45(1): 7–11. Available at: DOI:10.5006/1.3577891 (Accessed: 25 June 2019)
40. Wang QY., Pidaparti RM., Palakal MJ. Comparative study of corrosion-fatigue in aircraft materials. *AIAA Journal*. 2012; 39(2): 325–330. Available at: DOI:10.2514/3.14734
41. Rokhlin SI., Kim JY., Nagy H., Zoofan B. Effect of pitting corrosion on fatigue crack initiation and fatigue life. *Engineering Fracture Mechanics*. 1999; 62(4–5): 425–444. Available at: DOI:10.1016/S0013-7944(98)00101-5
42. Sriraman MR., Pidaparti RM. Crack Initiation Life of Materials Under Combined Pitting Corrosion and Cyclic Loading. *Journal of Materials Engineering and Performance*. Springer US; 20 February 2010; 19(1): 7–12. Available at: DOI:10.1007/s11665-009-9379-9 (Accessed: 25 June 2019)
43. Sriraman MR., Pidaparti RM. Life Prediction of Aircraft Aluminum Subjected to Pitting Corrosion Under Fatigue Conditions. *Journal of Aircraft*. 22 July 2009; 46(4): 1253–1259. Available at: DOI:10.2514/1.40481 (Accessed: 25 June 2019)
44. Wu X. Short fatigue crack behaviour of a submarine hull steel in inert and aggressive environments. 1995;
45. Xue Y. Modeling fatigue small-crack growth with confidence – A multistage approach. *International Journal of Fatigue*. Elsevier; 1 July 2010; 32(7): 1210–1219. Available at: DOI:10.1016/J.IJFATIGUE.2009.12.016 (Accessed: 25 June 2019)
46. Morse L., Khodaei ZS., Aliabadi MH. A multi-fidelity modelling approach to the statistical inference of the equivalent initial flaw size distribution for multiple-site damage. *International Journal of Fatigue*. Elsevier; 2019; 120(November 2018): 329–341. Available at: DOI:10.1016/j.ijfatigue.2018.11.010
47. Morse L., Sharif Khodaei Z., Aliabadi MH. A multi-fidelity boundary element method for structural reliability analysis with higher-order sensitivities. *Engineering Analysis with Boundary Elements*. Elsevier Ltd; 2019; 104(April): 183–196. Available at: DOI:10.1016/j.enganabound.2019.03.036
48. Choi S-K., Grandhi R., Canfield R. *Reliability-based Structural Design*. Springer-Verlag London; 2007.
49. ANSYS. White Paper: SMART Fracture. 2018.
50. Anderson TL. *Fracture Mechanics Fundamentals and Applications*. Taylor and Francis; 2005. 1–610 p.
51. BS 7910. BSI Standards Publication Guide to methods for assessing the acceptability of flaws in metallic structures. BSI Standards Publication. 2015; (UK): 490.
52. Saha JK. Corrosion of constructional steels in marine and industrial environment: Frontier work in atmospheric corrosion. *Engineering materials*. India: Springer; 2013. 1–173 p. Available at: DOI:10.1007/978-81-322-0720-7
53. Cerit M., Genel K., Eksi S. Numerical investigation on stress concentration of corrosion pit. *Engineering Failure Analysis*. Elsevier Ltd; 2009; 16(7): 2467–2472. Available at: DOI:10.1016/j.engfailanal.2009.04.004
54. Igwemezie V., Mehmanparast A., Kolios A. Materials selection for XL wind turbine support structures: A corrosion-fatigue perspective. *Marine Structures*. Elsevier Ltd; 2018; 61(December 2017): 381–397. Available at: DOI:10.1016/j.marstruc.2018.06.008

55. Martinez-Luengo M., Kolios A., Wang L. Parametric FEA modelling of offshore wind turbine support structures: Towards scaling-up and CAPEX reduction. *International Journal of Marine Energy*. 2017; 19(2017): 16–31. Available at: DOI:10.1016/j.ijome.2017.05.005
56. Drucker D., Prager W. Soil mechanics and plastic analysis or limit design. *Quarterly of Applied Mathematics*. 1952; 10(2): 157–165.
57. Damiani R. JacketSE : An Offshore Wind Turbine Jacket Sizing Tool Theory Manual and Sample Usage with Preliminary Validation. Denver West Parkway Golden, CO; 2016.
58. IEC. IEC 61400-1: Wind Turbines Part 1: Design Requirements. 2005;
59. DNV. DNV-OS-J101 Design of Offshore Wind Turbine Structures. May. 2014; (May): 212–214.
60. Sarpkaya TS. Wave Forces on Offshore Structures. Cambridge: Cambridge University Press; 2010. Available at: DOI:10.1017/CBO9781139195898 (Accessed: 7 October 2019)
61. Hassan T., Liu Z. On the difference of fatigue strengths from rotating bending, four-point bending, and cantilever bending tests. *International Journal of Pressure Vessels and Piping*. 2001; 78(1): 19–30. Available at: DOI:10.1016/S0308-0161(00)00080-6
62. Pook LP. Linear elastic fracture mechanics for engineers : theory and applications. WIT Press; 2000. 154 p.
63. Kühn M. Dynamics and Design Optimization of Offshore Wind Energy Conversion Systems. Sciences-New York. 1999.
64. (DNV) Det Norske Veritas. Structural Reliability Analysis of Marine Structures. DNV CN 30-6. 1992;
65. Yeter B., Garbatov Y., Soares CG. Reliability of Offshore Wind Turbine Support Structures Subjected to Extreme Wave-Induced Loads and Defects. *Proceedings of the ASME 2016 35th International Conference on Ocean, Offshore and Arctic Engineering*. Busan, South Korea; 2016.
66. BSI. BS EN 1990 Eurocode: Basis of Structural Design. British standard institute. 2002;
67. Reh S., Beley JD., Mukherjee S., Khor EH. Probabilistic finite element analysis using ANSYS. *Structural Safety*. 2006; 28(1–2): 17–43. Available at: DOI:10.1016/j.strusafe.2005.03.010
68. ANSYS. DesignXplorer User's Guide. 2018.
69. Hasofer A., Lind N. An exact and invariant second moment code format. *J. Engrg. Mech. Div ASCE*. 1974; 100(1): 111–121.
70. Zhang YM., Fan M., Xiao ZM., Zhang WG. Fatigue analysis on offshore pipelines with embedded cracks. *Ocean Engineering*. Elsevier; 2016; 117(May): 45–56. Available at: DOI:10.1016/j.oceaneng.2016.03.038
71. Adedipe O., Brennan F., Mehmanparast A., Kolios A., Tavares I. Corrosion fatigue crack growth mechanisms in offshore monopile steel weldments. *Fatigue and Fracture of Engineering Materials and Structures*. 2017; 40(11): 1868–1881. Available at: DOI:10.1111/ffe.12606
72. Mehmanparast A., Brennan F., Tavares I. Fatigue crack growth rates for offshore wind monopile weldments in air and seawater: SLIC inter-laboratory test results. *Materials and Design*. Elsevier Ltd; 2017; 114: 494–504. Available at: DOI:10.1016/j.matdes.2016.10.070
73. Igwemezie V., Mehmanparast A. Waveform and frequency effects on corrosion-fatigue crack growth behaviour in modern marine steels. *International Journal of Fatigue*. Elsevier Ltd; 1 May 2020; 134: 105484. Available at: DOI:10.1016/j.ijfatigue.2020.105484

74. Igwemezie V., Dirisu P., Mehmanparast A. Critical assessment of the fatigue crack growth rate sensitivity to material microstructure in ferrite-pearlite steels in air and marine environment. *Materials Science and Engineering A*. Elsevier Ltd; 29 April 2019; 754: 750–765. Available at: DOI:10.1016/j.msea.2019.03.093
75. Jacob A., Oliveira J., Mehmanparast A., Hosseinzadeh F., Kelleher J., Berto F. Residual stress measurements in offshore wind monopile weldments using neutron diffraction technique and contour method. *Theoretical and Applied Fracture Mechanics*. Elsevier B.V.; 1 August 2018; 96: 418–427. Available at: DOI:10.1016/j.tafmec.2018.06.001
76. Jacob A., Mehmanparast A., D'Urzo R., Kelleher J. Experimental and numerical investigation of residual stress effects on fatigue crack growth behaviour of S355 steel weldments. *International Journal of Fatigue*. Elsevier Ltd; 1 November 2019; 128: 105196. Available at: DOI:10.1016/j.ijfatigue.2019.105196
77. ASTM. ASTM E647: Standard test method for measurement of fatigue crack growth rates. 2016. Available at: DOI:10.1520/E0647-15E01.2
78. Mehmanparast A., Brennan F., Tavares I. Fatigue crack growth rates for offshore wind monopile weldments in air and seawater: SLIC inter-laboratory test results. *Materials & Design*. Elsevier; 15 January 2017; 114: 494–504. Available at: DOI:10.1016/J.MATDES.2016.10.070 (Accessed: 17 August 2019)
79. Fisher T., De Vries W., Schmidt B. Upwind Design Basis (WP4 Offshore foundations and support structures). project upwind contract No. 019945 (SES6); 2010. Available at: DOI:10.1016/S0140-6736(02)81074-1
80. Yeter B., Garbatov Y., Soares CG. Reliability of offshore wind turbine support structures subjected to extreme wave-induced loads and defects. *Proceedings of the ASME 2016 35th international conference on ocean, offshore and arctic engineering OMAE2016-54240*. Busan, South Korea; 2016. pp. 1–8.

6 COMPARATIVE STUDY BETWEEN SN AND FRACTURE MECHANICS APPROACH ON RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE JACKET FOUNDATIONS

Abdulhakim Adeoye Shittu, Ali Mehmanparast, Phil Hart, Athanasios Kolios

Statement of contributions:

Abdulhakim A. Shittu conducted the literature review, developed and validated the model, performed the simulations, generated all the results, drafted, and critically revised the manuscript. A. Mehmanparast, A. Kolios, and P. Hart provided supervision, reviewed and critically commented on the manuscript before submission.

Abstract

This paper investigates from a structural reliability assessment (SRA) perspective the fatigue reliability using the S-N curve approach compared with the fracture mechanics (FM) approach for a typical welded offshore wind turbine (OWT) jacket support structures. The FM formulation investigated include a crack growth formulation based on the bilinear crack growth law, considering both segments of the crack growth law as non-correlated and correlated in the calculation of the reliability index (RI). A non-intrusive formulation was developed for an OWT jacket support structure in 50 m deep water, which consists of a sequence of steps. First, stochastic parametric 3D (three-dimensional) Finite Element Analysis (FEA) simulations are performed which takes into account stochastic variables such as wind loads, wave loads and soil properties using facilities within the software package ANSYS. Secondly, the results obtained from the FEA are post-processed using an Artificial Neural Network (ANN) response surface modelling technique obtaining the performance functions expressed in terms of stochastic variables. Finally, the First Order Reliability Method (FORM) is applied in calculating the reliability index values of components. Also investigated, was the reliability of the structure reassessed and updated in the presence of structural health monitoring/ condition monitoring (SHM/CM) data. The results from the case study revealed that the fracture reliability is sensitive to the initial crack size and it is recommended to apply the S-N curve method at the design stage while the FM approach to be applied towards the end of the design life as the structure is approaching failure.

Keywords: Fatigue, reliability index, non-intrusive formulations, crack growth, offshore wind structures, artificial neural network

6.1 Introduction

By 2030, it was projected that a large contribution of wind energy capacity could come from offshore wind farms in the EU [1]. Offshore wind farms are favoured due to higher wind speeds, unrestricted space, and lower marine environmental impact [2]. These conditions have led to an increase in wind farm installations in Europe, particularly in the North Sea, Irish Sea and Baltic Sea [3]. A complete offshore wind turbine (OWT) consists of the wind turbine itself, installed on top of a support structure, which is resting on a foundation that is fixed in the soil. There are a number of different types of support structures; these are selected depending on the water depth, the environmental loads, the cost of production and installation, complexity of the design, etc. [2,4,5].

A majority of OWTs use monopile foundations, especially when installed in water depths of less than 50 m. But for larger wind turbines, monopiles become very large and impractical. Hence, space frame structures such as jackets are used instead, since they are more light-weight and stiffer than monopiles. Space frames can also be cheaper in deepwater circumstances. However, the design of space frames is time-consuming, especially if it is desired to withstand a wide set of dynamic loads. Thus, more efforts are needed to improve the design and analysis of jacket-type support structures [6,7], considering as well the optimisation needed to manufacture them in large volumes.

To design offshore structures effectively, fatigue damage is an important limit state criterion to consider because materials with higher static strength must now be introduced. Historically, the aircraft industry was the first to introduce fatigue as a criterion for design, followed by other industries such as nuclear, steel, offshore, and shipping. In the latter, the fatigue limit state (FLS) had to be explicitly defined, precisely because higher strength steels were used in the design. Usually, the S-N data are first obtained from laboratory experiments, which serve as basis for the design criteria against fatigue failure. Besides good design, in-service inspection, maintenance and repair (IMR), is needed to keep adequate structural safety and system integrity during the service life. This has led to the development of fracture mechanics (FM) and reliability-based methods to assess crack growth in any structure. The FM approach is essential for

understanding the relationship between different parameters and uncertainties involved in the fatigue damage process [8].

S-N curves have been applied extensively to do fatigue design checks under complex loading conditions. Inspection and repair can, in addition to safeguarding against fatigue failure, be used to increase the reliability in view of crack growth. More information about crack growth than obtained from S-N data are required in order to support inspection planning. Besides describing the gradual development of crack, the FM is also a potential tool which could account for the effect of structural health monitoring/condition monitoring (SHM/CM) data. As a result of the inherent uncertainties of the crack growth method and data, reliability methods can be used to support subsequent decisions. Extensive studies on the effect of inspection and repair on the reliability of structures can be found in [8–10]. The application of the FM-based bi-linear crack growth law has been introduced for fatigue analysis [11], which reduces the excessive conservatism believed to be implicit in the single slope Paris' law approach.

Nowadays, structural design and analysis are based on probabilistic- rather than deterministic-based methods, since the former can account for the uncertainties in the loads and the models that relate them. A key driver of design is the fact that a structure is expected to perform satisfactorily within its design life [21]. For an OWT, this means that the OWT structure must fulfil its function reliably, and hence, must not become unsafe, in general, over 25 years [12]. Several studies [9,13–19] have already applied the probabilistic-based structural reliability methods for the assessment of offshore structures. However, most of these studies assume that the system is time-invariant. In the reality, the system is actually time-variant due to the degradation brought by corrosion and fatigue as well as time-varying loads [20].

Models used in determining the response of OWT foundations could be classified into either the one-dimensional (1-D) beam models or three-dimensional (3-D) finite element analysis (FEA) models. The 3-D FEA models are preferable because they are able to simulate detailed stress distributions and accurately capture structural responses. Owing to their high fidelity, the 3-D FEA models have been applied extensively to simulate wind turbine structures [15,16,21–25], and hence, this study, will employ the FEA approach to model the responses of the jacket foundations for OWTs [20].

It is important to take into account soil-pile interactions so as to adequately capture the structural response because OWT jacket support structures are anchored via piles to the soil system. A simple approach in performing soil modelling is to use the p-y method which assumes the stiffness of the soil are represented by equivalent springs [26]. However, a drawback of this method is that it underestimates the deflection and the modal frequency. Defining 3-D FEA brick elements is a more reliable way to perform soil modelling as this gives more accurate results [27,28]. Due to its high fidelity, the 3-D finite element analysis with brick elements is employed in modelling the soil system in this study [20].

The problem of optimising the CAPEX (capital expenditure) to OPEX (operating expenditure) ratio is an issue of priority for the offshore wind industry, and hence any cost reduction activities need to ensure safety and serviceability performance [16]. By gathering and interpreting information from complex structures, it becomes possible to assess safety levels through probabilistic approaches, allowing optimisation of maintenance strategies and facilitate planning for critical repairs and retrofits. Advanced monitoring systems are now available at a lower cost, allowing the collection of loading and loading effects as well as structural response data. SHM and CM systems are designed to monitor such information over a relatively long service period in order to distinguish anomalies, detect degradation and identify damage [16,29].

Artificial neural networks (ANNs) are now extensively used within the field of Structural Reliability Assessment (SRA), as noted by several studies [30–35], owing to their universal function approximator property. In ANNs, the relationship between input and output variables are established during an iterative training process, in order to facilitate the prediction of outputs given any input. According to [35], the most widely used ANN architecture is multi-layer feedforward network. ANNs can predict highly nonlinear functions over the entire domain accurately [36]. Previous studies have already used the response surface method based on ANN [32,34] since it is more efficient compared with traditional response surface methods for reliability assessment. In [35], it is claimed that this is especially true for complex structures, as long as appropriate feature selection techniques are employed [20,37].

This paper aims to assess various fatigue reliability formulations using either S-N or FM approaches focusing on the FM bi-linear crack growth law. Fatigue reliability analysis (FRA) of a typical tubular OWT was carried out, whose jacket support structure is

designed for a site with a water depth of 50 m. In the bilinear FM method, it is assumed that both segments of the crack growth law are either correlated or uncorrelated in the calculation of the reliability index. An advanced reliability assessment of OWT jacket foundations is proposed through a combination of reliability analysis methods and SHM/CM technology. A 3D stochastic parametric FEA model of OWT jacket foundations is developed, incorporating the effect of soil-structure interactions. A series of stochastic FEA simulations of the OWT support structure is carried out, taking account of stochastic variables, such as wind loads, wave loads and soil properties. ANN-based response surface methodology (ANN-RSM) is then used to post-process the FEA results so that the performance functions are now expressed in terms of the relevant stochastic variables. FORM (first-order reliability method) is then used to compute the reliability indices, evaluating the reliability of the OWT support structure. Then the reliability of the structure is reassessed and updated, in the presence of SHM/CM data. The updated reliability index will provide valuable information regarding making decisions pertaining to the inspection and maintenance of the structure.

Part of this work involves investigating the time-variant reliability of the jacket reference support structure due to wind and wave loads as well as soil-structure interaction during the in-service life in the presence of SHM/CM technology data. It presents estimates of the effects of other important random parameters on the reliability index by sensitivity studies. This is necessary in order to aid in the decision-making process to achieve an optimal balance of the different safety measures via performing design and planning for IMR at the design stage. A failure-critical hot-spot location where the most cumulative fatigue damage takes place is selected for use in the FRA.

The remaining parts of this paper are structured as follows. Section 6.2 presents a review of related literature; Section 6.3 presents the basics of fatigue and fracture reliability assessments; Section 6.4 presents the application of the methodology in a case study; Section 6.5 presents the results and discussion, followed by conclusion in Section 6.6.

6.2 A review of previous studies and existing models

Ziegler and Muskulus [38], analysed crack growth on a Y-joint with simulations of structural response to aero- and hydrodynamic loading and Paris' law for crack propagation. An extensive review of the literature in the area of fatigue evaluation for ship structures can be found in [39]. Applications of the time-dependent SRA for the

design of offshore structures (i.e. in environments characterised by highly stochastic loads and resistance properties, thus necessitating the need for SRA to account for such uncertainties systematically) include [9,10,42–46,13,16,17,19,20,26,40,41]. In [14], the fatigue reliability of fixed offshore platforms was investigated by analysing different failure scenarios. The analysis was divided into a finite number of sub-scenarios in order to evaluate the occurrence probability of a special scenario. The Palmgren-Miner's rule and S-N curve were employed to estimate the accumulated fatigue damages in the limit state function (LSF). In [41], the fatigue life of welded tubular joints is estimated by using spectral fatigue damage approach. An LSF defined based on the Dirlik probability density function, and the S-N curve approach was developed. In [47] low cycle fatigue and crack growth reliability assessment of an OWT foundation during its design life was performed. The analysis included different loading scenarios, the uncertainties associated with structural geometrical characteristics, the size of the manufacturing, and during the design life materials properties, defects, crack growth, and numerical analysis model assumed were taken into account. Extensive research has been carried out in the area of probabilistic FM approach to fatigue reliability assessment, some of which include a critical review done by [48]. The same authors investigated the effect of the existing variability in crack growth model parameters by applying FM analysis of a case study crack. In [49], investigations conducted based on a reliability-based method to assess the structural integrity of offshore tubular joints were performed.

According to [50,51], a probabilistic methodology for FM analysis of nonlinear cracked structures was developed. This involved nonlinear FEA using well-established commercial codes; statistical models for uncertainty in material constitutive law, fracture toughness, and loads; and standard reliability methods for the evaluation of probabilistic characteristics of elastic-plastic fracture parameter. It was claimed that the methodology predicted probabilistic characteristics of the J-integral for use in elastic-plastic fracture mechanics (EPFM) accurately. The reliability assessment was carried out using the Monte-Carlo simulation (MCS) and FORM in which the crack, geometry, material and loading on the tubular joint were modelled as random variables to calculate safety levels of the joint. The linear elastic fracture mechanics (LEFM) principles were employed to evaluate the crack growth, and the estimated degradation to the reliability of the tubular component due to propagation of crack was assessed. The influence of the modelled variables considered stochastic on the reliability sensitivity was studied using case studies. Lee et al. [52], applied the FORM, SORM and MCS as well as FM in the

probabilistic integrity assessment of major nuclear components containing defects. In [53], a probabilistic approach considered incorporating FM to perform integrity assessment of gas pipelines was presented. According to [54], a stochastic model based on an FM description using FORM and MCS for evaluation of the probability of failure (POF) and its sensitivity to input parameters were obtained together with confidence bounds with respect to random input variables. It was claimed that results obtained could be employed in extending the life span of turbine disks such that an inspection schedule can be derived from the calculated result.

In [55], simplified strain-based FM equations, developed for external surface cracked pipelines subjected to external bending load, were presented and applied in the probabilistic evaluation of a pipeline girth weld. The model accounts for variability in crack depth, crack length, internal pressure and material hardening. The tangency criterion was used in determining the critical strain from ductile tearing in the cracked pipeline. The reliability problem was addressed by applying FORM and SORM techniques for various pipe dimensions and load levels. According to [8], to accurately evaluate the effect of an inspection and repair strategy of structures subjected to degradation resulting from crack growth, application of FM models are required to describe crack propagation. The reliability methods applied to account for inherent uncertainties with respect to selecting an optimal tool for making proper decision, which enables a balance between design criteria, and inspection and repair plans include S-N and FM formulations. These include a crack growth formulation based on bi-linear crack growth law assuming both crack growth law segment to be correlated and non-correlated in the POF calculation. The FORM and SORM as well as MCS were used to illustrate the effect of inspection in the updated reliabilities. It was asserted that crack initiation time, initial crack size and the crack aspect ratio play significant roles in the calibration of FM methods. In [56], the responses obtained from an FEA are employed for the study of fatigue and fracture reliability analysis of riser subjected to random waves. The LSF was established based on the S-N curve approach and FM approach considering uncertainties in loads, resistance etc. The SRA was employed by employing a combination of RSM and FORM and results compared with the MCS method. Also the influence of uncertainties in the random parameters on the riser fatigue reliability were reported.

According to [57], probabilistic assessment of cracked structures based on the LEFM subjected to mixed-mode loading conditions by employing the fractal finite element

method (FFEM) was presented. The method applies FFEM for computing fracture response characteristics; statistical models of uncertainties in load, material properties, and crack geometry, and the FORM predicts probabilistic fracture response and reliability of cracked structures. According to [58], a method based on high dimensional model representation (HDMR) and fast Fourier transform (FFT) was presented to evaluate the POF of structural systems subjected to random variables. The LSF was determined by linear approximation of the first-order HDMR component functions at the most probable point (MPP), and the convolution integral was solved using the FFT technique. In [59], probabilistic FM was performed whereby the RI of fatigue problems with stochastic definition was evaluated by applying the FORM and MCS. In [60], probabilistic fatigue simulations in order to ascertain the efficacy of inspection procedures with non-destructive inspection (NDI) modelled as probability of detection (POD) curves using the first-order sensitivity method of POF was developed. The sensitivity method calculates the partial derivatives of the POF with respect to a change in each region of a POD or multiple POD curves.

In [61,62], a methodology for the calculation of fatigue reliability (FR) of universal joint in an articulated offshore tower was presented. The dynamic analysis of double-hinged articulated tower under environmental conditions was performed in time domain. The hinge shear stress response histories were employed for the reliability assessment using advanced FORM (AFORM) and MCS. It was reported that the S-N curve approach yields a significantly conservative approximation of POF when compared to the FM approach. Dong et al., [9], performed the fatigue reliability of welded multi-planar tubular joints of the support structure of a fixed jacket offshore wind turbine in a water depth of 70m. The long-term statistical distribution of hot-spot stress ranges was fitted using a two-parameter Weibull function by combining time-domain simulation for the inherent environmental conditions (wind/ sea states) in operational condition. The S-N Miner-Palmgren approach based fatigue design criteria were satisfied by normalising the load histories and thus, the estimated safety levels refer to the fatigue design of tubular joints that meets design criteria. The FM analysis of crack growth was applied for the reliability analysis. The hot-spot stress range was increased assumed to be due to changes of the nominal stress and stress concentration factors produced by thickness thinning (wastage) effects of selected components with a general uniform corrosion model in order to account for the corrosion-induced crack growth rate. The influence of inspection and repair with and without considering corrosion were investigated based on the quality

of inspection in terms of probability of crack detection curves. According to [63,64], a reliability-based flaw assessment for cracks in the mooring chain of a floating type offshore structure was presented whereby the procedure set-out in BS7910 was combined with FORM and SORM in order to assess the acceptance of a given flaw considering uncertainties in the variables critical to flaw assessment. Other sources where important information on probabilistic FM research can be found include [39,65].

A sub-category under this area is the damage tolerance approach for probabilistic pitting corrosion fatigue life prediction performed by [20,66] wherein comprehensive mechanistic-based probabilistic models for pitting corrosion fatigue life prediction by including all stages were presented, and the FORM was implemented with the proposed models. In [20], a generic reliability assessment framework that combines parametric FEA modelling, RSM, and reliability assessment specifically for complex OWT jacket type support structures in the presence of highly stochastic variables, and taking into consideration, specifically, time-dependent phenomena such as fatigue as well as degradation mechanisms such as corrosion was developed. Two ANNs were trained to relate various stochastic variables for predicting the performance function. The two ANNs were employed in order to have an intermediate predictor for a stochastic variable, which is more advantageous because of the added interpretability of results. An advantage of the proposed methodology is that the first ANN architecture enabled a significant reduction in the computational cost, which would have been required to simulate global behaviour of the support structure thus allowing other global parameters to be incorporated. This has been previously developed by the authors and will stand as the basis for the present study.

6.3 Basics of fatigue and fracture reliability assessment

The basic failure probability in fatigue and fracture assessment may be defined by

$$P_f = P[g(t) \leq 0] = \Phi(-\beta) \quad (6-1)$$

where $g(t)$ is the limit state function (LSF) and β is the safety index. The case study investigated in the upcoming sections are expressed in terms of the reliability index (RI). $\Phi(\blacksquare)$ is the standard normal distribution function [67]. Probabilities of failure implied by Eq. (6-1) may be approximated by means of widely used methods such as first-order reliability method (FORM), second-order reliability method (SORM) and Monte-Carlo simulation (MCS) techniques [8,67].

The FORM method incorporates a number of uncorrelated standard normal random variables. The original variables, which may, in general, be correlated and non-normal, are transformed to the u-space using well-established transformations such as the Rosenblatt's transformation. The exact failure probability is the integral of the joint probability density function over the failure domain $g(u) < 0$. The first-order Taylor series expansion of the limit state surface $g(u) = 0$ is applied at the point with the shortest distance from the origin in the u-space. An RI, β can be referred to as the shortest distance from the origin to the limit state surface in this space. The point of which the distance from the origin is minimum to the limit-state surface denotes the worst combination of random variables and is thus called the design point or most probable failure point (MPP). The calculation of the RI then becomes an optimisation problem in locating the MPP on the limit-state surface. The Rackwitz-Fiessler algorithm can be employed in recursively searching for the MPP [67–69]. After computing the RI, β , the first-order approximation to the probability of failure can be determined by using the RHS Eq. (6-1) [66]. This method is very simple to use, and has been found to converge quickly in most cases.

Fracture and fatigue are failure modes of note for welded offshore structures. Fatigue is a very local phenomenon, which is influenced by factors such as the local geometry, and fabrication process-induced weld defects. Crack propagation normally starts from weld defects and are driven by tensile, cyclic stresses. Cracks in jackets are restricted to the tubular joints as a result of the large stress concentration in such joints [9].

6.3.1 S-N curve approach

Herein, time-variant FRA was performed according to the fatigue analysis procedure described in the DNV standard [70,71]. Consequently, the thickness-corrected D curve given by DNV-OS-J101 [71] is chosen for S-N curve approach to fatigue analysis. The intercept (A) and slope (m) of the S-N curve assumed for evaluating the fatigue life of steel structure in seawater is given as 15.606 and 5, respectively.

6.3.2 Fracture mechanics approach

6.3.2.1 Fracture mechanics analysis of planar flaws

Fatigue reliability is often based on an FM approach given by the Paris' crack propagation law [8]. As set out in the BS 7910 [11], there are two methods outlined for the assessment

of planar flaws both based on FM crack analysis under fatigue loading which consists of a general procedure and a simplified procedure related to S-N curves. In these methods, the fatigue life is calculated by integrating the crack growth law. The general procedure enables the cyclic stress intensity factor expressed accurately to be employed as well as specific data for fatigue crack growth. The quality category procedure entails the use of FM calculation results which have already been carried out and presented graphically.

The FM assessment usually employs conservative estimates of the various parameters required. However, it is imperative to use an alternative approach by applying reliability methods to take into account the randomness in the parameters. It is often assumed that a flaw is a crack with a sharp tip and its propagation is governed by the law related to crack growth rate, da/dN , and stress intensity factor range, ΔK , for a material containing flaws. The crack growth law is empirical and is normally depicted that a sigmoid curve can be used to represent the overall relationship between da/dN and ΔK in a $\log(da/dN)$ versus $\log(\Delta K)$ plot. It is reasonable to assume that the central portion of the plot follows a linear relationship (i.e. the Paris' law), or to represent the data by two or more straight lines to achieve greater accuracy. The crack growth rate is insignificant at low values of ΔK below the threshold stress intensity factor range, ΔK_0 . There is a rapid acceleration in the crack growth rate as the maximum stress intensity factor K_{max} , at high values of ΔK tends toward the critical stress intensity factor for static load failure, K_c . However, the assumption that the central portion is applicable to all ΔK values (from ΔK_0 up to failure) is valid. The Paris' law equation is expressed as [11,72,73]:

$$\frac{da}{dN} = C(\Delta K)^m \quad (6-2)$$

where C and m are material coefficients and also depend on environmental effects. For $\Delta K < \Delta K_0$, da/dN is assumed to be zero. The stress intensity factor range, ΔK , is a function of geometry, Y , stress range, $\Delta\sigma$, and instantaneous crack size, a , and is calculated from the following equation:

$$\Delta K = Y(\Delta\sigma)\sqrt{(\pi a)} \quad (6-3)$$

The overall life is calculated by substituting Eq. (6-3) into Eq. (6-2) and integrating the following equation [20]:

$$\int_{a_i}^{a_f} \frac{da}{Y^m (\pi a)^{m/2}} = C(\Delta\sigma)^m N \quad (6-4)$$

In BS7910 [11], the application of the bi-linear crack growth law for the fatigue assessment of welded structures is recommended. According to [8], a comprehensive data collection from several sources was carried out, and a crack growth law having two segments was recommended for steel structures. Different uncertainties in both segments of the crack growth law were reported with the (lower) near-threshold segment having the largest variability. The larger variability may be due to the proximity to the small-crack regime and hence the inherent uncertainty of the ΔK threshold whereby the material experiences no crack growth below this. In contrast, the upper segment has lower uncertainty because the crack growth rates behaviour is well inside the stable region with high values of ΔK . However, there is a lack of information on the degree of correlation between the two segments. According to [8], some studies assumed that the two segments of the crack growth law are uncorrelated. The effect of correlation in failure probability is investigated herein.

6.3.2.2 SMART[®] fracture

Simulations based on fracture has relied on two models: conventional cohesive zone modelling (CZM) and, of recent, the eXtended Finite Element Method (XFEM). The CZM is most appropriate for the simulation of de-bonding of adhesively attached surfaces. The CZM is commonly applied for simulating composites, but it is not ideal for simulating the crack growth in the bulk of a material [74].

The XFEM performs better when simulating internal cracks. As packaged in the ANSYS toolkit, in the XFEM, the need for re-meshing regions near the crack tip is eliminated. Instead, an extended finite element enrichment area is defined near crack tip regions where it is most likely that the crack propagates. In the XFEM, the special volume elements in the enrichment zone are split from its centre. Hence, a finer mesh is generated by splitting existing cells rather than re-meshing. However, a drawback of the XFEM is in its inability to limit the enrichment regions as it increases, thereby making it computationally costly, and as such, the simulation becomes time-consuming. Therefore, it is difficult to scale up the XFEM to large projects, and this led to the development of the SMART[®] fracture tool.

The Separating Morphing and Adaptive Re-meshing Technology, SMART[®] relies on the Unstructured Mesh Method (UMM) process. In the SMART[®] as a result of automatic crack propagation at each solution step, the mesh is being updated from crack-geometry changes. This function is as packaged in the ANSYS R19 facility. Rather than applying the enrichment technique, it employs a localised re-mesh function as the crack propagates. Unlike the XFEM, an advantage of the SMART[®] is that it enables the simulation to be scaled up for larger projects as a result of its property of limiting the re-mesh to a small area near the crack tip at each iteration. Another advantage of this technique is that the development of new elements is not required and default/ standard elements included already in mechanical, such as the conventional solid 187, 186, etc. can still be applied. Also, the software permits designers to enter alternative crack growth laws as these emerge from new research about the particular material being modelled. Further information on the characteristics of the SMART[®] fracture can be found in [20].

6.3.3 Limit state function based on the S-N curve approach

Significant cyclic loads induced by the environment are imposed on OWT jackets making their design to be driven by FLS. The FLS assessments can be performed by applying two methods, i.e. S-N curve method and FM method. According to the S-N curve method, the number of loading cycles to failure, N , can be determined from [43]:

$$\log N = A - m \log \Delta S \quad (6-5)$$

where A and m are the intercept, and the slope of the S-N curve on the log-log plot, respectively, and ΔS is the stress range. The intercept A and slope m are generally prescribed by design standards, e.g. DNVGL-ST-0126. The limit state function of FRA based on the S-N curve approach can be determined from [16,75]:

$$g_{f,SN} = \log N - \log N_t \quad (6-6)$$

where subscripts f and SN represents the FLS and S-N curve approach, respectively; N is the number of loading cycles to failure as obtained from Eq. (6-5), N_t is the number of loading cycles expected during the given design life. N_t is the number of loading cycles expected during the given design life. N_t can be calculated by using rated rotor speed n_{rated} and availability η_a (98.5%) on the site selected [22,76]. Hence, assuming a design life of 20 years, the number of cycles is given as:

$$N_t = \eta_a \cdot n_{rated} \times (20[year] \times 365[day/year] \times 24[hour/day] \times 60[min/hour]) \quad (6-7)$$

6.3.4 Limit state function based on fracture mechanics approach

Compared to the S-N curve method, the FM method is more detailed and involves evaluating crack growth. The failure function for fatigue as a function of time can be written as $g(t) = a_f - a(t)$. The performance function for FRA based on LEFM is given by:

$$g_{f,FM} = \int_{a_0}^{a_c} \frac{1}{Y(a)^m (\sqrt{\pi a})^m} da - C \Delta S^m (N(t) - N_0) \quad (6-8)$$

where subscript f and FM represents the fatigue limit state and FM approach, respectively; a_0 is the initial crack depth (or the crack depth at time t_0); a_c is the critical crack depth; $Y(a)$ is the compliance function; m and C are material constants; $N(t)$ is the total number of stress cycles in the time period $[t_0, t]$; and N_0 is the initial number of stress cycles.

According to [38], the FM approach is more complex than the S-N curve design, which increases the risk of gross errors. In this study, it is assumed that the errors due to the complexity of the FM approach may be reduced as a result of using the ANSYS SMART Fracture© FEA facility. Hence, in this study, owing to the high-fidelity of the FEA model, it was assumed that this has accounted for model uncertainties which may exist due to errors if analytical calculations were to be used. The Non-intrusive formulation used herein enables an enhanced analysis leading to more accurate results as it utilises the 3D simulation method as established in [20].

6.4 Application using a case study

6.4.1 Design considerations for OWT support structures

The reference case adopted for this analysis includes a baseline 10MW National Renewable Energy Laboratory, NREL wind turbine with wind speed of the site as 20 m/s, attached to an 88.4 m tower, a transition piece (TP) and is supported by a jacket foundation. The jacket is a vertical height of 66 m, and the structure is anchored by pile embedded 42 m into the soil system and submerged into 50 m deep water. The piles feature a batter angle as they are to be driven through the legs. The TP is 7 m in length

and connects together the jacket and the tower [6,7]. The OWT jacket support structure was modelled in the ANSYS workbench environment, which is well-established FEA software [43]. The schematic of the jacket wind turbine is, as shown in **Figure 6-1**. See also **Figure 6-2** and **Table 6-1** for more details. In the present study, the normal operating condition of the wind turbine is considered mainly, which is also defined as the design load case, DLC 1.2 in IEC 61400-3. The wind and wave forces are simulated to always assume the same direction, and all sea states considered to be in only one direction, such that the results of the long-term fatigue loads should be conservative. This is a simplified assumption of the DLC 1.2 as outlined in IEC 61400-3.

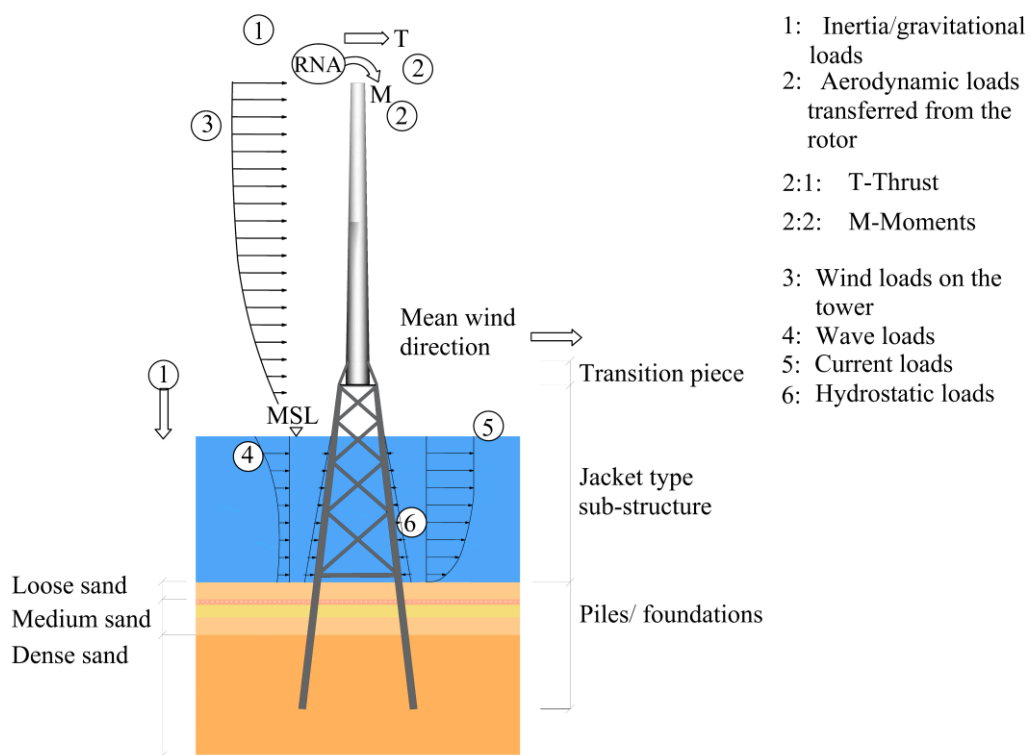


Figure 6-1. Representation of the loads on the support structure of the OWT and jacket geometry embedded in layered soil

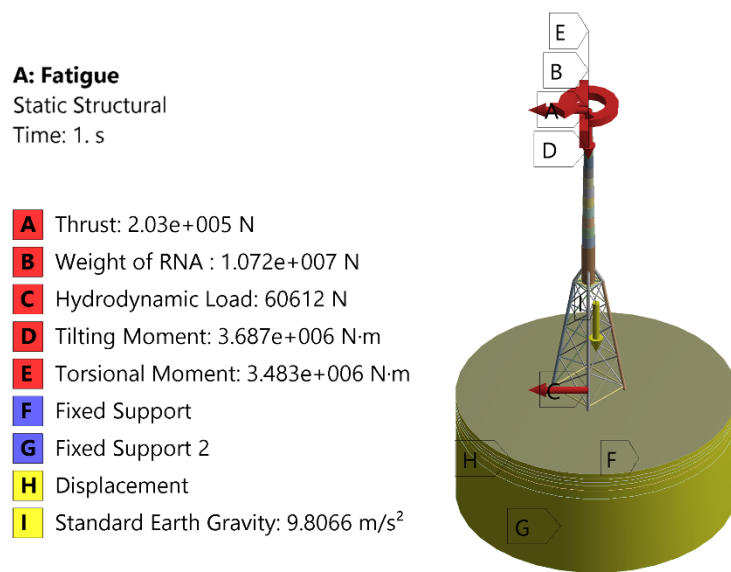


Figure 6-2: The 3D structural model with applied loads and boundary conditions on a global scale (Fatigue load case)

Table 6-1: Baseline 10 MW support structure parameters [6, 9, 10, 48, 49]

Parameter	Value
Deck height above mean sea level (MSL) (m)	16
Water depth (m)	50
Leg outer diameter (OD) (m)	1.74
Leg wall thickness (m)	0.030
Number of bays	4
Jacket batter	8.47
Height of TP (m)	7
Number of legs	4
Pile OD (m)	1.59
Pile wall thickness (m)	0.037
Mud brace OD (m)	0.762
Mud brace wall thickness (m)	0.017
x-brace outer diameter (m)	0.61
x-brace wall thickness (m)	0.016
Rotor-nacelle assembly (RNA) mass (kg)	1,072,000
Tower length (m)	88.4
Tower-top OD (m)	3.85

Tower-top thickness (m)	0.03
Tower-base OD (m)	7
Tower-base thickness (m)	0.055
Thrust associated with rated power ultimate load (UL) case (kN)	1700
Maximum rotor thrust taking into account dynamic amplification UL case (kN)	3400
Thrust fatigue load (FL) case (kN)	203
Torsional moment UL case (kN-m)	7876
Torsional moment FL case (kN-m)	3483
Tilting moment UL case (kN-m)	38567
Tilting moment FL case (kN-m)	3687

6.4.1.1 Parametric modelling of OWT jacket support structures: Geometry, materials, structural components and soil profile

The tower, TP, jacket, and piles are assumed to be made of S355 steel having Young's modulus of 210 GPa, density of 8500 kg/m^3 , and a Poisson's ratio of 0.3 [6,7]. Besides the OWT foundation, another design factor of note which could have an impact on the structural response model of the pile-jacket-tower assembly is the soil-structure interaction. In order to enhance the accuracy of results calculated, the soil-structure interaction aspects are incorporated in the present study [79]. Hence, the soil profile as simulated herein is based on data which corresponds to a K-13 deepwater site located off the coast of Netherlands. Six layers of sand representing the soil profile and their corresponding parameters as entered into the simulation are outlined in **Table 6-2**, and these are based on-site measurements. The soil system is modelled to have a cylindrical shape ($D=140\text{m}$, $H=50\text{m}$) consisting of six different strata in ANSYS (see **Table 6-2**). The Drucker-Prager Strength Linear model is assumed to describe the behaviour of the soil material [80]. This model is used to calculate the yield stress of each soil strata. The yield strength of the soil, σ_{ys} , according to the Drucker-Prager model, can be calculated from:

$$\sigma_{y,s} = \frac{6c \cos \phi}{\sqrt{3}(3 - \sin \phi)} \quad (6-9)$$

where, ϕ represents the angle of internal friction and the cohesion value is represented by c . The coefficient of friction between the soil and the pile, C_f can be calculated from [27].

$$C_f = \tan\left(\frac{2}{3}\phi\right) \quad (6-10)$$

Table 6-2: K-13 Deepwater site's soil profile [6,41]

Depth seabed (m)	below Unit weight N/m^3	Friction angle ($^\circ$)	Shear strength (N/m^2)	Young's modulus (MPa)
0-3	10,000	36	60,000	30
3-5	10,000	33	60,000	30
5-7	10,000	26	60,000	50
7-10	10,000	37	60,000	50
10-15	10,000	35	60,000	50
15-50	10,000	37.5	60,000	80

6.4.1.2 Mesh sensitivity analysis

A critical step which affects the performance of an FEA is the mesh generation. The ANSYS software package provides a reliable and powerful structure mesh generator with the capability of generating a consistent mesh in the whole structure with a minimal computational requirement. A mesh sensitivity analysis was conducted for optimising the element size, thereby enhancing the precision of results. The results are presented in **Table 6-3**. Based on the results from mesh sensitivity analysis, the Von-Mises (equivalent) stress converged at the soil element size of 2m and support structure element size at 0.5m, which corresponds to a total number of elements of 190,222. The display of the optimised mesh for the support structure as simulated in ANSYS is depicted in **Figure 6-3**.

Table 6-3: Mesh sensitivity [41]

Soil element size (m)	Jacket structure element size (m)	Number of elements	Maximum Von-Mises stress (Pa)
8	2	8047	2.5297E+08
4	1	36,164	2.5328E+08
2	0.5	190,222	2.5346E+08

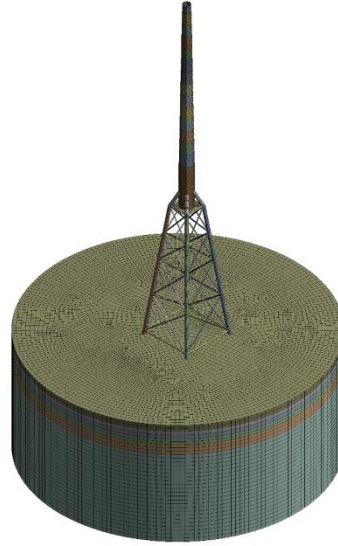


Figure 6-3. 3D display of meshing performed on the structural model [41]

6.4.1.3 Validation

In order to validate the structural model developed, the results of the deflection in static analysis and modal analysis for the support structure against data from the reference OWT [43]. Results of the modal analysis and deflection are depicted in **Figure 6-4**, and **Figure 6-5** and their comparison can be seen in **Table 6-4** and **Table 6-5**, which shows that the model approximately predicts the first eigen-frequency to the 3P frequency of the rotor. Moreover, the relative difference between the present study and as obtained from references is 0.12% as the eigen-frequency calculated is 0.21346 [7,77]. Also, the deformation at the elevation of the rotor-nacelle assembly (RNA) and at the base of the tower is 1.236 m and 1.6085×10^{-1} , representing -0.46% and -3.44% relative difference between the present model and as obtained in the reference [7]. These differences are considered to be acceptable.

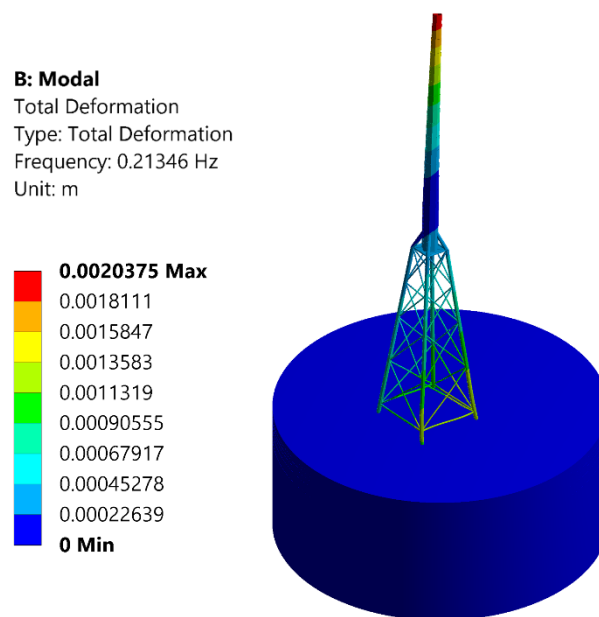


Figure 6-4. Display of structural model's modal analysis results showing the first mode frequency [41]

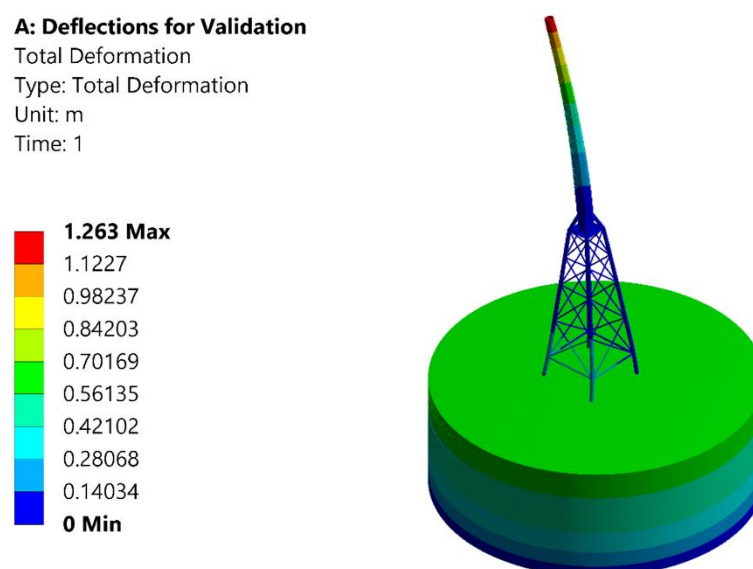


Figure 6-5. Display of results of total deformation showing the deflection at RNA level [41]

Table 6-4: Comparison of the support structure mode frequencies with reference values [41]

Mode frequencies (Hz)	Present	References [7,77]	% Difference
1 st side-to-side bending	0.21346	0.21320	0.12%
1 st fore-aft bending	0.22297	0.21629	2.99%
2 nd side-side bending	1.1602	1.0313	11.11%
2 nd fore-aft bending	1.5292	1.6561	-8.29%

Table 6-5: Static deformation of the baseline 10 MW wind turbine jacket [41]

Load	case	Displacement at RNA			Displacement at the tower base		
Mass/ Thrust	Present	Ref. [7]	% Diff		Present	Ref. [7]	% Diff
RNA/ 3.4 MN	1.263 m	1.2688	-		1.6085	1.6639×10^{-1}	-
			0.46%		$\times 10^{-1}$		3.44%

6.4.1.4 Calculation of loads on OWT support structures

In the present study, the normal operating conditions are assumed to represent the environmental conditions for the FLS design approach adopted. The wind, wave, and current loads are manually calculated and then entered in the parametric FEA model.

According to the IEC 61400-1 [81], the normal wind climate conditions assumed in the present study are considered to be cyclic structural loading conditions and are calculated as thus:

$$V(h) = V_{ref} \frac{\ln\left(\frac{h}{z_0}\right)}{\ln\left(\frac{h_{ref}}{z_0}\right)} \quad (6-11)$$

where z_0 is the roughness coefficient (see [71]). After generating the wind speed profile, the horizontal load exerted on the tower, TP and nacelle can be expressed as:

$$F_x = \frac{1}{2} C_D \rho_e (V_{max})^2 A \cos \alpha \quad (6-12)$$

where C_D is the cylindrical drag coefficient (for the tower and TP) and plate drag coefficient (for the nacelle), A is the area being pushed by the wind, and α is the

inclination angle of the wind with the horizontal axis. The effects of the blades are not taken into account in this study.

Morrison's equation is employed in the calculation of the wave forces. The equation is constituted of the drag and inertia terms, where the drag identified by the drag coefficient C_d , and the inertia identified by the inertia coefficient C_m [82]. Morrison's equation can be expressed as:

$$F = F_d + F_m = \frac{1}{2} \rho_w C_d D |u_x| u_x + \rho_w C_m \frac{\pi D^2}{4} \frac{dU}{dt} \quad (6-13)$$

where U is the undisturbed fluid velocity, $\frac{dU}{dt}$ is the acceleration of the fluid, ρ_w is the water density, and D is the diameter of the cylinder. See **Table 6-6** for the wave profile data.

Table 6-6: Water levels and wave data of interest for the K-13 Deepwater site [41]

Parameter	Value
Lowest Astronomical Tide, LAT (m)	-1.06
Tidal range, Δz_{tide} (m)	2.22
Storm surge, Δz_{surge} (m)	2.13
Air gap, Δz_{air} (m)	1.5
Significant wave height, H_s (m)	9.4
Maximum 50-year wave height, $H_{50,max}$ (m)	17.48
Maximum wave period range, T_{50} (s)	10.8 – 14
Max. wave height above still water for deck height calculation, ξ_w (m)	11.36

In terms of the structural integrity, environmental loads, such as the tidal currents and wind-driven currents, are not significant threats in shallow-water circumstances. However, these can contribute to other significant excitations such as those generated by the wind and waves. The tidal current profile at distance z from still water level can be denoted by the current speed ($v(z)$). The current speed variation from the current at the still water level v_0 through the distance to the topwater column can be described exponentially. This is expressed as:

$$v(z) = v_0 \left(\frac{h+z}{h} \right)^{\frac{1}{7}} \text{ for } z \geq 0 \quad (6-14)$$

where h is the water depth. The extreme tidal current is assumed to occur at approximately the mean water level, with zero tidal currents at high and low tide. Having obtained the tidal current profile, the assumption of a constant over depth current will be made. Wind-driven currents occur due to the action of shear forces on the water surface resulting from wind and thus, are likely to act in a similar direction with the wind. According to IEC61400-3, the sea surface wind-driven current can be estimated from:

$$U_{wind} \approx 0.01 U_{1h,10m in} \quad (6-15)$$

where $U_{1h,10min}$ is the hourly mean at 10m height.

The submerged parts of the jacket are subjected to a water column pressure referred to as the hydrostatic pressure. This can be calculated via a control volume analysis of an infinitesimally small cube of fluid, assuming a constant gravity and density through depth. Hence,

$$\begin{aligned} p(z) - p(z_0) &= \frac{1}{A} \int_{z_0}^z dz' \iint^P (z') g(z') dA = \int_{z_0}^z dz' \rho(z') g(z') \\ &= \rho g h \end{aligned} \quad (6-16)$$

where $p(z)$ is the pressure at a given height z , $p(z_0)$ is the pressure at z_0 , which is the top of the water column, Therefore, $p(z_0) = P_{atm}$, ρ is the water density (kg/m^3), g is gravity (m/s^2), $h = (z - z_0)$ is the liquid column height measured from the test volume to the zero reference point of pressure.

The rotor and nacelle are assumed to be concentrated or distributed masses as modelled in the FEA. Hence, the hub and blades are excluded from the parametric model. According to [79], modelling the blades will not be necessary since, besides the added mass acting on the tower top, the parked and feathered blades do not have a significant effect on the eigen-frequency of OWTs. The weight of the Rotor Nacelle Assembly (RNA) is assumed to be 10516 kN. A single horizontal axis wind turbine sustained by a jacket substructure is assumed in the present paper. Hence, this study does not cover wake effects associated with wind farm sites. Effective turbulence models are crucial in consideration of wake effects on fatigue reliability of OWT components in wind farms. More details on this can be found in [83].

The widely used standard, DNV-OS-J101 prescribes guidelines to assess the structural integrity of OWT support structures. As set-out therein, during design, OWT support

structures should be checked against four limit states FLS, Ultimate Limit States (ULS), Serviceability Limit State (SLS), and Accidental Limit State (ALS). Since according to several sources, fatigue is the design driving criteria for most components of OWTs, this study will, therefore, focus on the FLS [9,15]. Further description on limit state design can be found in [3, 6, 18, 50].

6.4.2 OWT support structure having flaws and subjected to corrosion-fatigue

6.4.2.1 Parametric FEA

In this subsection, a parametric FEA model of the three-dimensional space frame, tower and pile assembly (as shown in **Figure 6-2**), the jacket configuration, and the sources of loads are presented. The present study is based on analysis already carried out in [20,41]. In the upcoming sections, for the FM ANN architectures are used in approximating the performance by linking the input parameters with the output, the stress range. The parametric FEA developed for this study is presented below.

The critical joint in the parametric FEA model developed herein is assumed to contain an initial flaw or crack due to welding/ manufacturing imperfection. A section of this joint is modelled in the form of a curved plate within which the crack is located. This is performed so as to limit computational time/cost to practical levels.

The FEA model developed by the authors in [43] is adopted to calculate the equivalent stress at the vicinity of the crack, and this result is assumed to be exerted on the plate (see **Figure 6-6** and **Figure 6-7**). The Equivalent stress imposed on the plate as modelled was determined to be 58.63 MPa [20].

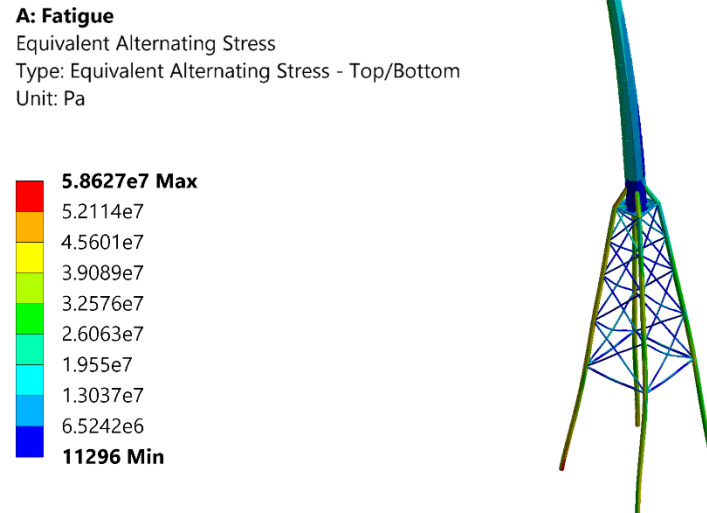


Figure 6-6. 3D display of structural model showing the equivalent alternating stress

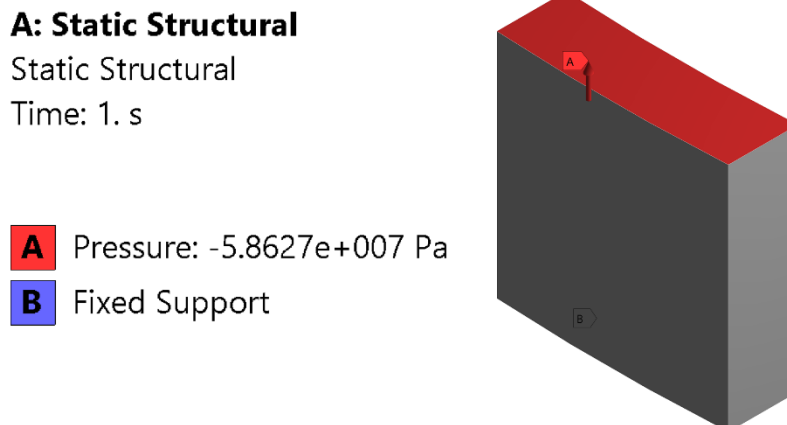


Figure 6-7. 3D structural model of curved plate with applied stress and BC in ANSYS [20]

6.4.3 Structural reliability assessment (SRA) of the OWT support structure

In this section, the SRA of the OWT support structure using first, the S-N curve approach and then second for the FM approach assuming the structure is subjected to corrosion-fatigue is carried out based on the damage-tolerance approach both considering FLS as

set-out in DNV-OS-J101 [71]. The fully parametric FEA model presented in Section 6.4.1.1 and Section 6.4.2.1 is employed in carrying out FEA modelling, accounting for stochastic variables, for the S-N curve and FM approach respectively. Then all results generated are then post-processed using a developed non-intrusive formulation.

6.4.3.1 Stochastic variables and FEA

The stochastic variables considered in this study are presented in **Table 6-7** for the S-N curve approach and FM approach, assuming the bilinear FM model. Seventeen (17) stochastic variables were considered for both methods. Ten stochastic variables were considered for the first ANN, and this set-up was arrived at as described in [84]: Initially, these included the thrust force, hydrodynamic load, torsional moment, tilting moment, the weight of RNA, and three young moduli at three soil strata. The total hydrodynamic load was considered differently due to its dependence on the wave period, wave height, and current speed. To calculate the peak hydrodynamic force acting on the system, the significant wave height and the current speed were assumed to follow a Weibull distribution, while the wave period was assumed to follow a lognormal distribution [3, 59, 60]. The total hydrodynamic load was then fitted into a Weibull-equivalent distribution. Distribution fitting algorithms (such as Akaike Information Criterion, Bayesian Information Criterion and Kolmogorov-Smirnov) are often applied in the determination of the shape coefficients of the most suitable statistical distributions, in the presence of observed data [17]. In the present study, the wind speed, significant wave height, wave period, and the current speed are reintroduced into the stochastic model and the equations incorporated in the LSF model of the FORM on implementation of the SRA.

Table 6-7: Stochastic variables.

Description	Mean values	COV	Distribution types	Reference
Young's modulus of steel ² (GPa)	210	0.1	Normal	[17]
The major radius of semi-elliptical crack ² (mm)	0.22	1	Exponential	[9,45]
The minor radius of semi-elliptical crack ² (mm)	0.11	1	Exponential	[9,45]
Wind speed, V ¹ (m/s)	20	0.05	Weibull	[6,77,87]

Tilting moment, M_{Tilt}^1 (kN.m)	3687	0.1	Normal	[15,20,41,86]
Torsional moment, $M_{Torsion}^1$ (kN.m)	3483	0.1	Normal	[15,20,41,86]
Maximum small crack size (mm)	0.276	1	Exponential	[9,45]
LnC_1	-29.11	1.69	Normal	[8,9,45,88]
LnC_2	-19.27	0.6	Normal	[8,9,45,88]
m_1	4.6	-	Fixed	[8,9,45,88]
m_2	1.64	-	Fixed	[8,9,45,88]
Thickness/ final crack depth (mm)	30	0.1	Exponential	[9,45]
Significant wave height, H_s^1 (m)	9.4	0.065	Weibull	[6,77,87]
Peak wave period, T^1 (s)	14	0.038	Lognormal	[6,77,87]
Current speed, U^1 (m/s)	1.2	0.1	Weibull	[6,77,87]
Young's modulus of soil stratum 1, E_{s1}^1 (MPa)	30	0.1		
Young's modulus of soil stratum 2, E_{s2}^1 (MPa)	50	0.1	Normal	[15,20,41,86]
Young's modulus of soil stratum 3, E_{s3}^1 (MPa)	80	0.1		
RNA Weight, W_{RNA}^1 (kg)	1,072,000	0.025		

¹Inputs to the first ANN architecture

²Inputs to the second ANN architecture

For both cases (i.e. assuming the S-N curve and FM approaches), after determining which variables are to be designated stochastic, a series of stochastic parametric FEA modelling of the OWT foundation was carried out adopting the FEA model developed in Section 6.4 using the Design of Experiments (DoE) function as packaged in ANSYS DesignXplorer©. This enables the various input parameters to be designated as stochastic with each assuming different distributions. DoE allows the generation of output parameter corresponding to the different design points as they are being varied.

6.4.3.2 Non-intrusive formulation

For the both approaches, having defined the stochastic parameters, the performance function is determined. For example for the FM approach this is determined by substituting the small crack regime life and long crack regime life into the FLS Equation as established in [20]. The resulting safety margin can be calculated from Eq. (6-17). Subsequently, the FORM is applied in estimating the fatigue reliability index.

$$g_{f,FM} = \int_{a_i}^{a_{tr}} \frac{1}{Y(a)^{m_s}(\sqrt{\pi a})^{m_s}} da + \int_{a_{tr}}^{a_f} \frac{1}{Y(a)^{m_l}(\sqrt{\pi a})^{m_l}} da - C_s \Delta S^{m_s} N(t_s) - C_l \Delta S^{m_l} (N(t_l) - N_0) \quad (6-17)$$

Figure 6-8 depicts a flow chart of the developed non-intrusive formulation for the FM approach used herein. The algorithm begins by defining the system, the FLS and the stochastic variables in the analysis. Next, a series of FEA simulations in ANSYS is executed by varying the inputs and recording the outputs corresponding to the limit state. The FEA simulations are varied using the ANSYS DoE package via the Latin Hypercube Sampling technique [89,90]. Theoretical details of ANSYS DesignXplorer© can be found in Ref. [41,91,92]. In this study, the generated data sets from ANSYS are then used to train artificial neural networks (ANN) in order to map the structural response over the domain of stochastic variables. Finally, the RI is calculated using the FORM, which has been entirely implemented by the authors in MATLAB. The iterative FORM algorithm has been validated against the MCS in previous studies [20,43]. The well-established FORM is used as it offers a good balance between efficiency and accuracy for realistic problems. One limitation of the MCS method is that a large amount of simulations is required to calculate the very low values of failure probability, which is a characteristic of complex offshore structures [43,89,90].

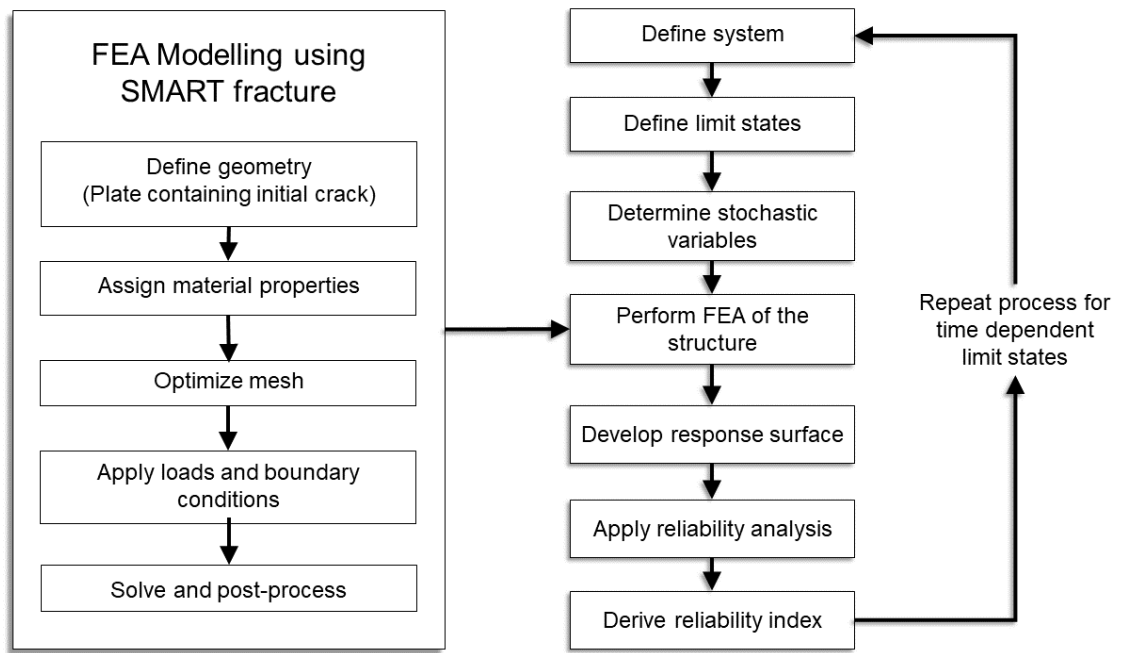


Figure 6-8. Flow chart of non-intrusive formulation for the FM approach [20].

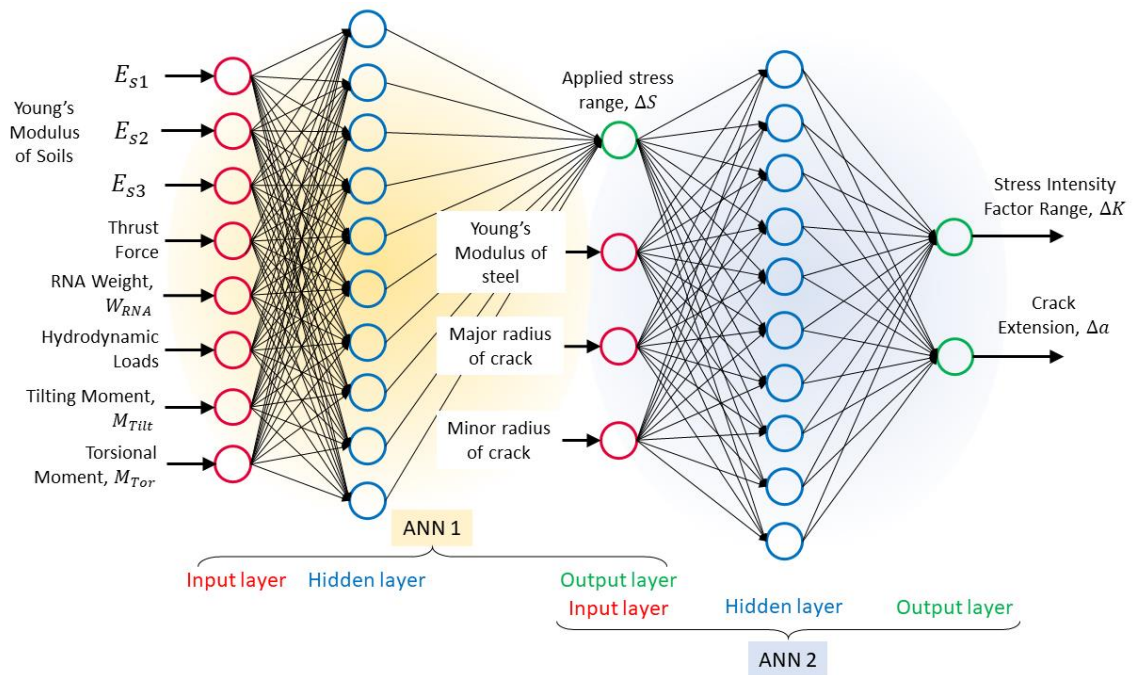


Figure 6-9. Two artificial neural networks (ANNs) that relate the variables given in Table 6-7 [20].

We now give further details to the ANN-based RSM, as follows. Two ANNs are used to predict the performance function using the stochastic variables as input. As shown in **Figure 6-9**, the first ANN aims to predict the applied stress range, while the second ANN aims to predict the stress intensity factor range and the crack extension. The architecture, the training, and testing results of these ANNs are the same as those provided in Ref. [21]. The readers may refer to **Table 6-7** for a summary of the variables involved. Having obtained the performance function from the ANN, the FORM is used to calculate the reliability index β using the HL-RF algorithm developed by the authors as described in [20,43,84].

6.5 Results and discussion

From the time-variant fatigue reliability index curve for the S-N curve method, it can be observed that the structure maintains a reliability index exceeding the defined threshold of target reliability as specified by DNV for the nominal 24 years of operation of the structure as shown in **Figure 6-10**. When the fatigue reliability over time is estimated, the inspection activities then need to be scheduled. In order to determine the times for IMR, a reliability index threshold for the inspection need to be identified. According to DNVGL standard [28], the target reliability index of OWT support structures is 3.71. Therefore, 3.71 is taken as the reliability index threshold in this study.

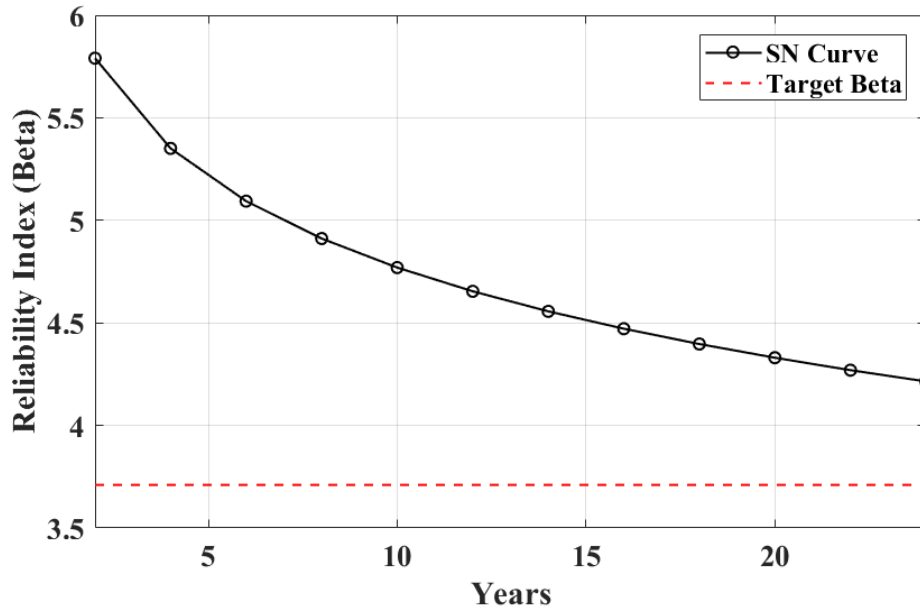


Figure 6-10. Fatigue reliability assessment using the S-N curve approach

6.5.1 Fatigue SRA results

Time-variant corrosion-fatigue reliability assessment was carried out employing the FM modelling approach, and the results are presented in **Figure 6-11**. It can be inferred that the structure failed the defined criteria after the year 9.65 as the reliability index β will fall below the defined threshold value of $\beta = 3.71$ [15–17,86].

6.5.2 Comparison between S-N curve and FM approaches

From **Figure 6-12**, it can be observed that at year 2 in the S-N curve approach, the $\beta = 5.79$ while in the FM-approach $\beta = 8.15$. Also, it can be seen that both curves intersect at year 7.05 when $\beta = 5$ whereas, at year 24 for the S-N curve approach, $\beta = 4.21$ while for the FM approach, $\beta = 1.24$. Hence, the structural reliability prediction produced following the S-N curve method gave conservative results compared to that produced using the FM approach at the start of the service life of the structure, but towards the end of the design life, the results may be overly optimistic. From the foregoing, we can establish that in terms of safety, it is better to apply the FM approach in the subsequent fatigue reliability assessments presented in the upcoming sections.

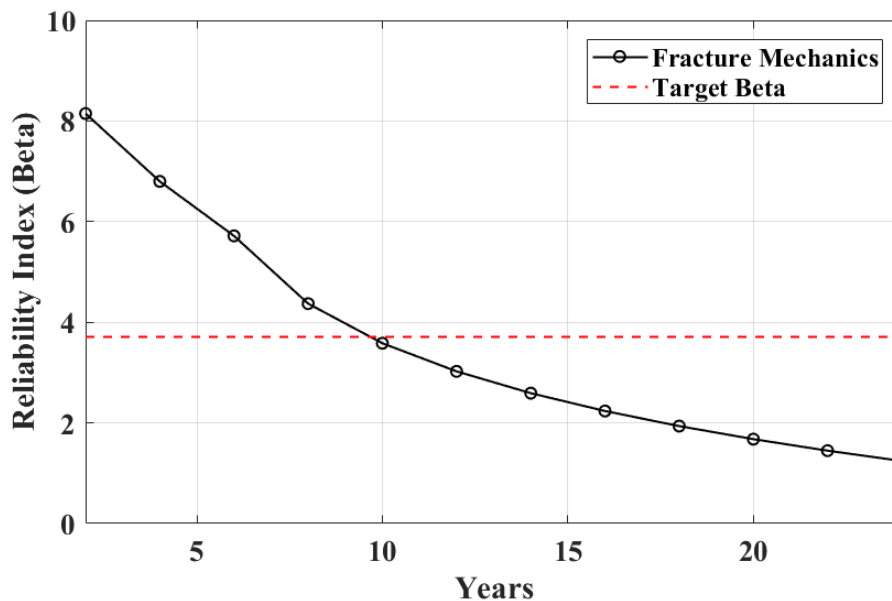


Figure 6-11. Fatigue reliability assessment using the FM approach

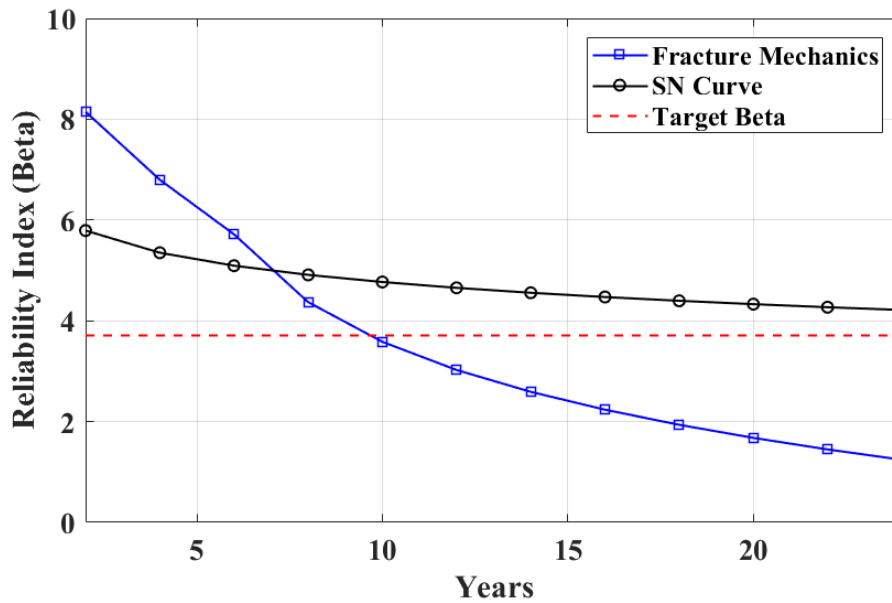


Figure 6-12. Comparison between the S-N curve and FM approaches

6.5.3 Sensitivity studies

The results of a sensitivity analysis to the fatigue reliability performed on the structure by varying different parameters is depicted in **Figure 6-13** to **Figure 6-20**. This depicts the most critical FM parameters that have a drastic impact on the response and reliability performance of the support structure. According to [8], apart from uncertainties in the Paris' law parameter C , other parameters of note of which their uncertainties often have significant impact on the fatigue reliability of welded components include the uncertainties in the crack initiation period, the initial crack size as well as in the crack aspect ratio development. It is argued therein, however, that due to the large number of microscopical defects introduced whilst the welding process as well as the stress raising effect of the geometry of the weld itself, the initiation time in welded structures is relatively small (10–15% of the total fatigue life). Hence, the initiation time is neglected herein, which is also a conservative assumption. In addition, it is assumed that corrosion-fatigue mechanism takes place, according to several studies [20,88,93–97].

In general, according to the data provided in the BS7910 [11], the uncertainties of the crack growth law constant C which corresponds to the lower segment are larger than that of the upper segment. As a result of both the inherent uncertainty in the behavior of very small crack propagation and the difficulty of carrying out measurements of such rates in the tests, this also entails that the near-threshold crack growth rates have an impact. In

addition, there is insufficient information with respect to the level of correlation which exists between both segments. This will have an impact on the RI results as calculated. The effect of correlation between C_1 and C_2 are analysed, as shown in **Figure 6-13**:

As can be observed the effect of variation in the correlation is pronounced at around years 6 and 8 of the operation of the structure. At this region of the FRA curves, the reliability index values decrease with an increase in the assumed correlation. It can be said that this may be at the small crack-to-long crack transition period. In other words, the reliability index curves diverge at the beginning (at the year 6 to be precise) and converge towards the end of the service life as the percentage correlation is increased correspondingly for the FM approach. As can also be seen from the same figure, with respect to the RI threshold based on the fatigue reliability curve having no correlation, 30% correlation, 60% correlation, and 90% correlation, the structure fails the defined criteria after the year 9.65, 9.43, 9.10, and 8.48 respectively. This indicates that correlation between the Paris' law constants assuming the bilinear FM model has a significant impact on the predicted fatigue RI.

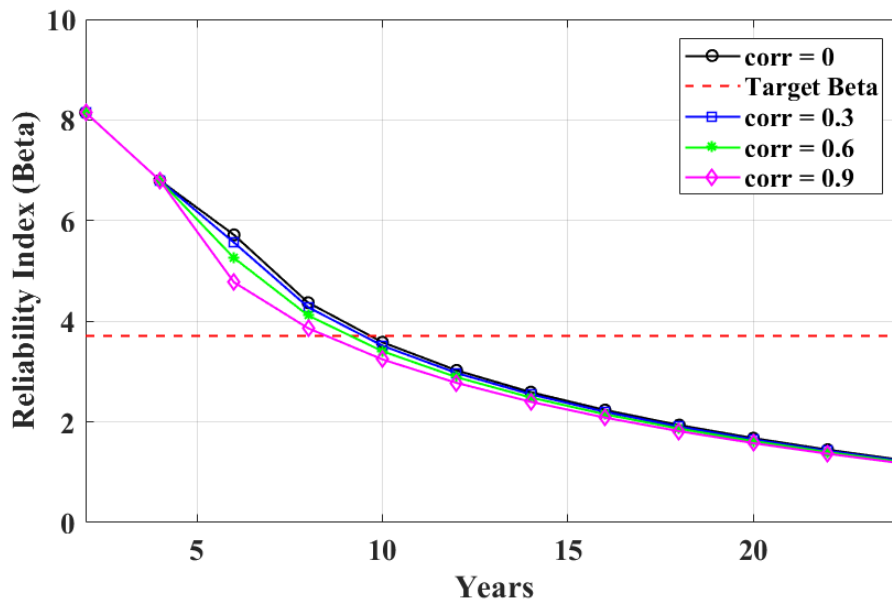


Figure 6-13. Fatigue reliability analysis assuming different levels of correlation between C_1 and C_2 .

It is crucial to emphasise that in the context of a bilinear FM law in seawater circumstances, majority of the propagation of surface cracks is affected by the uncertainties associated with the near-threshold rate of crack growth. For through-thickness cracks, the propagation is driven by larger crack growth rates far away from the influence of the uncertainties inherent to the knuckle of both slopes. The case study in this paper considers only surface cracks.

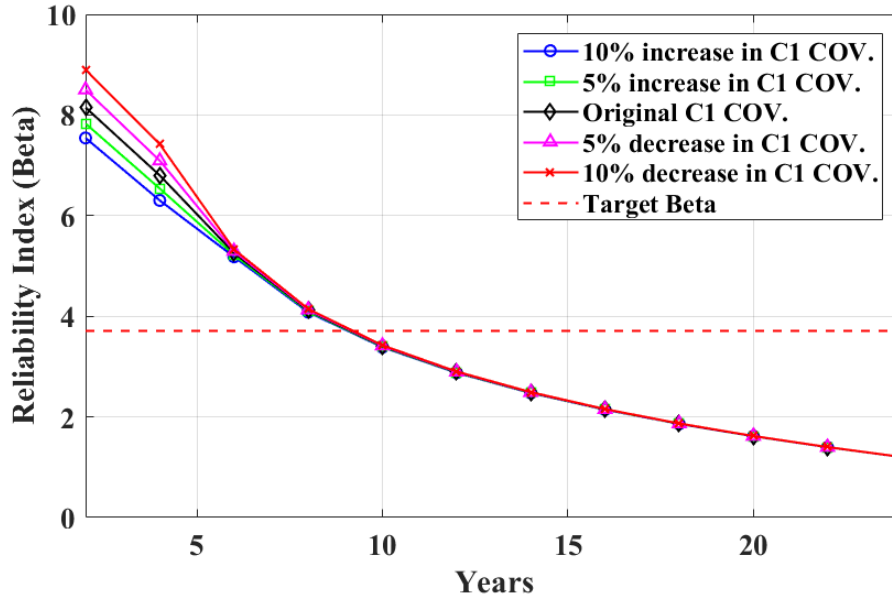


Figure 6-14. Fatigue reliability assessment using the bilinear FM model at different COV values of C_1

In the sensitivity studies presented in the followings, the correlated FM model is used, which is believed to represent most appropriately the bi-linear FM probabilistic formulation. In **Figure 6-14** for the bilinear FM model, as the uncertainty measured in terms of coefficient of variation (COV) in Paris' law constant C_1 increases, there is corresponding continuous decrease in the RI magnitude initially, which converges at the 10th year. **Figure 6-15** shows that as the uncertainty, measured in terms of COV in Paris constant C_2 increases, there is corresponding continuous decrease in the RI magnitude between years six and the year 22. As the COVs are increased there is no observed change at year 2, but the curves diverge at year four and then later converges at year 24. In **Figure 6-16**, the COVs of both terms C_1 and C_2 are increased simultaneously and it is observed that there is corresponding decrease in the RI value initially but the curves converge to the same RI at the end of the service life of the structure. Also, **Figure 6-15**

and **Figure 6-16** depicts that a change in the value of the coefficient of variation affects the time to failure/ inspection time for the structure.

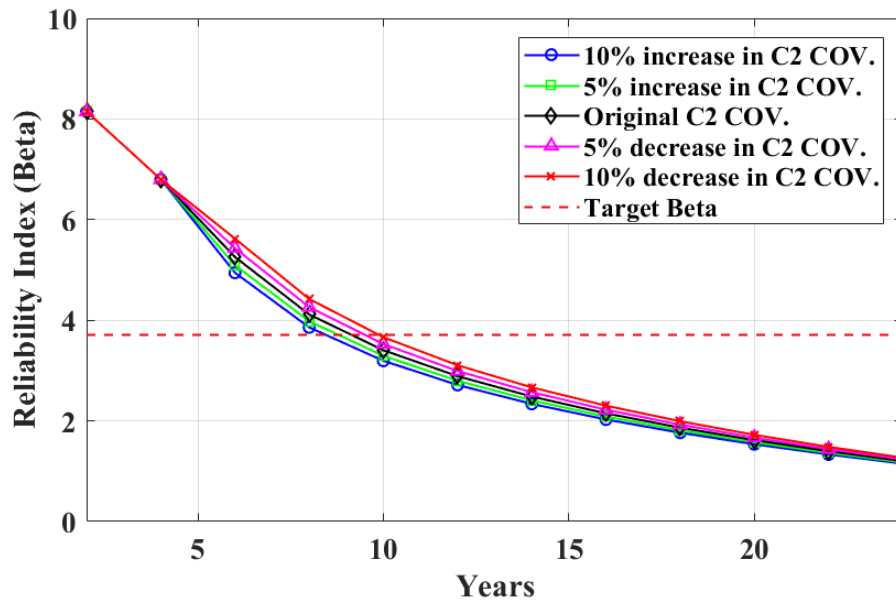


Figure 6-15. Fatigue reliability assessment using the bilinear FM model at different COV values of C_2

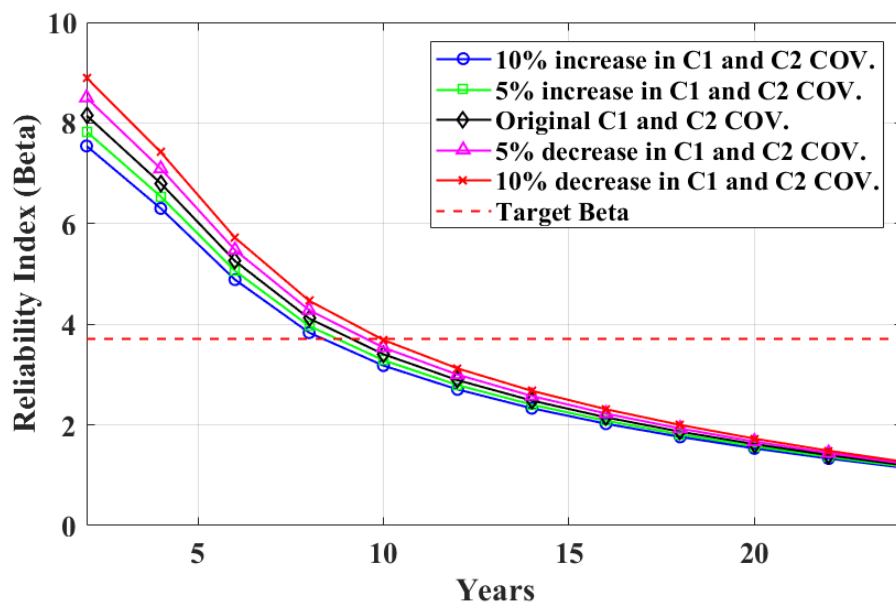


Figure 6-16. Fatigue reliability assessment using the bilinear FM model at different COV values of C_1 and C_2 (assuming the COVs of C_1 and C_2 are equal)

In this study, of interest is the initial size of a surface crack in a welded joint assumed to be induced by the welding procedure itself. The initial crack size, in principle, may be referred to as the depth (or length) from which the nucleation of a flaw from surface defects has occurred and will grow under the stable crack propagation regime until a final crack size or fracture. The probabilistic sensitivity factor (α) is used to quantify the influence of the initial crack size, a_i as shown in **Figure 6-17** and **Figure 6-18**. According to [66], these are obtained as the components of the unit gradient vector at the MPP of the limit state in the standard normal space. As can be seen in **Figure 6-17**, as the mean value of the a_i increases there is corresponding decrease in the value of the α . At the 6th year of the operation of the structure, the curves are observed to be converging after which an increase in the value of a_i leads to slight increase in the magnitude of α . The curve finally converge in the year 10 where there is no observed change in the magnitude of α as the mean value of a_i is changed. Also, from **Figure 6-18** a similar behavior is observed to the foregoing but this time a decrease in the COV leads to corresponding decrease in the magnitude of the α with the curves tending to converge as we are approaching the year 6. Hence, it can be inferred that the performance function by applying the FM approach is sensitive to the mean and COV of the a_i at the beginning of the service life of the structure.

These results show that it is not only the mean value of stochastic variables that control the reliability or safety of the structure, but COV also plays a very significant role in determining the reliability or safety of the structure. This study may prove to be efficient for optimisation and improvement of design.

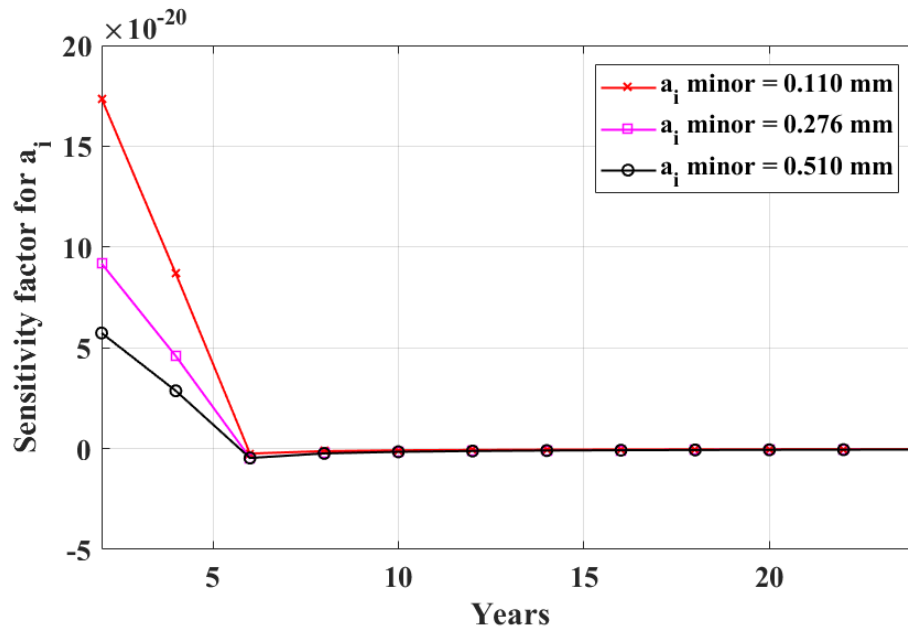


Figure 6-17: Variation of the sensitivity factor (α) with time at various mean values of initial crack depth (a_i).

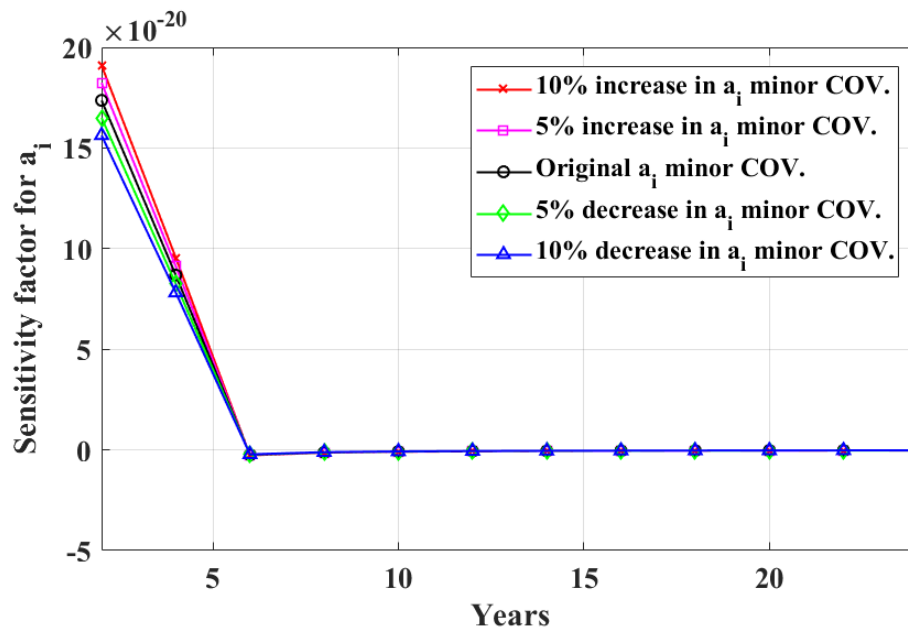


Figure 6-18. Variation of the sensitivity factor (α) with time at various COVs of initial crack depth (a_i).

6.5.4 Reassess reliability in the presence of SHM/CM data

With SHM/CM, the state of specific parameters (such as strain/stress and crack depth) can be monitored and measured during the operation of OWT support structures. In the presence of SHM/CM data, we can then reassess the fatigue reliability of OWT support structures based on the FM method.

6.5.4.1 Reassessment of fatigue reliability of OWT support structures based on measured strain/stress

For the initial fatigue reliability analysis, the fatigue stress range used in the FM method is predicted by the FEA modelling. During the operation of OWTs, the strain/stress history at the critical location can be monitored and measured with SHM/CM systems, and these measured data can be used to update the fatigue stress range. For instance, assuming the measured fatigue stress range after six years of operation is 10% or 20% higher than the original values predicted by FEA modelling, we can then reassess the fatigue reliability of OWT support structures based on the FM method and the measured stress values. An example is presented in **Figure 6-19**, showing the original and updated reliability index over time. As can be seen from the same figure, in the case of the measured stress at 10% higher than predicted, the updated reliability index curve was lower than the case at the originally predicted value. Thus a negative correlation is observed as a higher value of stress range yields lower reliability.

When the fatigue reliability over time is estimated, the inspection activities then need to be scheduled. In order to determine the times for inspections, a reliability index threshold for the inspection, maintenance and repair needs to be identified. As can be seen from the figure, the inspection based on the original reliability curve, and updated reliability curve with higher measured stress (i.e. 10% and then 20%) are 9.2, 9.08, and 8.75 years, respectively. This indicates the measured stress data from SHM/CM are valuable for updating the fatigue reliability index using the FM approach, optimising the inspection plan and saving OPEX of OWT support structures.

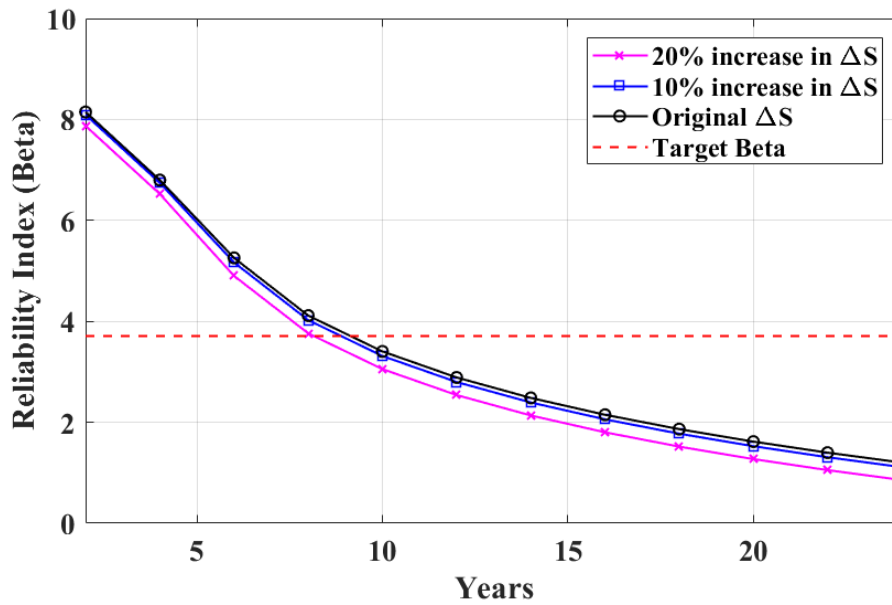


Figure 6-19. Fatigue reliability assessment using the FM approach at different values of the stress range

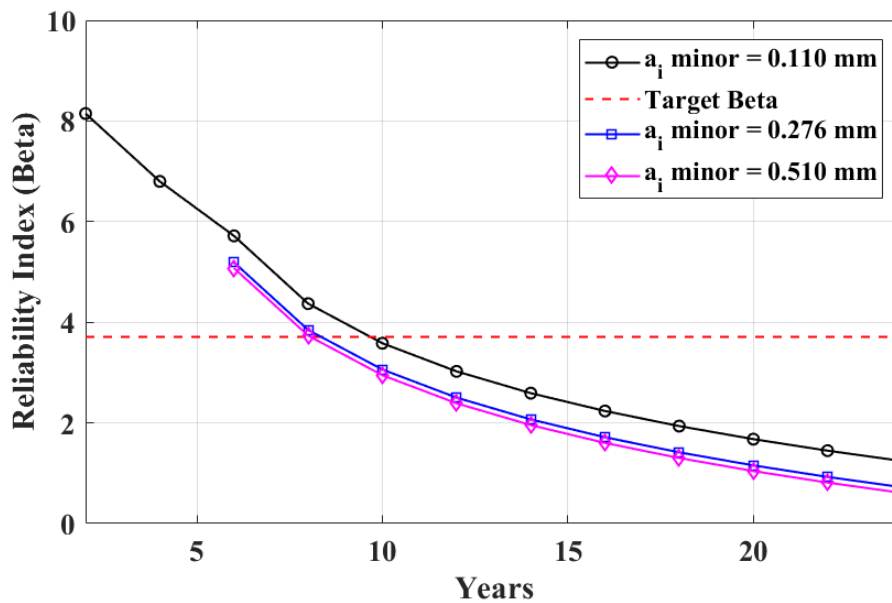


Figure 6-20. Fatigue reliability assessment at different values of initial crack size

6.5.4.2 Reassessment of fatigue reliability of OWT support structures based on measured crack depth

For the fatigue reliability analysis based on the FM method, an initial crack depth is generally assumed. During the operation of OWTs, the crack depth can be measured

with an SHM/CM system, and the measured data can be then used to update the reliability index calculated by the FM approach. Such an example is presented in **Figure 6-20**. The initial crack depth is 0.11mm.

The measured crack depth at Year 6 is assumed to be 0.276mm or 0.51mm, which are assumed to be measured crack depths at Year 6. The reliability threshold with a value of 3.71 is also presented in the figure. From the same figure, we can see that 1) in the case of a measured crack depth of 0.276mm and 0.51mm, the updated reliability index curve are both lower than the original curve, respectively; 2) larger crack depth leads to lower reliability; 3) the inspection time estimated by original reliability curve, updated curve with crack depth of 0.276mm and updated curve with crack depth of 0.51mm is 9.68, 8.34 and 8.10 years, respectively. Hence, it can be said that the reliability index β is sensitive to the initial crack size a_i . This indicates the measured crack depth from SHM/CM is valuable for updating the reliability index, optimising the inspection schedule and saving OPEX of OWT support structures [16].

6.6 Conclusion

In this work, S-N curve and FM approaches to fatigue reliability assessment were compared. A 3D parametric FEA model of OWT jacket support structures was developed, taking account of soil-structure interactions. In the FM approach, another FEA model of a curved plate was developed to simulate a part of the welded joint representing the failure-critical hot-spot location where the most cumulative fatigue damage occurs. A number of stochastic FEA simulations of the OWT were performed considering stochastic variables such as environmental and aerodynamic loads as well as soil properties. In the S-N curve approach, an ANN RSM was developed such that the result obtained from the 3D FEA simulations are used to derive the performance function expressed in terms of important stochastic variables. Whereas in the FM approach, this was achieved by linking the two FEA models developed via a second ANN developed for the surrogate modelling. Subsequently, the FORM is applied for both methods in calculating the fatigue reliability index of the structure. The results of the fatigue reliability assessment whilst comparing with the S-N curve approach revealed that the FM approach was optimistic at the beginning while it was found to be more conservative towards the end of the through-life of the structure. It can be concluded that the SN approach should be used during the design stage, while the FM approach should be used as the structure approaches failure. Furthermore, other fatigue reliability

assessment exercise performed include estimating the threshold inspection time for the support structure determined via updating the developed reliability framework with SHM/CM data. Hence, the updated reliability assessment provides valuable information for making decisions with respect to the IMR of OWT jacket support structures. Also, the fatigue reliability index calculated assuming a correlation between both segments of the crack growth law from the bilinear FM approach is sensitive to the initial crack depth, and a larger initial crack size leads to lower reliability.

Acknowledgement

Author Abdulhakim A. Shittu would like to acknowledge the Petroleum Technology Development Fund (PTDF), Nigeria, for doctoral study scholarship, award number: PTDF/ED/PHD/SAA/1142/17.

References

1. EWEA. Wind energy scenarios for 2030. Brussels, Belgium; 2015.
2. Kolios A., Mytilinou V., Lozano-Minguez E., Salonitis K. A Comparative Study of Multiple-Criteria Decision-Making Methods under Stochastic Inputs. *Energies*. MDPI AG; 21 July 2016; 9(7): 566. Available at: DOI:10.3390/en9070566 (Accessed: 29 June 2020)
3. Kallehave D., Byrne BW., LeBlanc Thilsted C., Mikkelsen KK. Optimization of monopiles for offshore wind turbines. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*. Royal Society of London; 28 February 2015; 373(2035): 20140100. Available at: DOI:10.1098/rsta.2014.0100 (Accessed: 29 June 2020)
4. Collu M., Kolios AJ., Patel M. A Multi-Criteria Decision Making Method to Compare Available Support Structures for Offshore Wind Turbines Platforms for Tidal Energy Converters View project HOME Offshore (<http://homeoffshore.org>) View project. *researchgate.net*. 2010. Available at: <https://www.researchgate.net/publication/200589330> (Accessed: 29 June 2020)
5. Kolios A., Wang L., Mehmanparast A., Brennan F. Determination of stress concentration factors in offshore wind welded structures through a hybrid experimental and numerical approach. *Ocean Engineering*. Elsevier Ltd; 2019; 178(February): 38–47. Available at: DOI:10.1016/j.oceaneng.2019.02.073
6. Damiani R., Song H. A Jacket Sizing Tool for Offshore Wind Turbines within the Systems Engineering Initiative. *Offshore Technology Conference, OTC 24140*. Houston, Texas, USA; 2013. Available at: DOI:10.4043/24140-MS
7. Damiani RR., Song H., Robertson AN., Jonkman JM. Assessing the Importance of Nonlinearities in the Development of a Substructure Model for the Wind Turbine CAE Tool FAST. *Volume 8: Ocean Renewable Energy*. 2013; 8(March): V008T09A093. Available at: DOI:10.1115/OMAE2013-11434
8. Ayala-uraga E., Moan T. Fatigue reliability-based assessment of welded joints applying consistent fracture mechanics formulations. *International Journal of Fatigue*. 2007; 29: 444–456. Available at: DOI:10.1016/j.ijfatigue.2006.05.010
9. Dong W., Moan T., Gao Z. Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection. *Reliability Engineering and System Safety*. Elsevier; 2012; 106: 11–27. Available at: DOI:10.1016/j.res.2012.06.011

10. Yeter B., Garbatov Y., Soares CG. Fatigue reliability of an offshore wind turbine supporting structure accounting for inspection and repair. In: Soares G, Shenoi E (eds.) *Analysis and Design of Marine Structures*. London, UK: Taylor & Francis Group; 2015. pp. 737–747.
11. BS 7910. BSI Standards Publication Guide to methods for assessing the acceptability of flaws in metallic structures. BSI Standards Publication. 2015; (UK): 490.
12. Silva JE., Garbatov Y., Guedes Soares C. Reliability assessment of a steel plate subjected to distributed and localized corrosion wastage. *Engineering Structures*. Elsevier Ltd; 2014; 59: 13–20. Available at: DOI:10.1016/j.engstruct.2013.10.018
13. Kim DH., Lee SG. Reliability analysis of offshore wind turbine support structures under extreme ocean environmental loads. *Renewable Energy*. Elsevier Ltd; 2015; 79(1): 161–166. Available at: DOI:10.1016/j.renene.2014.11.052
14. Gholizad A., Golafshani AA., Akrami V. Structural reliability of offshore platforms considering fatigue damage and different failure scenarios. *Ocean Engineering*. Elsevier; 2012; 46: 1–8. Available at: DOI:10.1016/j.oceaneng.2012.01.033
15. Wang L., Kolios A. A generic framework for reliability assessment of offshore wind turbine monopiles considering soil-solid interaction and harsh marine environments. 5th International Conference on Marine Structures, MARSTRUCT. Lisbon; 2017. pp. 931–938. Available at: DOI:10.1201/9781315157368-105
16. Kolios A., Wang L. Advanced reliability assessment of offshore wind turbine monopiles by combining reliability analysis method and SHM / CM technology. 2018; : 1412–1419.
17. Kolios A., Di Maio LF., Wang L., Cui L., Sheng Q. Reliability assessment of point-absorber wave energy converters. *Ocean Engineering*. Elsevier Ltd; 2018; 163(October 2017): 40–50. Available at: DOI:10.1016/j.oceaneng.2018.05.048
18. Kolios A. A multi-configuration approach to reliability based structural integrity assessment for ultimate strength. Cranfield University; 2010.
19. Jiang Z., Hu W., Dong W., Gao Z., Ren Z. Structural reliability analysis of wind turbines: A review. *Energies*. 2017; 10(12): 1–25. Available at: DOI:10.3390/en10122099
20. Shittu AA., Mehmanparast A., Shafiee M., Kolios A., Hart P., Pilario KE. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting Corrosion-Fatigue: A Damage Tolerance Modelling Approach. *Wind Energy*. John Wiley & Sons, Ltd; 12 July 2020; Early view. Available at: DOI:10.1002/we.2542 (Accessed: 17 July 2020)
21. Wang L., Kolios A., Nishino T., Delafin PL., Bird T. Structural optimisation of vertical-axis wind turbine composite blades based on finite element analysis and genetic algorithm. *Composite Structures*. Elsevier Ltd; 2016; 153(January 2015): 123–138. Available at: DOI:10.1016/j.compstruct.2016.06.003
22. Gentils T., Wang L., Kolios A. Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. *Applied Energy*. Elsevier Ltd; 2017; 199: 187–204. Available at: DOI:10.1016/j.apenergy.2017.05.009
23. Wang L., Quant R., Kolios A. Fluid structure interaction modelling of horizontal-axis wind turbine blades based on CFD and FEA. *Journal of Wind Engineering and Industrial Aerodynamics*. Elsevier; 2016; 158: 11–25. Available at: DOI:10.1016/j.jweia.2016.09.006
24. Achmus M., Abdel-Rahman K. Finite element modelling of horizontally loaded monopile foundations for offshore wind energy converters in Germany. *Frontiers in Offshore Geotechnics*. 2005; (August 2005). Available at: DOI:10.1201/NOE0415390637.ch38
25. Wang L., Kolios A., Delafin P-L., Nishino T., Bird T. Fluid structure interaction modelling of a novel 10MW vertical-axis wind turbine rotor based on computational fluid dynamics and finite element analysis. *European Wind Energy Association Annual Conference and Exhibition 2015, EWEA 2015 - Scientific Proceedings*. 2015; 44(0).
26. Yeter B., Garbatov Y., Guedes Soares C. Uncertainty analysis of soil-pile interactions of monopile offshore wind turbine support structures. *Applied Ocean Research*. Elsevier; 2019; 82(November 2018): 74–88. Available at: DOI:10.1016/j.apor.2018.10.014

27. Jung S., Kim SR., Patil A., Hung LC. Effect of monopile foundation modeling on the structural response of a 5-MW offshore wind turbine tower. *Ocean Engineering*. Elsevier; 2015; 109: 479–488. Available at: DOI:10.1016/j.oceaneng.2015.09.033
28. DNV GL AS. DNVGL-ST-0126 : Support structures for wind turbines. DNV GL - Standard Høvik, Norway: Det Norske Veritas; 2016 p. 182 pp. Available at: DOI:10.1016/j.jbiomech.2014.11.025
29. Martinez-Luengo M., Kolios A., Wang L. Structural health monitoring of offshore wind turbines: A review through the Statistical Pattern Recognition Paradigm. *Renewable and Sustainable Energy Reviews*. Elsevier Ltd; 2016. pp. 91–105. Available at: DOI:10.1016/j.rser.2016.05.085
30. McCulloch WS., Pitts W. A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*. Kluwer Academic Publishers; December 1943; 5(4): 115–133. Available at: DOI:10.1007/BF02478259 (Accessed: 24 June 2019)
31. Hornik K., Stinchcombe M., White H. Multilayer feedforward networks are universal approximators. *Neural Networks*. Pergamon; 1 January 1989; 2(5): 359–366. Available at: DOI:10.1016/0893-6080(89)90020-8 (Accessed: 24 June 2019)
32. Bucher C., Most T. A comparison of approximate response functions in structural reliability analysis. *Probabilistic Engineering Mechanics*. 2008; 23(2–3): 154–163. Available at: DOI:10.1016/j.probengmech.2007.12.022
33. Hosni Elhewy A., Mesbahi E., Pu Y. Reliability analysis of structures using neural network method. *Probabilistic Engineering Mechanics*. Elsevier; 1 January 2006; 21(1): 44–53. Available at: DOI:10.1016/J.PROBENGMECH.2005.07.002 (Accessed: 26 June 2019)
34. Gomes HM., Awruch AM. Comparison of response surface and neural network with other methods for structural reliability analysis. *Structural Safety*. Elsevier; 1 January 2004; 26(1): 49–67. Available at: DOI:10.1016/S0167-4730(03)00022-5 (Accessed: 26 June 2019)
35. Chojaczyk AA., Teixeira AP., Neves LC., Cardoso JB., Guedes Soares C. Review and application of Artificial Neural Networks models in reliability analysis of steel structures. *Structural Safety*. Elsevier Ltd; 2015; 52(PA): 78–89. Available at: DOI:10.1016/j.strusafe.2014.09.002
36. Cardoso JB., de Almeida JR., Dias JM., Coelho PG. Structural reliability analysis using Monte Carlo simulation and neural networks. *Advances in Engineering Software*. Elsevier; 1 June 2008; 39(6): 505–513. Available at: DOI:10.1016/J.ADVENGSOFT.2007.03.015 (Accessed: 26 June 2019)
37. De Santana Gomes WJ. Structural Reliability Analysis Using Adaptive Artificial Neural Networks. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*. American Society of Mechanical Engineers (ASME); 1 December 2019; 5(4). Available at: DOI:10.1115/1.4044040 (Accessed: 17 July 2020)
38. Ziegler L., Muskulus M. Comparing a fracture mechanics model to the SN-curve approach for jacket-supported offshore wind turbines: Challenges and opportunities for lifetime prediction. *Proceedings of the ASME 2016 35th International Conference on Ocean, Offshore and Arctic Engineering, OMAE2016*, June 19–24. Busan, South Korea: American Society of Mechanical Engineers (ASME); 2016. pp. 1–10.
39. Doshi K., Vhanmane S. Probabilistic fracture mechanics based fatigue evaluation of ship structural details. *Ocean Engineering*. Elsevier; 2013; 61: 26–38. Available at: DOI:10.1016/j.oceaneng.2012.12.039
40. Yeter B., Garbatov Y., Soares CG. Reliability of Offshore Wind Turbine Support Structures Subjected to Extreme Wave-Induced Loads and Defects. *Proceedings of the ASME 2016 35th International Conference on Ocean, Offshore and Arctic Engineering*. Busan, South Korea; 2016.
41. Yeter B., Garbatov Y., Guedes Soares C. System reliability of a jacket offshore wind turbine subjected to fatigue. *Proceedings of the 5th International Conference on Marine Structures, MARSTRUCT*. Lisbon; 2017. pp. 939–950.

42. Wang L., Kolios A. A generic framework for reliability assessment of offshore wind turbine monopiles considering soil-solid interaction and harsh marine environments. *Progress in the Analysis and Design of Marine Structures - Proceedings of the 6th International Conference on Marine Structures, MARSTRUCT 2017*. Lisbon; 2017. pp. 931–938. Available at: DOI:10.1201/9781315157368-105
43. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Applied Sciences*. MDPI AG; 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860 (Accessed: 15 June 2020)
44. Dong W., Nejad AR., Moan T., Gao Z. Structural reliability analysis of contact fatigue design of gears in wind turbine drivetrains. *Journal of Loss Prevention in the Process Industries*. Elsevier Ltd; 1 May 2020; 65: 104115. Available at: DOI:10.1016/j.jlp.2020.104115
45. Márquez-Domínguez S., Sørensen JD. Fatigue Reliability and Calibration of Fatigue Design Factors for Offshore Wind Turbines. *energies*. 2012; 5: 1816–1834. Available at: DOI:10.3390/en5061816 (Accessed: 6 December 2019)
46. Rendón-conde C., Heredia-zavoni E. Reliability assessment of mooring lines for floating structures considering statistical parameter uncertainties. *Physics Procedia*. Elsevier B.V.; 2015; 52: 295–308. Available at: DOI:10.1016/j.apor.2015.06.011
47. Yeter B., Garbatov Y., Soares CG. Reliability of offshore wind turbine support structures subjected to extreme wave-induced loads and defects. *Proceedings of the ASME 2016 35th international conference on ocean, offshore and arctic engineering OMAE2016-54240*. Busan, South Korea; 2016. pp. 1–8.
48. Amirafshari P., Stacey A. Review of available probabilistic models of the crack growth parameters in the Paris equation. *Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE*. Glasgow, Scotland, UK: American Society of Mechanical Engineers (ASME); 2019. Available at: DOI:10.1115/OMA2019-96161
49. Rajasankar J., Iyer N., Rao TA. Structural integrity assessment of offshore tubular joints based on reliability analysis. *International Journal of Fatigue*. 2003; 25: 609–619. Available at: DOI:10.1016/S0142-1123(03)00021-5
50. Rahman S. Probabilistic Fracture mechanics J-estimation and finite element methods. *Engineering Fracture Mechanics*. 2001; 68: 107–125.
51. Rahman S., Kim JS. Probabilistic fracture mechanics for nonlinear structures. *International Journal of Pressure Vessels and Piping*. 2001; 78: 261–269.
52. Lee S., Chang Y., Choi J., Kim Y. Structural Integrity Assessment of Major Nuclear Components using Probabilistic Fracture Mechanics. *Key Engineering Materials*. 2006; 308: 339–344. Available at: DOI:10.4028/www.scientific.net/KEM.306-308.339
53. Lee S., Chang Y., Choi J., Kim Y. Probabilistic Integrity Assessment of Corroded Gas Pipelines. *Journal of pressure vessel technology*. 2006; 128(November): 547–555. Available at: DOI:10.1115/1.2349566
54. Walz G., Riesch-Oppermann H. Probabilistic fracture mechanics assessment of flaws in turbine disks including quality assurance procedures. *Structural Safety*. 2006; 28: 273–288. Available at: DOI:10.1016/j.strusafe.2005.08.004
55. Sandvik A., Østby E., Thaulow C. Probabilistic fracture assessment of surface cracked pipes using strain-based approach. *Engineering Fracture Mechanics*. 2006; 73: 1491–1509. Available at: DOI:10.1016/j.engfracmech.2006.01.026
56. Khan R., Ahmad S. Dynamic Response and Fatigue Reliability Analysis of Marine Riser Under Random Loads. *Proceedings of the 26th International Conference on Offshore Mechanics and Arctic Engineering OMAE2007* June 10-15. Paper Number: OMAE2007-29235. San Diego, California, USA: American Society of Mechanical Engineers (ASME); 2016.
57. Reddy RM., Rao BN. Probabilistic Fracture Mechanics Using Fractal Finite Element Method. *Proceedings of PVP2008 ASME Pressure Vessels and Piping Division*

- Conference July 27-31. Chicago, Illinois, USA: American Society of Mechanical Engineers (ASME); 2008.
58. Chowdhury R., Rao BN. Structural Failure Probability Estimation Using HDMR and FFT. *Electronic Journal of Structural Engineering*. 2008; 8: 67–76.
 59. Steel K., Sorensen A. Reliability Analysis of a Circular Bridge Pier Subject to Intentional Vehicular Impact. *Vulnerability, Uncertainty and Risk*. 2014; : 2702–2709.
 60. Garza J., Millwater H. Sensitivity of the probability of failure to probability of detection curve regions. *International Journal of Pressure Vessels and Piping*. Elsevier Ltd; 2016; 141: 26–39. Available at: DOI:10.1016/j.ijpvp.2016.03.012
 61. Zaheer MM., Islam N. Reliability analysis of universal joint of a compliant platform. *Fatigue & Fracture of Engineering Materials & Structures*. 2010; 33: 408–419. Available at: DOI:10.1111/j.1460-2695.2010.01453.x
 62. Zaheer MM., Islam N. Fatigue and Fracture Reliability of Articulated Tower Joint Under Random Loading. *Proceedings of the ASME 2009 28th International Conference on Ocean, Offshore and Arctic Engineering*, May 31 - June 5, Paper Number: OMAE2009-79360. Honolulu, Hawaii, USA: American Society of Mechanical Engineers (ASME); 2009.
 63. Lee C., Kim Y. Probabilistic flaw assessment of a surface crack in a mooring chain using the first- and second-order reliability method. *Marine Structures*. Elsevier Ltd; 2019; 63(June 2018): 1–15. Available at: DOI:10.1016/j.marstruc.2018.09.003
 64. Kang B., Kim J., Kim Y. Engineering criticality analysis on an offshore structure using the first- and second-order reliability method. *International Journal of Naval Architecture and Ocean Engineering*. Elsevier Ltd; 2016; 8(6): 577–588. Available at: DOI:10.1016/j.ijnaoe.2016.05.014
 65. Ambühl S., Ferri F., Kofoed JP., Sørensen JD. Fatigue reliability and calibration of fatigue design factors of wave energy converters. *International journal of marine energy*. 2015; 10: 17–38. Available at: DOI:10.1016/j.ijome.2015.01.004
 66. Shi P., Mahadevan S. Damage tolerance approach for probabilistic pitting corrosion fatigue life prediction. *Engineering Fracture Mechanics*. 2001; 68(13): 1493–1507. Available at: DOI:10.1016/S0013-7944(01)00041-8
 67. Melchers R., Andre T. *Structural reliability analysis and prediction*. 3rd edn. Hoboken, USA: Wiley; 2018.
 68. Nowak AS., Collins KR. *Reliability of Structures*. Second Edi. CRC Press; 2012.
 69. Ayyub BM., McCuen RH. *Probability, Statistics, and Reliability for Engineers and Scientists*. Third. Probability, Statistics, and Reliability for Engineers and Scientists. 6000 Broken Sound Parkway NW, Suite 300, Boca Raton: Taylor and Francis Group; 2011. Available at: DOI:10.1201/b12161
 70. Det Norske Veritas. *Fatigue design of offshore steel structures*. Recommended Practice DNV-RPC203. 2010; (April): 37–41.
 71. DNV. *DNV-OS-J101 Design of Offshore Wind Turbine Structures*. May. 2014; (May): 212–214.
 72. Anderson TL. *Fracture Mechanics Fundamentals and Applications*. Taylor and Francis; 2005. 1–610 p.
 73. Newman JC., Raju IS. An empirical stress-intensity factor equation for the surface crack. *Engineering Fracture Mechanics*. Pergamon; 1 January 1981; 15(1–2): 185–192. Available at: DOI:10.1016/0013-7944(81)90116-8
 74. ANSYS. *White Paper: SMART Fracture*. 2018.
 75. Pook LP. *Linear elastic fracture mechanics for engineers : theory and applications*. WIT Press; 2000. 154 p.
 76. Kühn M. *Dynamics and Design Optimization of Offshore Wind Energy Conversion Systems*. Sciences-New York. 1999.
 77. Damiani R. *JacketSE : An Offshore Wind Turbine Jacket Sizing Tool Theory Manual and*

- Sample Usage with Preliminary Validation. Denver West Parkway Golden, CO; 2016.
78. Fisher T., De Vries W., Schmidt B. Upwind Design Basis (WP4 Offshore foundations and support structures). project upwind contract No. 019945 (SES6); 2010. Available at: DOI:10.1016/S0140-6736(02)81074-1
 79. Martinez-Luengo M., Kolios A., Wang L. Parametric FEA modelling of offshore wind turbine support structures: Towards scaling-up and CAPEX reduction. *International Journal of Marine Energy*. 2017; 19(2017): 16–31. Available at: DOI:10.1016/j.ijome.2017.05.005
 80. Drucker D., Prager W. Soil mechanics and plastic analysis or limit design. *Quarterly of Applied Mathematics*. 1952; 10(2): 157–165.
 81. IEC. IEC 61400-1: Wind Turbines Part 1: Design Requirements. 2005;
 82. Sarpkaya TS. *Wave Forces on Offshore Structures*. Cambridge: Cambridge University Press; 2010. Available at: DOI:10.1017/CBO9781139195898 (Accessed: 7 October 2019)
 83. Richmond M., Antoniadis A., Wang L., Kolios A., Al-sanad S., Parol J. Evaluation of an offshore wind farm computational fluid dynamics model against operational site data. *Ocean Engineering*. Elsevier Ltd; 2019; 193(October): 106579. Available at: DOI:10.1016/j.oceaneng.2019.106579
 84. Shittu AA., Mehmanparast A., Amirafshari P., Hart P., Kolios A. Sensitivity analysis of design parameters for reliability assessment of offshore wind turbine jacket support structures. Under review. 2020;
 85. BSI. BS EN 1990 Eurocode: Basis of Structural Design. British standard institute. 2002;
 86. (DNV) Det Norske Veritas. *Structural Reliability Analysis of Marine Structures*. DNV CN 30-6. 1992;
 87. Velarde J., Kramhøft C., Sørensen JD. Global sensitivity analysis of offshore wind turbine foundation fatigue loads. *Renewable Energy*. Elsevier Ltd; 2019; 140: 177–189. Available at: DOI:10.1016/j.renene.2019.03.055
 88. Igwemezie V., Mehmanparast A. Waveform and frequency effects on corrosion-fatigue crack growth behaviour in modern marine steels. *International Journal of Fatigue*. Elsevier Ltd; 1 May 2020; 134: 105484. Available at: DOI:10.1016/j.ijfatigue.2020.105484
 89. Morse L., Sharif Khodaei Z., Aliabadi MH. A multi-fidelity boundary element method for structural reliability analysis with higher-order sensitivities. *Engineering Analysis with Boundary Elements*. Elsevier Ltd; 2019; 104(April): 183–196. Available at: DOI:10.1016/j.enganabound.2019.03.036
 90. Morse L., Khodaei ZS., Aliabadi MH. A multi-fidelity modelling approach to the statistical inference of the equivalent initial flaw size distribution for multiple-site damage. *International Journal of Fatigue*. Elsevier; 2019; 120(November 2018): 329–341. Available at: DOI:10.1016/j.ijfatigue.2018.11.010
 91. Reh S., Beley JD., Mukherjee S., Khor EH. Probabilistic finite element analysis using ANSYS. *Structural Safety*. 2006; 28(1–2): 17–43. Available at: DOI:10.1016/j.strusafe.2005.03.010
 92. ANSYS. *DesignXplorer User's Guide*. 2018.
 93. Larrosa NO., Akid R., Ainsworth RA. Corrosion-fatigue: a review of damage tolerance models. *International Materials Reviews*. Taylor & Francis; 2018; 63(5): 283–308. Available at: DOI:10.1080/09506608.2017.1375644
 94. Li SX., Akid R. Corrosion fatigue life prediction of a steel shaft material in seawater. *Engineering Failure Analysis*. Elsevier Ltd; 2013; 34: 324–334. Available at: DOI:10.1016/j.engfailanal.2013.08.004
 95. Igwemezie V., Mehmanparast A., Kolios A. Materials selection for XL wind turbine support structures: A corrosion-fatigue perspective. *Marine Structures*. Elsevier Ltd; 2018; 61(December 2017): 381–397. Available at: DOI:10.1016/j.marstruc.2018.06.008
 96. Adedipe O., Brennan F., Kolios A. Review of corrosion fatigue in offshore structures:

- Present status and challenges in the offshore wind sector. *Renewable and Sustainable Energy Reviews*. Elsevier; 2016; 61: 141–154. Available at: DOI:10.1016/j.rser.2016.02.017
97. Adedipe O., Brennan F., Mehmanparast A., Kolios A., Tavares I. Corrosion fatigue crack growth mechanisms in offshore monopile steel weldments. *Fatigue and Fracture of Engineering Materials and Structures*. 2017; 40(11): 1868–1881. Available at: DOI:10.1111/ffe.12606

7 OVERALL DISCUSSION

Offshore wind turbines (OWTs) are deployed in harsh environments often characterised by highly stochastic loads and resistance properties, thus necessitating the need for structural reliability assessment (SRA) to account for such uncertainties systematically [1]. Structural reliability can be defined as ‘the ability that a structure complies with given requirements under specific conditions during the intended life for which it was designed’ [2]. This project puts forward novel SRA techniques combining FEA with FORM through response surface/ surrogate modelling in a single framework for application to nonlinear complex offshore structures. In this Chapter, an overall discussion of the results of this thesis is presented, and the specific contributions of this thesis are summarised. This is done by showing that the results from Chapters 2-6 can be linked together in a logical thought process, demonstrating coherence towards achieving the overall aim. Hence, the findings are consolidated, the approach to fulfilling the objectives are presented, and thus, the contribution of the thesis is substantiated. The overall contribution of this study is organised into three categories: novelty, scientific soundness and value to different practitioners. **Table 7-1** summarises the objectives of the research project, how these are addressed through various research activities, coupled with the contribution of each objective in terms of novelty, scientific soundness and value to different stakeholders.

The first objective was accomplished via an extensive literature review by addressing a research question: which SRA methods are applicable to design of complex offshore structures in the presence of stochastic variables including limit state design approaches? In addition, the study aims to identify key applications of each method and its proposed variations, qualifying characteristics, advantages and limitations. The systematic literature review method was employed, whereby keywords were selected to enable key references to be included in a transparent, systematic, and duplicable way, while also alleviating the reviewer’s bias. The benefit of this study is such that the findings can provide invaluable insights to researchers and academics about the state-of-the-art on SRA methods with applicability to the analyses of complex offshore structures and serve as an important piece of work where large number of research works conducted on SRA was documented [2].

Table 7-1. Research contribution presented by means of novelty, scientific soundness and value for each objectives

Objective	Novelty	Scientific soundness	Value
	<i>What is new?</i>	<i>What methods have been used and how have they been validated?</i>	<i>Who will benefit from this part of the work?</i>
Carry out an extensive literature review on structural reliability analysis methods including limit state design approaches	In Chapter 2, The review paper produced responds to the research question: Which options are most suitable/ most promising for SRA of complex offshore structures. Also, the study aims to identify key applications of each method and its proposed variations, qualifying characteristics, advantages and limitations.	This involved a systematic literature review approach which enables relevant references to be included based on the use of predefined words and combination of words so as to restrict the bias of the researcher.	The findings in the review paper can provide invaluable insights to researchers and academics about state-of-the-art methods used for analyses of complex offshore structures and serve as a piece of work where a large number of research efforts conducted on SRA is documented.
Carry out the Stochastic Parametric Finite Element Analysis (FEA) on a complex frame type structure, using sequential steps of a high capability tool and to validate results obtained from the parametric FEA model with those found in the literature.	In Chapter 3, a comparative analysis on the structural reliability of an OWT support structure between a commercial package and a purpose-developed, non-intrusive stochastic formulation was presented. Both methods start by defining the limit states taking account of the various design constraints. A 3D parametric FEA model of a typical OWT jacket-type support structure was developed, taking account of soil-structure	Both the modal frequencies and deflection in static analysis of the OWT support structure computed from the parametric FEA model show reasonable agreement with reference values, which confirms the validity of the FEA model used.	The study allows for verification of the non-intrusive formulation and the findings avail designers of a solution to multiple problems of complex nature probabilistically, alleviating the need for an integrated, application-specific tool to be developed, instead of with the proposed modular formulation.

	interaction and stochastic variables.		
A corrosion-fatigue model based on the pit and crack growth will be developed whereby the nucleation/development and growth to the critical size of the corrosion pits are predicted using data obtained from the literature. A pit-to-crack transition prediction model at the critical joint will be formulated using the fracture mechanics tool (SMART© crack growth analysis) packaged in ANSYS and subsequently building a stochastic parametric FEA model (with the aid of DoE inbuilt in DesignXplorer©). Afterwards, the stochastic parametric FEA model will be validated.	In Chapter 5, the SRA of an OWT support structure subjected to pitting corrosion-fatigue was performed by employing the damage tolerance model approach. The reliability assessment for the corrosion pit growth regime was performed using empirical equations from classical corrosion mechanism methodologies, while the SRA for crack propagation regimes which includes the pit-to-small crack transition and the small crack-to-long crack transition regimes was performed using a stochastic parametric FEA model.	Two ANNs were trained to relate various stochastic variables for predicting the performance function. The two ANNs were employed in order to have an intermediate predictor for a stochastic variable, which is more advantageous because of the added interpretability of results. Another advantage of the proposed methodology is that the first ANN architecture enabled a significant reduction in the computational cost, which would have been required to simulate global behaviour of the support structure thus allowing other global parameters to be incorporated. The SMART© fracture FEA tool was validated against experimental data and the 'theoretical analysis' as there was good agreement in the fatigue crack growth rate predicted as well as the fatigue life using the same test set-up.	A generic reliability assessment framework that combines parametric FEA modelling, RSM, and reliability assessment specifically for complex highly nonlinear OWT jacket type support structures in the presence of highly stochastic variables, and taking into consideration, specifically, time-dependent phenomena such as fatigue as well as degradation mechanisms such as corrosion was developed which serves as an invaluable tool to researchers. In addition, the stochastic parametric FEA carried out in this study is beneficial because this addresses the issue of randomness in the values of the shape factor, compared with the traditional methods which apply deterministic values.
Explore methods of structural reliability using meta-model methods	In Chapter 3-6, time-variant and time-invariant SRA were performed	In Chapter 3, good agreement is achieved when comparing the	The comprehensive mechanistic-based probabilistic models for

for the consideration of stochastic loads and time-dependent phenomena such as fatigue and corrosion on structures. This will involve the use of Stochastic Response Surface Methodology (SRSM) which involves incorporating the responses of the structure obtained from the FEA with widely used numerical reliability techniques such as FORM/ SORM and MCS through Multivariate Polynomial Regression (MPR)/ Artificial Neural Networks (ANN) and to validate results obtained from the SRA method with those found in the literature. The surrogate/ meta-model is employed to aid in the expression of the Limit State Function (LSF) in terms of important stochastic variables.	on a 10MW OWT support structure deployed at 50m deep water to evaluate for the inherent stochastic conditions to ascertain whether or not the structural components can safely withstand such conditions based on the results from the comparison made between the calculated reliability index values against an allowable value from design standards. Also, to demonstrate the novel non-intrusive formulation developed can address the issue of calculating the very small probability of failure values for the realistic, complex nonlinear structure as well as limiting computational costs involved in such analysis to practicable levels.	reliability index calculated for the probabilistic tool packaged in ANSYS and the non-intrusive formulation for all limit states, cross-verifying applicability of both methods studied. Also, the reliability assessment performed revealed that the structure maintains a reliability index exceeding the defined threshold of target reliability as specified by DNV for all limit states, as the calculated beta index clearly exceed the target reliability index set at 3.71. The fatigue limit state is found to be dominant in the design thus confirming the result is correct. In Chapter 5, the FORM algorithm used was validated against the MCS since a good agreement was achieved when comparing the probability of failure calculated between both methods.	pitting corrosion fatigue life prediction, which includes all stages and the accompanying FORM implemented with the proposed models will be indispensable to designers with respect to the damage tolerance approach. The results of the SRA study in Chapter 3 among others confirmed that the Jacket space frame structures are stiffer alternative OWT support structures since high reliability index values were recorded for the deformation limit state.
To perform reliability sensitivity analysis for the structure based on the SRA framework developed in Chapter 3.	In Chapter 4, a comprehensive sensitivity analysis was performed, and this can be described as the most critical variables that can radically impact on the reliability performance of the structure. The proposed method was used to	The sensitivity of the reliability indices and probability of failure to mean value and standard deviation of different stochastic variables were evaluated at varying levels of uncertainties measured in terms of coefficient of	The SSA framework developed will be an invaluable tool for designers with respect to reliability-based design optimisation. This will enable researchers to focus on the parameters with uncertainties having a significant impact on the

	investigate the influence of several stochastic variables on the reliability of the structure. The proposed non-intrusive method involves a sequence of steps: incorporating responses obtained from parametric FEA with the iterative FORM-based SSA via multivariate quadratic polynomial regression for the approximation of more reliable levels of sensitivities with respect to the various design variables. The SSA adopts an approach which determines the search direction based on function gradients.	variation. The iterative FORM algorithm employed for the SSA has been validated successfully in Chapter 3 and 5 against direct simulation methods.	reliability sensitivities, and assume deterministic values for those having negligible influence.
To perform a comparative study between the SN-curve to the FM approaches to fatigue assessment from a structural reliability perspective for a typical welded OWT jacket support structure using a combination of SRA frameworks similar to that developed in Chapter 3-5, and based on the results obtained explore reliability sensitivity analysis with respect to important stochastic variables focussing specifically on the fatigue reliability analysis.	In Chapter 6, a stochastic parametric FEA similar to that used in Chapter 3 was adopted for the FM and SN-curve approaches. For the FM approach, a second ANN was developed using results obtained from FM FEA model similar to that used in Chapter 5. This enabled application of the methodology to the case of a welded joint assumed to contain flaws and subjected to corrosion-fatigue.	A test was carried out to evaluate the safety of the structure assuming cases were variables such as initial crack size, stress range, and bilinear FM crack growth law parameters are different from their original values owing to phenomena such as weld/ fabrication imperfection, etc. Later, the framework was assumed updated using typical SHM/ CM stress/ strain data and the time to failure of the structure is determined to allow efficient/	Offshore wind industry practitioners can harness the capability of the framework developed to address the problem of optimising the CAPEX to OPEX ratio which is an issue of priority and hence allows cost reduction activities needed to ensure structural safety and efficient performance of the OWT foundation.

		<p>optimised planning for IMR. Errors which may emanate from complexity associated with performing FM calculations has been addressed by the use of the FEA FM model developed coupled with the fact that this incorporates 3D effects.</p>	
--	--	---	--

The second objective was to carry out the stochastic parametric FEA on a complex frame type structure, using sequential steps of a high capability tool, ANSYS and to validate results obtained from the parametric FEA model with those found in the literature. In Chapter 3, a comparative analysis on the structural reliability of an OWT support structure between a commercial package and a purpose-developed, non-intrusive stochastic formulation was presented. Both methods start by defining the limit states taking account of the various design constraints. The design constraints considered in this study were as follows: stress (ULS), fatigue (FLS), deformation (SLS), buckling (ULS), and vibration (SLS). A 3D parametric FEA model of a typical OWT jacket-type support structure was developed, taking account of soil-structure interaction and stochastic variables (i.e., soil properties, wind, wave, and current loads). The results of this study, among others confirmed that the Jacket space frame structures are stiffer alternative OWT support structures since high reliability index values were recorded for the deformation limit state [1,3,4].

The third objective was to develop a corrosion fatigue model based on pit and crack growth. In Chapter 5, the SRA of an OWT support structure in the presence of pitting corrosion-fatigue was performed by employing the LEFM approach. A number of structural responses corresponding to varying input stochastic parameters were predicted using high capability FEA tools. Issues such as numerical simulation being under the influence of non-Gaussian and non-white noise typical of the dynamic response function of OWTs was addressed by the validation exercise for eigen-frequency carried out in Chapter 3 coupled with the fact that uncertain variables were modelled stochastically. Both the crack growth rate and fatigue life curves computed from the parametric FEA model show reasonable agreement with that computed using the theoretical analysis. It can be concluded that the validity of the FEA model used therein is confirmed. A generic reliability assessment framework that combines parametric FEA modelling, RSM, and reliability assessment specifically for complex highly nonlinear OWT jacket type support structures in the presence of highly stochastic variables, and taking into consideration, specifically, time-dependent phenomena such as fatigue as well as degradation mechanisms such as corrosion was developed which will serve as an invaluable tool to engineers [3,4].

The fourth objective was to explore methods of structural reliability using meta-model methods for the consideration of stochastic loads and time-dependent phenomena such

as fatigue and corrosion on structures. This objective is an integral part of this study and was achieved in Chapters 3-6, time-variant, and time-invariant SRA were performed on a case study OWT support structure to evaluate for the inherent stochastic conditions whether the structural components can safely withstand such conditions based on a comparison between the calculated reliability index values against allowable values from design standards. Also, to demonstrate the novel non-intrusive formulation developed can address the issue of calculating the very small probability of failure values for the realistic, complex nonlinear structure as well as limiting computational costs/ times involved in such analysis. In the same Chapter, good agreement is achieved when comparing the reliability index calculated for the probabilistic tool packaged in ANSYS and the non-intrusive formulation for all limit states, cross-verifying applicability of both methods. Also, the time-variant fatigue reliability assessment performed revealed that the structure maintains a reliability index exceeding the defined threshold of target reliability as specified by DNV for the nominal 20 years of operation. The sensitivity charts show that the thrust has a significant impact on the stress, fatigue, deformation and buckling design constraints, whereas the structure self-weight has the most significant impact on the vibration constraint. While in Chapter 5, good agreement is achieved when comparing the probability of failure calculated for the FORM and the MCS, which implies that the numerical reliability technique employed in the study is valid [1,3–5].

Next, the fifth objective was to perform reliability sensitivity analysis for the structure based on the SRA framework developed in Chapter 3. In Chapter 4, a comprehensive sensitivity analysis was performed, and this refers to the most critical variables that can radically impact on the reliability performance of the structure. The reliability of the structure can be improved by reducing the uncertainties by virtue of statistical parameters for the design variables having an insignificant impact on the reliability. The proposed method was used to investigate the influence of several stochastic variables on the reliability of the structure. The proposed non-intrusive method involves a sequence of steps which include: incorporating responses obtained from parametric FEA with the iterative FORM-based SSA via multivariate quadratic polynomial regression for the approximation of more reliable levels of sensitivities with respect to the various design variables. The sensitivity of the reliability indices and probability of failure to mean value and standard deviation of different stochastic variables were evaluated at varying levels of uncertainties measured in terms of coefficient of variation. The iterative FORM

algorithm employed for the SSA has been validated successfully in Chapter 3 and 5 against direct simulation methods. [5]. And finally, the sixth objective was to perform a comparative study between the SN-curve to the FM approaches to fatigue assessment from an SRA perspective for a typical welded OWT jacket support structure using a combination of SRA frameworks similar to that developed in Chapter 3-5 and based on the results obtained explore reliability sensitivity analysis with respect to important stochastic variables focussing specifically on the fatigue reliability analysis. In Chapter 6, a similar stochastic parametric FEA similar to that used in Chapter 3 was adopted for the FM and SN-curve approaches. For the FM approach, a second ANN was developed using results obtained from FM FEA model similar to that used in Chapter 5. This enabled application of the methodology to the case of a welded joint assumed to contain flaws and subjected to corrosion-fatigue. A test was carried out to evaluate the safety of the structure assuming that variables such as initial crack size, and stress range may be different from the original values owing to phenomena such as residual stress, weld/fabrication imperfection, etc., as well as uncertainties in the bilinear FM crack growth law parameters measured in terms of COV. The framework was updated using typical SHM/CM stress/ strain data, the structural reliability re-assessed, and, hence, the time to failure of the structure is determined to allow optimised planning for IMR. Errors which may emanate from complexity associated with performing FM calculations had been addressed by the use of the high-fidelity FEA FM model developed coupled with the fact that this incorporates 3D effects [4].

The methodology developed in this study enables the performance of existing structures to be evaluated when they are deployed and their safety determined once deployment location-specific data are obtained thus leading to increased service life (through service life extension) and safer operation. In the presence of critical cracks, the probabilistic approach can produce reliability assessment results, which is a valid input for a better-informed decision making on whether to repair, continue or cease to operate. The methodology developed herein can allow comparison between different structures on the common ground of reliability. This is very important as this leads to the design of new structures, and the emergence of new engineering practices. Furthermore, the methodology developed serves as the first step towards reliability-based optimization based on its being robust, sophisticated, and computationally efficient. This can also be applied in other engineering applications where uncertainties in input data sets play a crucial role. Hence, this approach can be extended to the reliability evaluation and

designing structures at a higher level such as floating offshore structures which are not covered in design standards and are of superior complexity due to the multiple configurations that exist.

References

1. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Applied Sciences*. MDPI AG; 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860 (Accessed: 15 June 2020)
2. Shittu AA., Kolios A., Hart P., Amirafshari P., Mehmanparast A. A systematic review of structural reliability analysis methods with applicability to the design of advanced metal structures. Under review. 2020;
3. Shittu AA., Mehmanparast A., Shafiee M., Kolios A., Hart P., Pilario KE. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting Corrosion-Fatigue: A Damage Tolerance Modelling Approach. *Wind Energy*. John Wiley & Sons, Ltd; 12 July 2020; Early view. Available at: DOI:10.1002/we.2542 (Accessed: 17 July 2020)
4. Shittu AA., Mehmanparast A., Pilario KE., Hart P., Kolios AJ. Comparative study between SN and fracture mechanics approach on reliability assessment of offshore wind turbine jacket foundations. Under review. 2020;
5. Shittu AA., Mehmanparast A., Amirafshari P., Hart P., Kolios A. Sensitivity analysis of design parameters for reliability assessment of offshore wind turbine jacket support structures. Under review. 2020;

8 CONCLUSIONS AND FUTURE WORKS

8.1 Conclusions

Since Offshore Wind Turbines (OWTs) are deployed in harsh environments often characterised by highly stochastic loads and resistance properties, it becomes increasingly necessary to propose an accurate and efficient approach for the assessment of uncertainties in material properties and operating environments. Structural Reliability Assessment (SRA) as a form of uncertainty analysis has been demonstrated to be a useful tool in the design of structures because it can directly quantify how uncertainty about input parameters can affect structural performance [1,2]. The overall aim of this thesis is to apply the surrogate modelling methods in the advanced structural reliability assessment/ evaluation of a complex offshore wind turbine jacket type support structure in the presence of highly stochastic variables.

The first objective was to assess which options out of the currently existing techniques are most suitable/ most promising for SRA of complex offshore structures identifying their key applications, proposed variation, qualifying characteristics, advantages and limitations. Hence, an extensive literature review on SRA methods was performed, and then the SRSM/ SM/ MM was highlighted among these methods [1].

The next objective was to perform Stochastic Parametric FEA on a complex frame type structure, using sequential steps of a high capability tool. This was developed for an OWT jacket support structure in the presence of stochastic variables accounting for soil-pile interactions and was validated against reference models for the modal frequencies and deflection in static analysis using FEA facility as packaged in ANSYS. Furthermore, this was extended to accommodate an imperfect structure having flaws resulting from corrosion using the SMART© crack growth analysis tool in ANSYS. This FEA model was validated by comparing the crack growth rate curves as well as the fatigue life results obtained from the simulation against theoretical and experimental results found in the literature [2,3].

The next objective was to perform the SRA to evaluate the safety level of the jacket type support structure using the SRSM non-intrusive formulation. This was achieved by applying the DoE tool DesignXplorer© packaged in ANSYS in combination with MPR/ ANN and FORM algorithms as coded in MATLAB to calculate the reliability indices of members [3]. Furthermore, sensitivity analyses were performed to evaluate which

stochastic variable has a significant influence on the reliability performance of the structure [4].

The last objective was to perform a comparative study between the SN-curve to the FM approaches to fatigue assessment from an SRA perspective for a typical welded OWT jacket support structure. Consequently, we can use the framework developed to determine which method is more suitable at the beginning and towards the end of the service period of the OWT support structure. In addition, this analysis brought about making a proper decision with respect to effective planning for IMR based on reassessment through updating of the structural reliability framework using SHM/CM data and results from the comparison between the FM and SN-curve approaches [5].

8.2 Future Works

These works have established a framework for the SRA of a complex frame type structure employing a non-intrusive stochastic method. The objectives accomplished in this study can form the basis for future studies, some of which are summarised thus:

- In order to further address uncertainties in calculating wind and wave loads acting on the support structure to improve accuracy, including factors such as wake effects, fluid-structure interactions, etc. computational fluid dynamics model could be incorporated in a coupled way since high computational power is increasingly becoming available. The fatigue analysis may be expanded to include variable amplitude loads employing methods such as Rain flow counting method, etc. and again other load combinations, load ratios (R) can be tested.
- The framework may be expanded to test other soil types such as clay soils and incorporate other soil parameters such as void ratio, friction angle, and conditions such as pre-consolidation stress, etc. to be designated as stochastic.
- The framework could be expanded to include push-over analysis such that the influence of having redundancy in the structural configuration is addressed. Another aspect that can be studied is the reliability analysis considering the accidental limit state.
- The sensitivity analysis framework developed in this thesis may be used for reliability-based design optimisation by focusing specifically on the design parameters with

uncertainties having a significant impact on the reliability levels and designating those having negligible impact as deterministic.

- The effective initial flaw size distribution (EIFSD) method as proposed in [6,7] which is an alternative solution to the K-T diagram and can provide a better estimate for the lower segment of the bilinear crack growth law can be explored in order to be included in the analysis.

References

1. Shittu AA., Kolios A., Hart P., Amirafshari P., Mehmanparast A. A systematic review of structural reliability analysis methods with applicability to the design of complex offshore structures. Under review. 2020;
2. Shittu AA., Mehmanparast A., Wang L., Salonitis K., Kolios A. Comparative Study of Structural Reliability Assessment Methods for Offshore Wind Turbine Jacket Support Structures. *Applied Sciences*. MDPI AG; 26 January 2020; 10(3): 860. Available at: DOI:10.3390/app10030860 (Accessed: 15 June 2020)
3. Shittu AA., Mehmanparast A., Shafiee M., Kolios A., Hart P., Pilario KE. Structural Reliability Assessment of Offshore Wind Turbine Support Structures Subjected to Pitting Corrosion-Fatigue: A Damage Tolerance Modelling Approach. *Wind Energy*. John Wiley & Sons, Ltd; 12 July 2020; Early view. Available at: DOI:10.1002/we.2542 (Accessed: 17 July 2020)
4. Shittu AA., Mehmanparast A., Amirafshari P., Hart P., Kolios A. Sensitivity analysis of design parameters for reliability assessment of offshore wind turbine jacket support structures. Under review. 2020;
5. Shittu AA., Mehmanparast A., Pilario KE., Hart P., Kolios AJ. Comparative study between SN and fracture mechanics approach on reliability assessment of offshore wind turbine jacket foundations. Under review. 2020;
6. Morse L., Sharif Khodaei Z., Aliabadi MH. A multi-fidelity boundary element method for structural reliability analysis with higher-order sensitivities. *Engineering Analysis with Boundary Elements*. Elsevier Ltd; 2019; 104(April): 183–196. Available at: DOI:10.1016/j.enganabound.2019.03.036
7. Morse L., Khodaei ZS., Aliabadi MH. A multi-fidelity modelling approach to the statistical inference of the equivalent initial flaw size distribution for multiple-site damage. *International Journal of Fatigue*. Elsevier; 2019; 120(November 2018): 329–341. Available at: DOI:10.1016/j.ijfatigue.2018.11.010