CRANFIELD UNIVERSITY

TOSIN ADEDIPE

DECOMMISSIONING STRATEGY TO REDUCE THE COST AND RISK-DRIVING FACTORS IN THE OFFSHORE WIND INDUSTRY

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
PhD in Energy and Power

PhD
Academic Year: 2018 - 2021

Supervisor: Professor Phil Hart
Associate Supervisor: Dr Mahmood Shafiee
May 2021

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ABSTRACT

With the increasing number of wind turbines approaching their end of life, there has to be a decommissioning strategy in place as the removal of these assets is not as direct as reverse installation. Offshore asset decommissioning involves technical, financial, operational, safety, policy, and environmental considerations on handling offshore marine assets at their end-of-life, with phases from the planning to site clean-up and monitoring. Offshore decommissioning activities cost significantly more than onshore; thus, adequate financial and safety provisions are essential, and more research required in this area. Decommissioning projects have hitherto been performed on a small scale, but with large-scale aging structures, they must be optimised for lowered costs and risks. In terms of planning, execution and costs, there have been significant cost overruns on decommissioning projects, which are not profit-generating projects.

These forecasted large-scale decommissioning activities also have associated risks. Although risk management is a well-researched area, there is limited literature on offshore wind decommissioning risk management. This research thus, applies risk management methods and strategies to develop a robust decommissioning risk framework. In addition, to improve decommissioning processes and technologies, there is a need to develop new protocols for decommissioning. This research identifies potentials for computational simulations and automations that need to be developed to identify and manage the highest cost and risk-drivers. This study seeks to close the research gap in understanding how to decrease decommissioning costs and risks. This research addresses potential opportunities in cost and risk estimation research, impact analysis and reduction frameworks that can be adapted to decommissioning activities specific to the offshore wind industry.

Keywords:

Offshore wind; Decommissioning; Cost management; Cost breakdown structure (CBS); risk assessment; risk management; Bayesian networks (BN); safety-critical factors; cost-critical factors.

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LIST OF ABBREVIATIONS

ALARP	As low as reasonably practicable
BMA	Bayesian model averaging
BN	Bayesian network(s)
BSA	Bayesian Search Algorithms
CBM	Condition-based maintenance
CBS	Cost breakdown structure
CGBS	Concrete gravity-based structure
CLC	Cut-lift-carry method
CM	Corrective maintenance
COLREG	International Regulations for Preventing Collisions at Sea
CPN	Cost Priority Number
CPT	Conditional probability table
DBN	Dynamic Bayesian network
DAG	Directed acyclic graphs
DT	Detach-tow method
EC	Eddy current
EIA	Environmental Impact Assessment
EOL	End-of-life
ETA	Event tree analysis
EUC	Equipment under control
FANP	Fuzzy analytic network process
FL	Fuzzy logic
FLS	Fatigue limit state
FMECA	Failure mode, effects and criticality analysis
FOWT	Floating offshore wind turbines
FTA	Fault tree analysis
FTD	Fault tree diagram
GEV	Generalised extreme value
GUI	Graphic user interface
GWEC	Global Wind Energy Council
HAZID	Hazard identification
HAZOP	Hazard operability

HBA	Hierarchical Bayesian analysis
HBN	Hybrid Bayesian network
HLV	Heavy lift vessel
HRA	Human reliability assessment
HSE	Health and Safety Executive
ID	Influence diagrams
IMO	International Maritime Organisation
JU	Jack-up barges
K-B	Kalman-Bayesian
LCC	Life cycle costing/Lifecycle costing
LCCA	Life cycle cost assessment
LCOE	Levelised cost of energy
LFT	Lift-float-tow method
LR	Linear regression
LTIF	Lost time injury frequencies
MB_DRA	Manoeuvring-based dynamic risk assessment
MCA	Markov chain analysis
MCMC	Markov chain Monte-Carlo
MCS	Monte-Carlo simulation
ML	Machine learning
MLSSVM	Multi-output least square support vector machine
NDT	Non-destructive testing
NN	Neural network(s)
O&M	Operation and maintenance
OFTO	Offshore transmission owner
OPEX	Operating expenditure
OSS	Offshore substation
OSV	Offshore support vessel
OWE	Offshore Wind Energy
OWF	Offshore Wind Farm
PDF	Probability density function
PM	Preventive maintenance
PN	Petri Nets

POD	Probability of detection
PPE	Personal protective equipment
QRA	Quantitative risk analysis
PRA	Probabilistic risk assessment
RBI	Risk-based inspection
RBM	Risk-based maintenance
R-FR	Robust functional regression
RIF	Risk influencing factors
ROV	Remotely operated vehicle(s)
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
S-FR	Sparse Bayesian-based functional regression
SM	Scheduled maintenance
SPIV	Self-propelled installation vessel
SWL	Safe working load
TE	Top event
TLP	Tension-leg platform
TRIR	Total recordable injury rates
ULS	Ultimate limit state
VBLR	Vibrational Bayesian-based linear regression
VOI	Value of information
VR	Vector regression
V-T	Vessel-turbine collision
V-V	Vessel-vessel collision
WF	Wind farm
WTG	Wind turbine generator(s)
WTIV	Wind turbine installation vessel

NOMENCLATURE

Symbol	Description	Units
α	Percentage of wait-on-weather	-
β	Planning & project management percentage	-
A_{WF}	Area of wind farm	Km^2
C_{accom}	Cost of accommodation	£
C_{amend}	Amendment expenses	£
C_{audit}	Audit cost	£
$C_{cable\ decom}$	Cost of cable decommissioning	£
$C_{Consult}$	Consulting cost	£
$C_{Conting}$	Contingency costs	£
$C_{conting}$	Contingency cost	£
$C_{decom-total}$	total decommissioning cost	£
C_{disc}	Cost of disconnection from grid	£
C_{E-Plan}	Cost of engineering planning	£
$C_{EIA-Survey}$	Environmental Impact Assessment Survey	£
$C_{eqt/day}$	Equipment cost per day	£
C_{EX}	execution	£
$Cert$	Certification	£
C_{EX}	Cost of execution	£
$C_{fixt./unit}$	Cost of fixtures/unit	£
C_I	Crane integrity	£
C_{insure}	Insurance cost	£
$C_{i/day}$	Daily vessel rate of each vessel	£
$C_{k/day}$	Crew labour cost per day	£
$C_{L\&R}$	Cost of lifting & removal	£
$C_{landfill}$	Cost of landfill	£
$C_{Lo\&D}$	Logistics & disposal	£
$C_{Lo\&WM}$	Cost of logistics and waste management	£
$C_{logistics}$	Cost of logistics	£

C_{misc}	Miscellaneous cost	£
$C_{Nav-mark}$	Cost of navigation markings	£
$C_{OSS-decom}$	Cost of offshore substation decommissioning	£
$C_{P\&RC}$	cost of planning & regulatory approval	£
$C_{P-Decomm}$	Cost of post-decommissioning	£
C_{Permit}	Permit cost	£
C_{PM}	Project management	£
$C_{port/annum}$	Cost of port/annum	£
C_{port}	Cost of port	£
C_{POST-D}	Post-decommissioning	£
C_{prep}	Cost of turbine preparation	£
C_{RA}	Regulatory approval	£
C_{rem}	Cost of remediation	£
$C_{revision}$	Cost of revision	£
C_{Sc}	Cost of site clearance	£
C_{Sm}	Cost of site monitoring	£
C_{surv}	Cost of surveys	£
$C_{truck/km}$	Cost of truck/ km	£
$C_{w-OTransp}$	Cost of waste transportation	£
C_{w-proc}	Cost of waste processing	£
C_{WM}	Cost of waste management	£
D	Duration of activity	days
$D_{eqt.}$	Good equipment design	-
F_{crew}	Crew fatigue	-
H	Human error-related incidents	-
$I_{freq.}$	Inspection frequency	-
K	Indicative fee per wind farm size	-
M	Mechanical/electrical incidents	-
M_F	Mechanical failure	-
N_{crew}	Number of personnel per operation	-
N_{fixt}	Number of fixtures	-
N_i	Number of vessels required	-

N_k	Number of personnel	-
N_L	Number of lifts	-
N_{WT}	Number of wind turbines	-
N_γ	Number of trips required to shore	-
P	Proper procedures/Procedural incidents	-
r	Discount rate	%
$R(t)$	Net cash flow	£
t	Time (in discounted rate)	years
$t_{cable-decom}$	Time for decommissioning of inter-array and export cables	days
t_j	Time taken to complete all subtasks	days
$t_{L\&R-B\&N}$	Time for lifting and removal of blade and nacelle	days
$t_{L\&R-found}$	Time for lifting and removal of foundation	days
$t_{L\&R-misc}$	Time for lifting and removal of miscellaneous components	days
$t_{L\&R-T\&TP}$	Time for lifting and removal of tower and transition piece	days
$t_{L\&R-WTG}$	Time for lifting and removal of WTG	days
$t_{MG-remov.}$	Time for marine growth removal	days
$t_{OSS-\ drain}$	Time for offshore substation draining	days
$t_{OSS-decom}$	Time for offshore substation decommissioning	days
$t_{pre-survey}$	Time for pre-decommissioning survey	days
t_{prep}	Time for preparation	days
$t_{WT-drain}$	Time to drain lubricating fluids	days
t_γ	Distance to and from shore	days
V	Visibility	-
WD	Water depth	m
W_G	Good weather	-
${W_j}^R$	Weight of recyclable materials	tonne
WT_{thick}	Thickness of wind turbine	m
W_{truck}	Capacity of truck	tonne

Wt_j	Weight of materials	tonne

1 Motivation for decommissioning cost and risk assessment in the offshore wind industry

1.1 Problem statement

Offshore wind farm (OWF) decommissioning is a relatively new area compared to oil and gas asset decommissioning. With the recent decommissioned wind farms, it has been seen that decommissioning costs have been higher than initially estimated at the development stage of the asset lifecycle (Topham and McMillan, 2017; ARUP, 2018). Thus, there is a need to improve cost estimations for use by asset managers and regulatory authorities alike. The OWF decommissioning risks, on the other hand, have hitherto not been researched. Due to the repetitive nature of OWF decommissioning operations, we propose that a start of project risk assessment should not be conducted once for all activities within a decommissioning project. Instead, a risk assessment model that can allow for updates before and after each structure is removed will provide a better risk analysis. Thus, this study also investigates the potential incidents and the risks posed during offshore wind farm decommissioning operations using a multi-criteria impact assessment and risk ranking methods.

In order to understand the relationship between the different risks, Bayesian network (BN) applications in the offshore wind industry were investigated. BNs were found to have the potential to provide more robust risk assessments based on their capacity to be updated when new information becomes available. Another benefit of applying BNs to this study was the ability to include utility nodes that can incorporate cost estimates into the risk assessment, providing insights into how contingency cost estimates may be estimated for future projects. Therefore, this study presented a first foray into the use of BNs for decommissioning risk assessments in offshore wind applications in order to improve decommissioning risks and incorporate the costs, which will be useful for updating contingency allowances and other costs.

This study can significantly help offshore wind farm operators, asset owners, offshore construction organisations and regulators better understand the cost and

risk dynamic for improved whole life cost estimates and for improved safety management during decommissioning. The methods proposed seek to reduce cost and improve safety during OWF decommissioning.

1.1.1 Offshore decommissioning trends

The offshore wind industry is growing in terms of increased number and types of installations including the design, installation, operation and maintenance (O&M), life extension and the decommissioning phases. Although a lot of attention has been paid to the initial phases of the asset lifecycle (design, installation and O&M), very little attention has been paid to the decommissioning phase until recently (Topham and McMillan, 2017). A number of first-generation offshore wind farms are being decommissioned and there is anticipated increase in activity in the next few years. The most recent decommissioning operations began in 2017 with the Vindeby offshore wind farm (4C Offshore, 2020). Offshore wind farm decommissioning is defined as the execution of all planning, transportation, dismantling and waste management activities performed in order to sustainably remove offshore wind farm installations and return the land or seabed to a safe condition (Topham and McMillan, 2017; Kaiser and Snyder, 2018). Asset decommissioning knowledge transfer from the oil and gas energy industry has been the norm in the offshore wind energy industry. This research shows that OWF decommissioning activities should be classified into four phases, these being the planning and consenting phase, execution phase, logistics and waste management phase, and post-decommissioning phase. Within each phase, stakeholder interests must be optimally satisfied whilst ensuring cost-effectiveness and safety. With this approach, costs are better understood and both deterministic and probabilistic methods can be applied.

Decommissioning trends show that more attention needs to be paid to end-of-life asset management. The two core premises for this research are firstly, that decommissioning cannot be seen simply as reverse installation; secondly that with the increase in the number of offshore assets to be decommissioned, there is a need for increased research and operational improvement efforts to reduce the costs and risks associated in the activities. Cost estimations have been higher

than estimated and risk analysis research trends have shown very little attention to OWF decommissioning. Also, safety concerns should not be overlooked especially because of the age of these decommissioned structures. To lay the foundation for this study, potential advanced analytical tools/techniques were investigated to understand current applications and potential outlooks for use in OWE. Bayesian networks were identified as the candidate technique as it is capable of modelling the possible scenarios in (near) real-time and can provide a prompt response to any changes in operational/environmental conditions. They also exhibit improved updating capacity and have the ability to allow addition of costs in the assessment. Following that, this study determined the baseline critical cost and risk-factors that can impact OWF decommissioning projects.

This study investigated strategies for improving offshore wind farm decommissioning cost and risk management, making three key arguments: firstly, that decommissioning cost management can be improved by adopting a cost breakdown structure (CBS) adapted to OWF. This can serve to highlight the cost-driving factors more clearly and easily than other methods. Secondly, that safety can be improved if the decommissioning risk-driving factors are adequately identified and assessed using granular techniques to mitigate/control them to as low as reasonably practicable (ALARP). Thirdly, that Bayesian reasoning can be used to improve OWF decommissioning risk assessment. With its capacity to readily update results when there is new information this alludes towards automation of the risk management process. In addition, costs can be incorporated into Bayesian networks to create an influence diagram (ID) that can inform contingency planning in cost assessments.

1.2 Research aim and objectives

The opportunity for improved understanding of the offshore decommissioning sector and the small amount of literature available to date present the need to develop knowledge and better approaches to reduce decommissioning costs and risks. Thus, an improved understanding of the factors that affect decommissioning cost and risks is imperative. The overall research aim of this thesis is ***to evaluate offshore wind energy system decommissioning***

***activities, develop improved cost and risk assessment models in order to determine the highest cost and risk-drivers. These key drivers will be used to propose cost and risk reduction pathways to improve operational efficiency and safety in the critical activities involved*.**

Various methods, techniques and protocols were adapted for improved cost and risk estimation in order to help stakeholders focus improvements on critical areas. The research objectives are listed as follows:

1. To conduct a systematic literature review of the current offshore wind energy sector applications of semi-automated tools and techniques (Bayesian networks) in the different phases of the asset lifecycle.
2. To develop an integrated framework to identify, evaluate and estimate cost-critical activities in decommissioning of offshore wind energy.
3. To develop a systematic risk analysis framework to identify, evaluate and mitigate risk-critical activities in decommissioning of offshore wind assets.
4. To identify, evaluate and assess innovative solutions to reduce/mitigate the cost/risks associated with decommissioning of offshore wind assets.
5. To collect and analyse existing offshore wind farm decommissioning protocols, cost and risk factors, in view of the theoretical assessment findings, and provide recommendations for improved industry practices.

1.3 Significance of this research

The research contributes to the development of costs and risk identification and reduction methods in OWF decommissioning due to the increasing number of operations, which will become large scale in the near future. In addition, the identification of OWF decommissioning cost and risk-critical factors will enable asset managers, owners, and regulators to choose the required strategic areas of focus and better shape policy, safety guidelines, technological improvement, and operational improvement targets. Past studies have looked very little into the decommissioning phase and this research shows that a holistic view such as the one proposed - incorporating the entire OWF asset lifecycle costs and risks - will improve existing decision making, safety and asset management practices. Stakeholders will be able to prevent unnecessary asset whole life financial loses

and project costs caused by inadequate understanding of the operational inefficiencies and safety threats in decommissioning.

1.4 Thesis outline and research publications

Each objective, methodology, result, and finding are addressed in 4 journal publications and presented in this thesis according to the chapter structure as seen in Table 1-1. The research aims and objectives are addressed in each of the following sections: Chapter 1 presents the motivation for decommissioning cost and risk assessment in the offshore wind industry. Chapter 2 presents a literature study on Bayesian network modelling for the wind energy industry (publication 1). Chapter 3 discusses the economic model for decommissioning of offshore wind farms using a cost breakdown structure (CBS) (publication 2). Chapter 4 presents Offshore wind energy infrastructure: risk analysis of decommissioning operations with a focus on lifting and loading operation application (publication 3). Chapter 5 presents Bayesian network applications for risk assessment of offshore wind farm decommissioning (using influence diagrams) for updating decommissioning risk and cost estimates with updated information (publication 4). Chapter 6 discusses the outcomes from the expert elicitation conducted to obtain a view of current industry practices and synthesises the cost and risk assessment conducted. Chapter 7 presents the conclusion and recommended future works.

The study results show that: (i) CBS proves promising for not only identifying cost-driving factors but for developing robust mathematical models, which may be used for both deterministic and probabilistic estimations. (ii) based on the wind farm case study used to test the validity of the CBS model, the top three cost contributors were identified as related to: foundation and turbine removal cost, planning and regulatory/consenting costs and logistics costs. (iii) the risk assessment for decommissioning provides more insight to asset managers on a granular level and conducting the assessment using four key matrices proves to be a better approach. (iv) the highest critical risks are related to crane operation failures, including the weight of component in relation to crane capacity and number of crane inspections per set of lifts. (v) Bayesian networks proved to be

a robust probabilistic risk analysis (PRA) method compared to Fault Tree Analysis (FTA), updatable in real time. BNs were developed to update the estimates when new information is available (and may be performed after each lift).

The findings from the results analysis show that: (i) number of wind turbines (N_{WT}), weight of the wind turbines (W_{WT}), number of crew (N_{crew}) and number of lifts (N_L) are the *common* cost and risk-critical drivers during OWF decommissioning. (ii) decommissioning costs can be decreased by reducing the related activity durations which could subsequently reduce whole life cost of OWFs. (iii) contingency cost planning can be related to the risk assessment estimates if a semi-automated tool like Bayesian networks (BN) is employed for decommissioning risk assessment. (iv) there may be more avenues to increase the profit margins from waste management efforts – as this is a way to develop earnings in a typically non-profit generating project.

1.5 Links between the chapters – the four themes

This study brings to light different factors that should be at the forefront of decommissioning research and operations to reduce associated costs and risks. No other study presented or highlighted the important factors proposed and presented in this study. *There are four themes that link all 5 chapters*, namely: mathematical relationships, key cost drivers of cost and risks, frameworks for decommissioning cost and risk management, and BN applications in end-of-life offshore wind asset management. These are presented in Figure 1-1. In the first theme the mathematical relationships are seen in Chapters 3, 4 and 5, which present the new mathematical models and variable relationships that this study developed and validated. The cost descriptors that showed the highest were used as a baseline for what was explored for the risk management study. The factors identified in Chapter 3 were used as inputs in Chapter 5 to explore advanced model applications for decommissioning. In Chapter 5 crane operations proved to reduce the negative risk most significantly after the crane operational factors were treated. Thus, the mathematical descriptors were developed for the highest risk-critical factors.

Within the second theme, the key cost and risk- drivers are presented in Chapters 3, 4 and 5, which propose the main levers that asset managers should use to manage decommissioning cost and risk in planning, decommissioning operations, and regulatory development. Although the highest cost and risk activity was lifting and removal (loading) operations, the highest cost-critical factors were number of resources, vessel rental costs and duration. Whereas the highest risk-critical factors were inaccurate signal, improper hooking, and vibrational impact from the crane activities. The key drivers (mathematical descriptors) - based on the identified factors - fed into Chapter 6, where the overlaps between both cost and risk-critical parameters were determined.

In the third theme, the frameworks for decommissioning cost and risk management are seen in Chapters 3 and 6 where the foundational frameworks upon which decommissioning research and operational practices can be further developed. These frameworks can support mitigation approaches and value engineering practices tailored to offshore wind decommissioning management.

In the final theme, a pathway for the use of advanced models in offshore wind end-of-life management is seen in Chapters 2 and 6. Chapter 2 presents a systematic literature review offshore wind research that focused on the use of advanced uncertainty modelling techniques. The results from the systematic literature review in Chapter 2 and the risk assessment conducted in Chapter 4 were used as an input in Chapter 6.

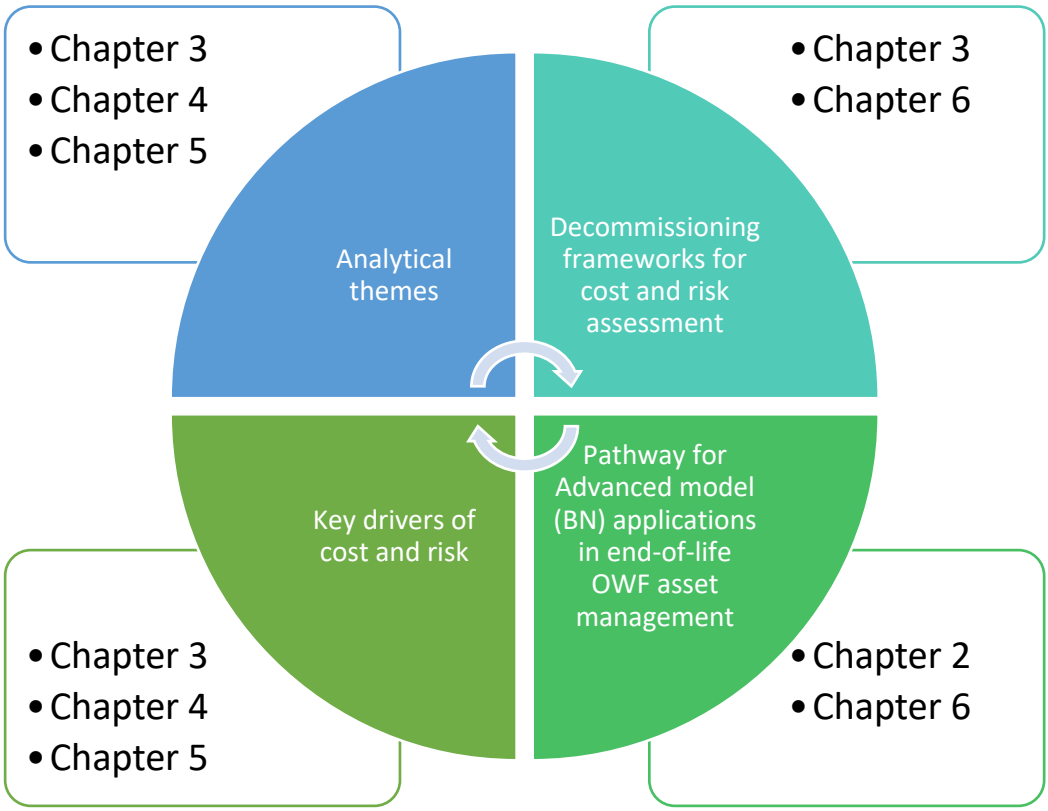

Figure 1-1 Themes of the thesis and links between chapters

Table 1-1 Chapter and paper organisation

Chapter	Title	Objective	Journal	Back-up Journal	Status
1	Introduction: Motivation for decommissioning cost and risk assessment in the offshore wind industry	1 - 5	-		-
2	Bayesian network modelling for the wind energy industry	1, 4	Journal of Reliability Engineering and System Safety		Published
3	An economic analysis model for decommissioning of offshore wind farms using a cost breakdown structure	2, 5	The International Journal of Life Cycle Assessment		Published
4	Offshore wind energy infrastructure: Risk analysis of decommissioning operations	3	International Journal of Sustainable Energy	Ocean Engineering	Under review
5	Bayesian network applications in risk assessment of offshore wind farm decommissioning	1,3,4	Journal of Reliability Engineering and System Safety	Journal of Automation in Construction	Under review
6	Synthesis chapter and comparison with current industry practices	5	-		-
7	Conclusion and future works	-	-		-

2 Bayesian network modelling for the wind energy industry

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Abstract

Wind energy farms are moving into deeper and more remote waters to benefit from availability of more space for the installation of wind turbines as well as higher wind speed for the production of electricity. Wind farm asset managers must ensure availability of adequate power supply as well as reliability of wind turbines throughout their lifetime. The operating conditions in deep water environments often change very rapidly and, therefore the decision metrics used in different phases of a wind energy project's lifecycle will have to be updated on a very frequent basis, to guarantee higher wind energy system reliability levels. For this reason, there is a crucial need for the wind energy industry to develop advanced computational tools/techniques that are capable of modelling the possible scenarios in (near) real-time and provide a prompt response to any changes in operational/environmental conditions. Bayesian network (BN) is a popular machine learning (ML) method used for system modelling and decision-making under uncertainty. This paper provides a systematic review and evaluation of existing research on the use of BN models in the wind energy

sector. To conduct this literature review, all relevant databases from inception to date were searched, and a total of 70 sources (including journal publications, conference proceedings, PhD dissertations, industry reports, best practice documents and software user guides) which met the inclusion criteria were identified, excluding references used in other sections of the text for discussion. Our review findings reveal that the applications of BNs in the wind energy industry are quite diverse, ranging from risk management to wind power and weather forecasting, fault diagnosis and prognosis, structural analysis, reliability assessment, and maintenance planning and updating. Furthermore, a number of case studies are presented to illustrate the applicability of BNs in practice. Although the paper details information applicable to the wind energy industry, knowledge can be transferred to many other sectors.

Keywords: Wind energy; Bayesian network (BN); Risk assessment; Operation and maintenance (O&M); Reliability; Machine Learning (ML); Fault diagnosis and prognosis; Forecasting.

2.1 Introduction

Wind energy is one of the fastest growing and most cost-effective means of power generation worldwide. A large number of wind energy farms are currently being built or are planned to be built – either on land (onshore) or at sea (offshore) – in different countries throughout the world. As reported by the Global Wind Energy Council (GWEC) in 2019, the global onshore wind capacity is 568 GW, with China contributing the highest at 36% (206 GW) followed by the USA and Germany contributing 17% (96 GW) and 9% (53 GW), respectively. In the offshore wind industry, the United Kingdom has the highest installed offshore capacity of 7.9 GW followed by Germany and China contributing 6.38 GW and 4.59 GW, respectively (Global Wind Energy Council, 2019). The total installed capacity of onshore and offshore wind power in Europe has increased from 66GW, as of the end of 2008, to more than 189GW, as of the end of 2018 (see Figure 2-1). Among the European countries, Germany ranked first in terms of new installations in 2018 (with 29% of the total installed capacity), followed by the United Kingdom (with 16%), France (with 13%) and Sweden (with 6%) (WindEurope, 2019). The

total wind power capacity in Europe is estimated to reach 342GW and 840GW by 2030 and 2050, respectively.

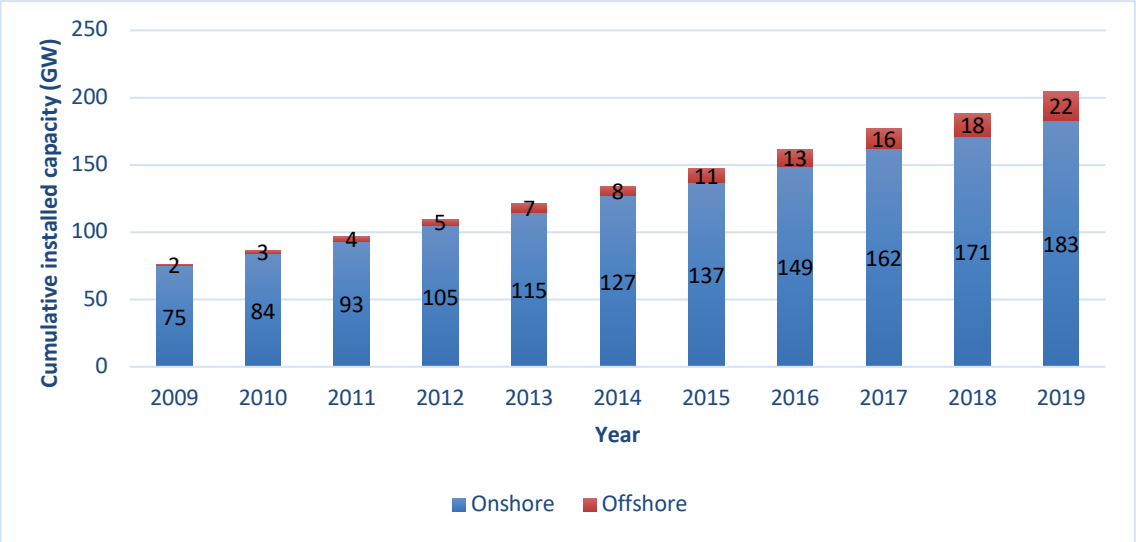

Figure 2-1 Total installed capacity of onshore and offshore wind power in Europe between 2008 and 2018.

In recent years, there has been a significant increase in the number of wind energy projects deployed in deep water and remote offshore locations (Presencia and Shafiee, 2018). These locations have more space available for the installation of large-scale wind turbines as well as more consistent wind resources for the production of electricity. Nevertheless, deepwater wind energy farms involve a lot more complexities than their onshore or shallow water counterparts. The operating conditions in deepwater environments are highly dynamic and often change very rapidly over time. Any variation in operational and environmental conditions may alter the behaviour of offshore wind turbines and their support structures and also impact the accessibility of operation and maintenance (O&M) personnel to offshore sites. Therefore, the decision metrics used in different phases of a wind energy project's lifecycle will have to be updated on a very frequent basis.

According to the European Technology and Innovation Platform on Wind Energy (2018), O&M is a key priority for improvement in the European wind energy sector, aiming to reduce the levelised cost of energy (LCOE). Wind farm O&M is

attracting more and more attention from industry and policy-making organizations due to its huge potential in increasing safety, efficiency, and power production. In general, there are two strategies adopted for O&M of wind energy farms: corrective and preventive. The corrective maintenance (CM) is a type of maintenance carried out after a failure has occurred. This strategy may lead to large production losses due to potentially long system downtime when a failure occurs. The preventive maintenance (PM) strategy, on the other hand, refers to scheduled maintenance (SM) and condition-based maintenance (CBM). The former requires scheduling of maintenance activities at predetermined time intervals, as estimated based on system's reliability, environmental conditions and other factors. The latter uses equipment condition – as assessed based on inspection reports, interpreted Supervisory Control and Data Acquisition (SCADA) data, or information gathered by sensors embedded in different parts of the wind turbines – to identify maintenance requirements. The sensor readings are recorded, inspection information is analysed, and a maintenance decision is made to address degradation before it causes a failure within the system (Shafiee, 2015).

The reliability analysis and O&M planning of wind energy farms, in particular in deep water locations, is a complicated task as it is a function of several contributing factors such as meteorological conditions (e.g., wind speed, wave height, visibility, and sea state), failure rate of wind turbine components, distance to shore and water depth, availability of resources required to execute maintenance tasks (e.g. transport vessels, service crew, spare parts and special tools), etc. In order to optimise the availability of wind energy farms at the lowest operating cost, an efficient planning and reporting system is crucial. Correspondingly, several quantitative and qualitative decision-making methods for reliability analysis and O&M planning of wind energy farms have been developed in recent years. The most common methods include: Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Event Tree Analysis (ETA), Markov Chain Analysis (MCA), Monte-Carlo Simulation (MCS), Petri Net (PN) and Fuzzy Logic (FL) (for more see Shafiee and Sørensen, 2019).

Advanced methods for the prediction of reliability and remaining useful life (RUL) of various wind farm assets (including turbines, foundations and transition pieces, export and inter-array cables, offshore substations, etc.) can contribute to the strategic O&M planning and efficient resource allocation in wind energy farms. Thus far, reliability assessment and RUL modelling have been performed using accelerated life testing data and failure mode analysis. However, with the development of advanced sensor technologies and condition monitoring systems in the wind energy industry, a great volume of information about the external loading to the wind turbine structures as well as conditions of the surrounding environment (such as temperature, humidity, wind speed, etc.) becomes available in continuous time (Shafiee and Finkelstein, 2015). Therefore, it is necessary to develop advanced computational tools/techniques that are capable of incorporating (near) real-time data obtained from inspection results, condition-monitoring sensors or SCADA systems in order to optimise energy output and improve O&M planning of wind energy farms. In this context, the use of Machine Learning (ML) algorithms in various applications has grown enormously in the past few years.

ML methods are capable to learn from training datasets, capture complex interactions that are difficult to model through analytical methods, and predict possible outcomes based on new observations. Of all the ML tools and techniques, the Bayesian Network (BN) seems to be the most promising framework for updating the information in (near) real-time. This is useful in situations where there is limited information about a complex system and the network has to be updated when additional information becomes available. BNs have been utilised in several industries, particularly because of their ability to treat uncertainties found in many applications. Wind energy farms, as complex systems that function under a high degree of uncertainty, can benefit from BN models by mitigating uncertainties inherent in the system's operational conditions or the surrounding environment. It is proposed that the use of Bayesian models in assessment of reliability as well as scheduling of wind farm O&M activities can bring benefits in terms of reduction of maintenance costs and increase of power production.

The aim of this paper is to review the state-of-the-art of BN models and identify their applications in the onshore and offshore wind energy sectors, especially as they relate to the reliability of wind energy systems. Relevant databases have been searched using appropriate keywords and the studies investigating the use of BNs in the wind energy industry have been identified. These studies range from journal articles and conference papers to university dissertations, industry reports, best practice documents and software user guides. Our review findings show that the applications of BN modelling in the wind energy industry are quite diverse. The application areas include: system design, wind speed forecasting, power output modelling, data analytics, risk management, degradation modelling, fault diagnosis, cost optimisation, system reliability evaluation, as well as O&M planning and updating. Further supporting evidence will be provided via a number of case studies found in the literature.

The organisation of this paper is as follows. Section 2 presents an overview of BNs and describes different tools that can be used for Bayesian model development and analysis. In Section 3, we discuss the review methodology adopted in this study to identify the most and least researched areas to date. Section 4 describes the case studies reported in the literature. Section 5 discusses the BN models and their application areas in the wind energy sector and, finally, Section 6 concludes the review with a discussion of major findings and additional suggestions of future research.

2.2 Overview of BN

2.2.1 Fundamentals of BN

Bayesian networks (BNs) are directed acyclic graphs (DAGs), which encode relationships among random variables represented by nodes and links (Jensen and Nielsen, 2007; Baraldi *et al.,* 2015). The mathematical background of a BN relies on Bayes' theorem. This theorem supports the fact that the belief regarding the outcome of a system has to change when new evidence (to make probabilistic inference based on available information and quantify uncertainty when information) becomes available. Thus, BNs are also known as Belief networks (Pearl, 1988). BNs are used to solve decision-making problems based on

recorded or prior knowledge about the system dynamics and their resultant effects. Bayes' theorem can be expressed in terms of prior probability, likelihood function and a normalisation constant to produce the posterior probability. With reference to the probability of occurrence of events, this can be expressed mathematically as:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}, \qquad \textbf{2-1}$$

where $P(A|B)$ is the posterior probability (it is the conditional probability of event *A* given the observation of evidence *B*), $P(A)$ is the prior probability distribution of event *A*, and $P(B|A)$ is the likelihood function of observing evidence *B* when event *A* has occurred.

A simplified BN model for events *A* and *B* is presented in Figure 2-2. The prior probability distributions are dependent on inputs from experts or data from inspection reports, SCADA or condition-monitoring systems, that represent stochastic or uncertain variables. Hence, the accuracy of the network depends on the quality of the input data and for the updating terms, on the quality of the newly acquired data. BNs also offer a graphical way to represent a problem space in which conditional relationships exist between two or more parameters of a system. This is also useful for making informed inference based on the output information (i.e. posterior probability distribution). For further reading, the readers can refer to the literature (Compare *et al.*, 2017; Li *et al.*, 2017; Fan *et al.,* 2019).

Figure 2-2 A simplified BN model for events A and B.

When developing a BN structure, some important steps should be followed. These steps include: identifying the key variables and classifying the variables, obtaining *prior* data, and establishing links between different nodes to construct the model. The steps of BN development can be facilitated using some well-

established software development techniques. These techniques include systematic requirements engineering, ontologies, design patterns, refactoring, object-oriented and component-based techniques (Baclawski, 2004). Different BN structures can be developed that are explained below.

2.2.1.1 BN structure and learning

In principle, a BN is made up of nodes and arrows which represent the system states/events and their relationships with one another, but not necessarily causality. The quantitative part of a BN is made up of conditional probability tables (CPTs) which express the quantitative relationships between the events. These CPTs represent the dependence structure within a system. The nodes in a BN represent random variables, which can be either discrete or continuous but mutually exclusive in nature. A node may take the form of a parent node (referred to as a root if it has no preceding nodes) or a child node (if it is the last node in the chain of events it will be referred to as a leaf node). The arrows, on the other hand, depict the direction of relationships within the system, where the child node is conditionally dependent on the parent node with the CPT showing the conditional relationship between a child node and a parent node (Cai *et al.*, 2016). The nodes are connected via links to form different structures, including serial, converging and diverging. Fundamentally, Bayesian reasoning is used to revise beliefs based on updated evidence; thus, when a variable/node receives an evidence, it is said to be *instantiated*. There are two stages involved in the BN learning process (learning the manner in which BN distributions can be obtained from complete or incomplete datasets): learning the network structure and learning the parameters of the distributions. Further details about BN structures can be found in Ibe, 2011; Boudali and Dugan (2005a) and Jensen and Nielsen (2007).

2.2.1.2 Dynamic BNs and influence diagrams

A dynamic Bayesian network (DBN) is a type of graphical model applicable to time-varying probabilistic inference and causal analysis under system uncertainty. The DBN was developed to compensate for the limitations of the static networks. A time stamp is used to model a time domain (either finite-horizon

or infinite-horizon*)* at any given time point *t*; this is referred to as a time slice (Jensen and Nielsen, 2007). The two processing alternatives used to model continuous variables include discretisation and direct use of continuous variables. Also, BNs can be amended to form influence diagrams (ID) by including *utility* and *decision nodes*. A node representing a random variable in an influence diagram is called a *chance node*. The influence diagram also contains decision nodes, which have direct influence on other chance nodes. These decisions represented by the nodes can have cost implications, which can be represented by utility nodes. For further reading, the readers are referred to Yang and Frangopol (2018).

2.2.2 Bayesian inference

Bayesian inference is the use of BNs to compute the posterior distribution within a problem space when new observations or data are available. Owing to the flexibility of Bayesian modelling, a BN can be used to study system behaviour whilst incorporating new information when it becomes available. Therefore, the network will be updated whenever any changes are made within the system. The new information may be provided from different sources, including regular inspections or continuous monitoring of a parameter in machinery (vibration, temperature, etc.). For instance, when a wind turbine is inspected, new measurements from the inspection are inputted into the network and the posterior distribution will be updated based on the new information. In a problem space where updates are made on only one variable, the influence of other uncertain variables also will change within the network. This will cause a corresponding change in CPTs which quantify the interactive relationships between nodes/variables. In order to model continuous variables, which are inherent in dynamic processes, approximation methods/techniques will be useful. It is also quite challenging to input feedback loops to a BN as they are fundamentally acyclic in nature. In addition, Bayesian inference can become restrictive when the number of nodes is very large, which can result in a lower level of accuracy in the model. The need to accommodate larger system interdependencies has, therefore, led to algorithmic development in the form of approximations.

When computing the posterior distribution in Bayesian updating, inference algorithms are needed. These algorithms can be of two types: exact or approximate. The exact inference algorithms (such as junction tree algorithm, variable elimination algorithm, arc reversal method, etc.) are used for static BNs with discrete variables; whereas the approximate inference algorithms (such as loopy belief propagation algorithm, etc.) are particularly used for dynamic processes. The approximate inference algorithms are in general divided into two major categories: time-slice methods and event-based methods (Li and Mahadevan, 2018). The time-slice methods include temporal BN, DBN, network of dates, and modifiable temporal BN; whereas, the event-based methods include Temporal Nodes BN (TNBN) and the Net of Irreversible Events in Discrete Time (NEIDT) (Borunda *et al.*, 2016; Boudali and Dugan, 2005b). Different inference approximation techniques have been proposed in the literature. These include discretisation, mixtures of truncated exponents, variational approximations, Bayesian search algorithms (BSA), etc. One of the advantages of BN is that it represents systems' behaviour and their interactions including both explicit and implicit connections. By using approximation inference algorithms for continuous variable inputs, two objectives are achieved: the integrity of the BN is maintained, and the model remains capable of making inferences when it is updated with new information. Nevertheless, there still remains gaps in the approximate inference methods applicable to BNs. For further reading on some of these gaps, the readers are referred to Friis-Hansen (2000); Langseth *et al.* (2009) and Luque and Straub (2016).

2.2.3 BN software tools

A number of software packages have been developed to date for BN modelling. These include: Microsoft MSBNx, Netica, Hugin, WinBUGS, BayesiaLab, OpenBayes, AgenaRisk and Bayesfusion. Some of these software tools have gained popularity in real life applications, depending on the context for which they are used and the scale to which they can be applied. The most widely used tools are briefly described in the following sub-sections.

2.2.3.1 Microsoft MSBNx

This is a component-based Windows application for creating, assessing, and analysing BNs (Horvitz *et al.*, 2001). The tool is used to extract information from input database patterns as well as to show dependencies (conditional probabilities) between variables in a network. It can be used to incorporate inspection results and repair information to help asset managers perform fault diagnosis and analyse the costs/benefits of repair actions in a more timely and precise manner. An advantage it offers is that it can be integrated with other programmes to help with inference and decision-making when uncertain parameters or variables are involved. It uses Value of Information (VOI) analysis to estimate the benefit of obtaining improved posterior probabilities (Friis-Hansen, 2000). In the context of wind energy industry, this software tool was used in Li *et al.* (2015).

2.2.3.2 Netica

The Netica application is useful for developing belief networks and influence diagrams, which add decision and utility nodes to the Bayesian belief networks. The conditional probabilities in the network nodes can be inputted in different ways: either as individual conditional probabilities using equations or from data file inputs. It is used in Bayesian inference using different algorithms and can help in optimal decision-making when influence diagrams are set up (for more see Norsys, 2021).

2.2.3.3 HUGIN

HUGIN stands for Handling Uncertainty in General Inference Network. The tool is used to model parameters in a probabilistic network that are connected conditionally. It has different modules to develop, edit and analyse the BNs. These modules include a graphic user interface (GUI) module, an editor module and a compiler module. HUGIN develops a causal probabilistic network in such a way to support updating with new information for creating improved posterior probability distribution results (Andersen *et al.*, 1989). In the context of wind energy industry, this software tool was used in Ciobanu *et al.* (2017).

2.2.3.4 WinBUGS

WinBUGS is an offshoot of the BUGS (Bayesian inference Using Gibbs Sampling) software tool (University of Cambridge, 2021). It was developed for processing DAGs such as BNs. It is a user-friendly software that can be utilised to analyse different Bayesian models using different simulation methods or algorithms. With Gibbs sampling, when there is an update, each node is assigned an updated value based on the conditional dependence on the other nodes in the network. The modules can be extended by adding more components to the network and inputting new distribution functions within the system. The models can be presented by text or graphical form – if in text format, it is written in BUGS language. The modules making up the WinBUGS include graph, updater, monitors, BUGS, samples and Doodle. In the context of wind energy industry, this software tool was used in Li and Shi (2010).

2.2.3.5 BayesiaLab

BayesiaLab is a desktop application that uses a GUI to support modelling, diagnosis, evaluation, simulation and optimisation (Bayesia, 2021). This application is made up of optimised learning algorithms that can execute both exact and approximate inferences with a property called observational inference. It also updates conditional probabilities of variables and analyses how this update may affect the network propagations, allowing the analyst to find explanations for the observations within the network. BayesiaLab discretises all the continuous data inputted. It has the capability to capture the conditional probability of all variables even when the inputs are not defined, no matter how large they are. It has a ‘clustering’ feature which allows for data and parameter grouping, and this is useful for large input datasets (Conrady and Jouffe, 2013).

2.2.3.6 AgenaRisk

The AgenaRisk software is used to build BN models for qualitative risk assessment problems (Agena Limited, 2021). In order to produce the posterior probabilities, it uses algorithms such as dynamic discretisation algorithm and ranked mode method, which are both useful for modelling the continuous and ranked variables, respectively. The software can be used for ‘what-if’ simulations

and sensitivity analysis, because new observations (from, for instance, the inspections) can be inputted into any of the nodes within the network. Even when there is insufficient data, the model can be updated with new information. It is possible that both forward and backward inferences are made for new probability distributions. The output can also show the risk impact of different variables considered in the model. A major advantage of this tool is that it eliminates the need for user-defined discretisation of the continuous variables through its dynamic discretisation feature. This improves the model accuracy for improved risk assessment outputs. It also has an interactive feature, which makes it easy to use. A major drawback to its widespread use is that individual licenses are restricted, and they are only available on a large scale for multi-user access (Fenton and Neil, 2014). In the context of wind energy industry, this software tool was used in Su and Fu (2014) and Ashrafi *et al*. (2015).

2.3 BN applications in wind energy industry

2.3.1 Review methodology

In this study, the literature from academic and industry sources including journal articles, conference proceedings, PhD dissertations, industry reports, best practice documents and software user guides were collated for review. Different databases such as Scopus, Web of Science, IEEE Xplore Digital Library and Google scholar were searched to identify relevant studies published on the subject. The search was based on two keywords of “Bayesian network” and “wind energy” and some inclusion and exclusion criteria were defined to streamline the search content to relevant literature for the review. After reviewing the titles, abstracts and the full texts, 70 documents were eventually considered for analysis. Our analysis indicates that, in recent years, there has been a significant increase in the number of studies applying BNs in the wind energy industry. Figure 2-3 shows the number of studies published every year between the years 2000 and 2019.

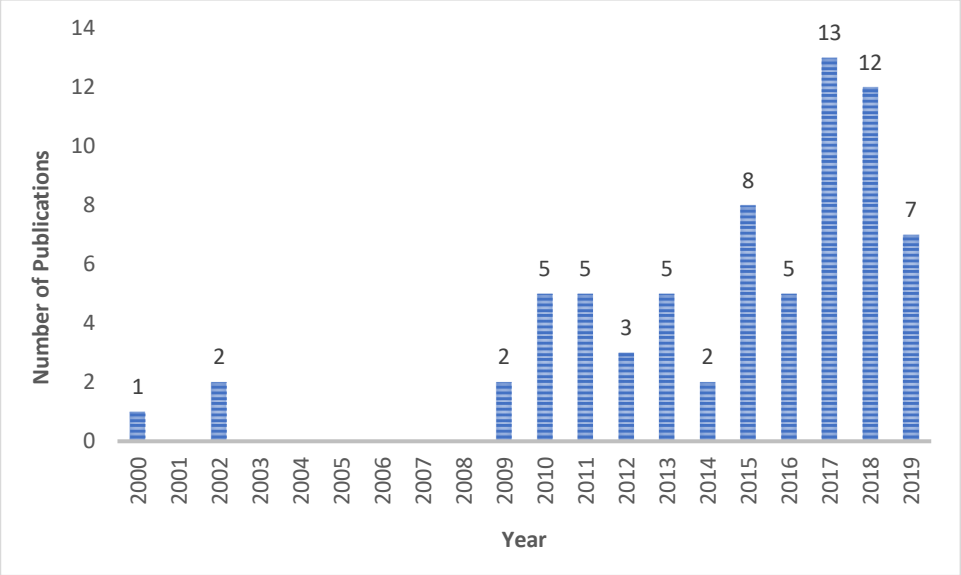

Figure 2-3 Number of publications about BNs in the wind energy industry

Among the academic journals, the "Renewable Energy" and "Reliability Engineering & System Safety" journals contained the largest number of articles; whereas among the conference proceedings, the "International Conference on Ocean, Offshore and Arctic Engineering" was the most represented conference.

2.3.2 Applications

BNs have been applied in different areas of the wind energy industry. These areas include: wind speed forecasting, wind power generation forecasting, risk assessment, fault diagnostic and prognostic, system reliability studies, structural analysis, O&M planning, etc. These application areas can come under the umbrella of improved wind energy systems reliability. A brief description of these application areas is provided below.

2.3.2.1 Wind speed forecasting

Wind speed forecasting is very important to the operation of wind energy farms as it provides information that can help wind farm managers make better decisions about energy production as well as resource planning for maintenance purposes. In order to characterise stochastic variables such as wind speed, different techniques such as Bayesian model selection and Bayesian model averaging (BMA) can be used. These techniques have been used in criteria

selection based on input data as well as model selection by taking into account uncertainties. BMA has the capability to predict the maximum attainable wind speed using sparse training data to generate posterior probability distributions. Numerical forecasts, and not raw wind speeds, have been used for generating the prior probability distributions (Sloughter, 2010). The posterior distribution obtained with BMA has an advantage in that it can incorporate parameter uncertainty and model uncertainty from different sets of distributions. This allows BMA to be used for creating models that can show the long-term wind speeds, while maintaining its reliability. Li and Shi (2010) applied the Markov chain Monte-Carlo (MCMC) method as a sampling method for generating wind speed distributions that may be used for wind speed forecasting. The BMA method was used to obtain the weighted average of different models for more reliable probabilistic wind speed forecasting distributions. Using the BMA method, the study demonstrated that a model generating the largest relative posterior probability would be the most ideal model to adopt for wind power forecasting.

The hybrid Bayesian-Kalman filtering and sparse Bayesian learning have also been researched for wind speed modelling. In a study by Wang *et al.* (2019b), a Sparse Bayesian-based robust functional regression (R-FR) model was proposed to forecast future wind speed for power generation estimation in wind energy farms. The input parameters were optimised using Bayesian inference algorithms for multi-steps ahead wind power and to create a template forecast for a wind turbine site in relation to other sites. The Bayesian learning and variational inference were found to be useful for reduction of 'noise' implication variables in wind forecast outputs and parameter optimisation in wind turbines, respectively. In Du (2019), an ensemble wind forecast was performed by combining three ML algorithms using BMA. This was aimed at improving the grid reliability by improving the forecasting accuracy. Some comparative studies between Bayesian and other methods for wind speed forecasting have been performed in the literature. Kumar and Sahay (2018) showed that the BN regularisation algorithm is the best method for forecasting wind speed. The common theme in the wind forecasting applications are in the application for optimisation purposes and for averaging different distribution models. Other research papers on this

subject area are Galanis *et al.* (2017); Pobočíková *et al.* (2017); and Han *et al.* (2018).

2.3.2.2 Wind power generation forecasting

Although stochastic in nature, wind power generation forecasting is essential to estimating the reliability of the wind energy resource for the electric grid supply as well as making the electricity price competitive and maximise the revenue from wind energy projects. The power output from a wind farm can be estimated for both the short and long terms. Carta *et al*. (2011) used BN classifiers for wind speed and energy output estimation in long-term. Neural Network (NN) with Bayesian learning, DBN, advanced Bayesian methods and Bayesian-based regression models have also been applied to wind power generation forecasting. Some studies in this regard include Blonbou (2011); and Wang *et al.* (2017).

Some Bayesian methods such as Sparse Bayesian Learning can be used in conjunction with numerical methods to improve accuracy and evaluation capacity of wind power generation forecasting (Pan *et al.,* 2015). Park and Law (2016) developed a Bayesian Ascent algorithm composing of two iterative stages: learning stage and optimisation stage. The authors tested their method on a case study to show its capability for improving the targeted wind farm power output, controlled in real-time. In another study, Xie *et al*. (2019) used BNs to forecast the short-term wind power generation by taking into account the uncertainty in stochastic behaviour of wind and also in the model for operational decision-making applications. A review on the applications of BN models in wind energy conversion systems was conducted by Li and Shi (2012). In Otero-Casal *et al.* (2019), the authors used a hybrid filter (Kalman-Bayesian) for improved wind forecasting, useful for reliable wind production forecasts. Other papers on this subject area include: Ciobanu *et al.* (2017); Yang *et al.* (2017); Afshari-Igder *et al.* (2018); and Wang *et al.* (2019a).

2.3.2.3 Risk assessment

The purpose of risk assessment is to systematically identify all hazards which can potentially lead to major incidents, assess the risks which may arise from those hazards, and decide on suitable measures to eliminate or reduce the risks.

Several researchers have conducted risk assessment studies using either a single tool or a combination of two or more tools in order to combine the advantages within different tools and make up for areas in which one of them may fall short. For example, Hazard Identification (HAZID), Failure Mode, Effects and Criticality Analysis (FMECA) and BN have been combined for risk assessment studies, as reported in Kougioumtzoglou and Lazakis (2015).

In order to carry out a well-detailed risk assessment and an effective risk management strategy, wind energy managers employ advanced tools and techniques for decision-making regarding system safety. BNs have been adopted in recent years to assess the risks and make strategic O&M decisions in the wind energy industry. Risk assessment and management frameworks can be developed using BNs. A BN model has the capability to take into account complex combinations of wind turbines' structural, electrical, mechanical, natural, political and social environmental factors, and also to show how the parameters (representing these factors) relate with one another when making sound risk-based decisions. BNs can also provide information on the effect of changes in one of the factors when there is an update in another factor, e.g. the changes in conditional reliability when there is a change in safety factors. (Dai *et al.*, 2013; Ashrafi *et al.*, 2015). An observed limit to BNs' ability to combine as many complex factors as possible lies in the presentation/graphic user interface (GUI), which has had very limited improvement thus far, thus it can look very cluttered and take away from the graphical property advantage. Safety assessment need to be made without the difficulties related to the GUIs in order to ensure improved wind turbine safety.

In Hybrid Bayesian Network (HBN) models, the variables associated with both static and dynamic systems can be considered. The AgenaRisk tool is useful for creating a HBN model, which provides posterior probability information about the system reliability based on system factors like time to failure of different components within a wind turbine system. Different factors affecting the reliability of the wind turbine can be incorporated in a HBN model and the risks associated with different elements can be quantified (Ashrafi *et al.*, 2015).

2.3.2.4 Fault diagnosis and prognosis

In order to ensure wind energy system reliability, faults must be adequately monitored. The faults found in wind turbines can be caused by inherent material defects in components, cyclic loading or cracks. Some wind turbine components such as generator and drivetrain components are more failure-prone than others and it is crucial to adequately diagnose faults in these components for optimal maintenance planning. When a fault occurs, it can be detected either by inspection techniques such as non-destructive testing (NDT) or using advanced analytics on SCADA-based condition-monitoring data. Critical components whose failure can lead to significant downtime on a wind farm, especially the mechanical and electrical subsystems, are often continuously monitored.

With the growing use of condition monitoring and predictive maintenance on wind turbines, there has been an increasing interest in the use of BNs for fault detection and diagnosis (see Asgarpour and Sørensen, 2018a). BNs are useful in detection and diagnosis of faults in different wind turbine components. One of the early studies done on the subject of fault diagnosis and prognosis of wind turbine gearboxes using BNs is by Chen and Hao (2011). BNs can also be applied to train SCADA data in order to perform fault diagnosis with the aim of lowering O&M costs. Plumley *et al*. (2012) conducted a fault diagnosis and prognosis study on wind turbine gearboxes by means of DBN. The authors used the lubricant condition as an input data to model the gearbox degradation. Chen *et al.* (2012) applied BNs for diagnosis of failures within the pitch system of a wind turbine. They utilised SCADA data to train the BN model for determining root-causes of service failures in the wind turbine pitch system. A future outlook in this application anticipates an even better improvement when real-time data is collected for wind system fault diagnosis and prognosis. This will in turn improve the safety assessments, especially if it leads to less false positives or false negatives, requiring the deployment of personnel offshore, who may be exposed to additional unnecessary risks.

In a study by Stutzmann *et al.* (2017), BNs were used to improve the detectability of fatigue cracks in an offshore wind monopile support structure using the

inspection outcomes. The fatigue life after each inspection was estimated using a Bayesian updating method. In another study, Sinha and Steel (2015) proposed a BN model to incorporate qualitative information into the estimation of failure probability. They considered four major factors, namely, system faults, operational factors, human factors and external factors (environment) in the analysis. Jing *et al.* (2017) matched possible fault modes with the outputs of a BN model to detect anomalies in a faster and more accurate manner. The model was a two-layer Probabilistic Signed Directed Graph (PSDG), which was made up of sensor data input and a possible-fault list input. Two sets of possible fault rankings were collected from the two layers of data input until they match. The authors used stochastic techniques to convert qualitative data into quantitative data, for ease of running the model. The method, then, uses a ranking technique to select the main faults from both layers to select the most appropriate fault type. These steps are iterated for a number of times to ensure the right fault is selected. Other references in this field include: Fernández-Cantí *et al.* (2015); Cai *et al.* (2016); De Bessa *et al.* (2016); Joshuva and Sugumaran (2018) Asgarpour and Sørensen (2018b); Moghaddass and Sheng (2019) and Zhong *et al.* (2019).

2.3.2.5 Reliability assessment

BNs have garnered attention in reliability assessment studies within different industries and the wind energy industry is not an exception. Reliability improvement is closely linked with lowering O&M costs of wind turbines and consequently, reduction of LCOE. In one of the studies reviewed, Mardfekri and Gardoni (2013) used the BN technique for reliability assessment of offshore wind support structures. The analysis showed that fatigue life estimation of wind turbine support structures would benefit from Bayesian updating.

BNs have found applications also as a RUL estimation tool. Accurate estimation of RUL is important for wind farm owners and operators as well as wind turbine manufacturers. RUL estimation must be updated when inspection data is collected or new information from wind turbines is provided. DBNs are useful for incorporating updates when new information is obtained from inspections. An application of such model to wind turbine blades can be found in Nielsen and

Sørensen (2017). BNs can also be used as a decision-making tool for cost-benefit analysis as well as reliability analysis of repair/replacement actions on different wind turbine components. They can be used either as a standalone tool or in conjunction with other tools such as FTA (see Herp *et al.*, 2018; Reder and Melero, 2018; Lazakis and Kougioumtzoglou, 2019). The application of Bayesian classification methods in wind turbine health state monitoring has also been studied in Song *et al*. (2018).

Reliability assessments are dependent on the quality of NDT techniques, which have inherent uncertainties. These techniques will not be able to detect cracks within structural members if the length of cracks is below a certain limit. Reliability assessments are also dependent on the type of system's deterioration mechanisms, environmental factors, etc. These all will pose uncertainties to the reliability assessment, making BNs the most ideal method to quantify and update decisions when there is additional information.

Condition monitoring data can be incorporated into structural reliability analysis by fatigue failure models. Rangel-Ramírez and Sørensen (2009) presented a BN model to incorporate information from the second year of operation of an offshore wind turbine support structure into fatigue life assessment. The fatigue life updates facilitated the improvement of risk-based inspection (RBI) plans for use in fatigue prone components of offshore wind turbine structures. The wind turbine components that have mostly been studied in the past include: generator, blade, gearbox and support structure. Other papers that addressed reliability assessment of wind farms include: Sørensen and Toft (2010); Wang *et al.* (2013); Su and Fu (2014); Li *et al.* (2015); Mardfekri and Gardoni (2015); Tatsis *et al.* (2017); Ding *et al.* (2018); Song *et al.* (2018); and Valeti and Pakzad (2019).

2.3.2.6 Structural analysis

The wind turbines should be designed with sufficient strength and stiffness to withstand the forces to which they may be subjected during operation. The typical forces on wind turbines include: wind and wave forces, forces due to current acting on the sea, tides, temperature forces, ice forces, and earthquakes. During wind turbine design, advanced tools are required to model the components'

behaviour under real environmental conditions. These models are often subject to uncertainties due to inputted data, assumptions and prediction errors. BNs can therefore be used in structural analysis during the design stage as a decision-support tool to compare different design alternatives. This potential of BNs as a decision-support tool is seen in studies on damage growth modelling for structural reliability analysis, which have been carried out using Bayesian updating in order to analyse the impact of new inspection data on structural integrity (Garbatov and Soares, 2002).

Bayesian analysis methods and Bayesian spline models can be applied to compute the effects of potential extreme events on wind turbines (see Cheng *et al.*, 2002; Lee *et al.,* 2013). Bayesian analysis has also been applied to study the effect of uncertainty in lifetime distribution parameters on structural integrity of wind turbines in order to select the most suitable distribution model for use in extreme response analysis (Cheng *et al.*, 2002). The design of wind turbines will benefit from the use of probabilistic methods such as BNs. The ultimate limit state (ULS) and fatigue limit state (FLS) of wind turbine components can be modelled by Bayesian updating methods. Bayesian methods have been used to update the ULS and FLS functions for wind turbine blades. Also, Bayesian statistics and maximum-likelihood (ML) methods have been applied to update the reliability of wind turbine components (such as blades) after obtaining design data or inspection test results (Toft and Sørensen, 2008; Toft and Sørensen, 2011). Bayesian updating has been studied and shown to have the potential to help decision makers improve RUL predictions (see Nabdi *et al.*, 2017; Ziegler, 2018). Improvements in structural analysis will improve the safety associated with wind energy system operations.

2.3.2.7 O&M planning and updating

O&M planning has a significant impact on availability as well as operating expenditure (OPEX) of wind farms (Shafiee *et al.*, 2016). O&M planning is not only crucial for increasing the power generation of wind farms but also plays a key role in reducing the cost of electricity production. Risk-based O&M planning using Bayesian decision theory and DBNs have been studied in the offshore wind

energy industry (see Nielsen and Sørensen, 2010a; Florian and Sørensen, 2017). Sørensen (2009) proposed a framework for risk-based O&M planning of wind farms using BNs. This framework is illustrated in Figure 2-4.

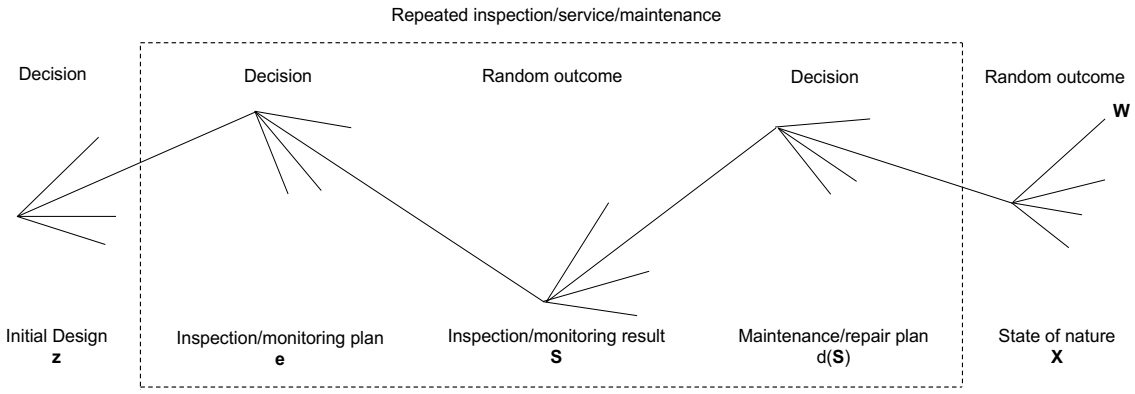

Figure 2-4 A BN decision model for risk-based O&M planning (Sørensen, 2009)

As can be seen, there are three types of decisions, namely, the initial design **z**, inspection/monitoring **S**, and maintenance/repair plan $d(\mathbf{S})$. This corresponds to a pre-posterior decision problem, where the state of nature at one point is affected by previous decisions. For instance, the reliability of components is influenced by the decision on initial design, **z**, and the O&M cost of wind turbines is influenced by the decision on how and when to carry out repair tasks, given by the decision rule $d(\mathbf{S})$.

Some Bayesian methods such as Bayesian Ascent algorithms have also been applied in order to maximise wind energy production from improved O&M (Park and Law, 2016). Bayesian classifiers have been used in conjunction with multivariate higher order moments to carry out wind turbine performance analysis. Herp *et al*. (2016) showed possible application of Bayesian classifiers in performing reliability assessment whilst updating inspection plans to make risk-informed O&M decisions (Pattison *et al*., 2016). Wind farm power optimisation can also be performed using Bayesian method and Bayesian inference functions, as proposed in Park *et al.* (2017) and Mahmoud and Oyedeji (2018). The O&M planning of wind turbines can also be carried out by combining subjective techniques like expert judgment with BNs (see Uzunoğlu, 2018). Additional references on O&M planning using BNs are: Sørensen (2009); Nielsen and

Sørensen (2011a); Nielsen and Sørensen (2011); Nielsen and Sørensen (2014); Florian and Sørensen (2017); and Nielsen and Sørensen (2017).

2.3.3 Comparison between BNs and other tools

In several studies reviewed, the results obtained by BNs have been compared with those determined by other methods. In Fernandez-Canti (2013), the performance of Bayesian approaches for fault detection in wind turbines was compared to other set-membership techniques such as subpaving method. The BN method performed better in terms of runtime. In Wang *et al.* (2019b), the performance of conventional models for wind speed forecasting was compared with the functional regression models. The conventional models included linear regression (LR), multi-output least square support vector machine (MLSSVM) and variational Bayesian-based linear regression (VBLR), whereas the functional regression models included Bayesian robust functional regression (R-FR) and sparse Bayesian-based functional regression (S-FR). The Bayesian robust functional regression model was shown to have the best performance rating compared to the other techniques.

In Galanis *et al*. (2017), the performance of Kalman-Bayesian (K-B) filtering was compared with the conventional Kalman filter and it was found out that the K-B model did not overestimate the wind data, which would lead to more reliable predictions. In Carta *et al.* (2011), BNs were compared with linear regression (LR) and vector regression (VR) methods. BNs were found to be more superior to the other two methods because the output from BN had the least line of best fit with the cumulative wind frequency histograms. In Wang *et al.* (2017), Bayesian models were compared with prediction interval forecasts and it was shown that BNs performed much better because of their ability to generate an interval forecast at any confidence level. The authors concluded that variational Bayesian methods can be used to optimise variables and generate continuous probability density functions (PDFs) for wind power forecasting. In Friis-Hansen (2000), BN was compared with FTA and ETA for risk analysis as well as the Bogdanoff model for risk-based inspection planning. It was concluded that BNs are more efficient and flexible method compared to FTA and ETA. With respect to inspection

planning, BN was found to be easier for parameter estimation. Influence diagrams (IDs) were also seen to be superior to decision trees, as they do not require a supplementary tool when performing probabilistic fatigue crack growth and probabilistic risk modelling. BN was also compared with neural network (NN) and linear regression models for vessel design. It was observed that BNs, being iterative in nature, reduce the solution space for design parameters. Also, compared to NNs, the BN does not need to be relearned when new queries are made.

2.4 Relevant case studies

In this section, a number of relevant case studies from the reviewed literature are identified and described in detail. Some authors demonstrated BN applications with software tools using input data from different sources. Other authors focused on generating posterior probability density distributions based on large datasets.

2.4.1 Case studies in wind speed forecasting

Li and Shi (2010) used the BMA method for forecasting the wind speed in nine wind farm sites. They applied eight distribution functions (including Weibull, Log-Normal, etc.) to generate the prior distribution sample data. In order to generate samples for the posterior inference estimation, MCMC sampling simulations were performed. The samples were then used for each distribution model to calculate the average posterior probability distribution for all the models, the combined likelihood of the prior distribution data to fit each model, and the posterior mean and variance of the BMA posterior probability model. The BMA posterior probability distribution curve was found to have a greater standard deviation than when only one model was considered. The posterior probability of each distribution for the nine sites was also calculated. The results included curves and histograms showing the best fitted model as well as the PDF of the BMA model. The PDF when superimposed with the individual PDFs for each site showed a complete overlap with the appropriate distribution model(s). This makes the method reliable and robust for modelling the wind speed distributions.

2.4.2 Case studies in wind power forecasting

In a study by Xie *et al.* (2019), the wind power output was forecasted using hourly input data from a wind farm in 2006, and then the results were compared with other models. Gibbs sampling was used to produce different data scenarios for probabilistic wind power forecasts, in order to quantify the estimation uncertainty. The authors used two step-by-step algorithms to generate the posterior probability samples for the forecasting model and also scenarios to quantify the estimation uncertainty. Posterior probability distributions were estimated using different approaches. The non-parametric Bayesian method was found to perform better than other models when there is additional prior distribution data. The R software was used to execute the algorithms and the runtime was calculated for different volumes of data. In a dataset containing 100 variables, the runtime was 6 seconds and standard deviation was 0.6 seconds, whereas a dataset with 500 variables had a runtime of 29 seconds and a standard deviation of 1.6 seconds. The Bayesian method was found to be a more accurate forecasting tool when considering wind speed fluctuations.

2.4.3 Case studies in risk assessment

In a case study about risk assessment of wind turbines, Ashrafi *et al.* (2015) captured both continuous and discrete parameters using the AgenaRisk BN software and presented several factors for a more robust analysis. The environmental, organisational, human and technical factors were considered to improve the conditional probabilistic output. The continuous nodes represented the time to failure whereas the discrete nodes represented the system states. The BN technique was used to make inference regarding the system's reliability given the different contributing factors. The case study showed that the BN analysis was useful for monitoring the risk level and system's reliability and safety in continuous operation. Kougioumtzoglo (2015) performed a study where BNs were used for ranking the criticality of wind turbine components based on their probability of failure. The results generated by the HUGIN software were compared with the results obtained by the FMECA analysis and some differences were found. A reason for such differences may be because the BN model permits

adding more details when performing the analysis. Based on the study outcome, the authors further proposed the application of BNs to HAZID analysis.

2.4.4 Case studies in fault diagnosis and prognosis

In a study, Plumley *et al.* (2012) applied the BN method to diagnose failures in wind turbines. The method was tested with a diagnostic program within the LabVIEW software (National Instruments Corp., 2021) to simulate different failure modes in a wind turbine gearbox. The input variables included the parameters related to lubricant condition within the system (temperature, ferrous particle count and viscosity). Three sensors were used for data collection, which underpinned a condition monitoring method for estimating the system condition given input data. The reporting was done based on a traffic light system to help maintenance decision-makers. The second case study generated a DBN to determine the degradation rate of a wind turbine gearbox system under different conditions. The GeNIe software tool (New Wave Concepts Limited, 2021) was used to create the DBN model. The condition monitoring data from the sensors were used to estimate the degradation state of the gearbox. The DBN probability estimates were based on updates from new data (temperature and particle count), which were fed into new time slices of the continuous model. It presented the application of probabilistic estimates based on the updates to inform PM decisions.

In another study by Stutzmann *et al.* (2017), fatigue crack size distribution for an offshore wind turbine monopile structure was calculated using inspection data obtained by eddy current (EC) technique. An analysis was performed to reduce the uncertainty posed by the method of inspection. The probability of detection (POD) by EC technique was found to be higher than that by other NDT techniques. A Bayesian analysis was then performed to estimate the fatigue crack propagation based on the crack size distribution and inspection results. From the distributions generated, the fatigue life for the crack sizes between 0.03–0.06mm was estimated to range between 30 and 40 years. The median and the standard deviation of the fatigue life were estimated as 33 years and 47 years, respectively. The standard deviation of the fatigue life estimation was compared

for two cases, including: (*i*) when the defect is detected, and (*ii*) when the defect is not detected. The standard deviation showed a large decrease irrespective of the inspection results. The study, therefore, concluded that the inspection serves to reduce or eliminate the risks only when the length of the crack on monopile structures is sufficiently large.

2.4.5 Case studies in reliability assessment

Song *et al.* (2018) applied a Bayesian approach to assess the health state of wind turbines. The case study was based on two 1.5MW wind turbines. The 10-minutes data was obtained from SCADA system for a period of two month. The three input variables included in the model were wind speed, power output and generator speed. Two case studies were provided, including a classical case involving the use of wind speed and power output variables and another case involving all three input variables, to evaluate how reliable and robust the results from Bayesian approach are when more data is available. This was because whenever inferences are made, it will be easier to make a trade-off between accuracy and data training. The second case involved splitting the data set into five subsets. Four subsets were used to develop the model, and the fifth one was used to test the model accuracy. The models were run five times and their performances were evaluated. The collected input data was pre-processed to identify abnormal data points. Three methods were used for this purpose, namely, the bin method, the multivariate normal distribution, and the copula method. The copula method was found to be the most robust of the three. The BN model demonstrated good health state monitoring capacity; however, the authors focused on binary health state monitoring (i.e., normal and abnormal states). Since the reliability of BN method is dependent on the input data, the authors suggested Bayesian updating to minimise issues arising due to insufficient data. The study concluded that the multivariate and copula methods are best to be used for 1-hour ahead predictions.

2.4.6 Case studies in structural analysis

In order to illustrate the use of Bayesian analysis in studying the wind turbine's rotor blade displacement, Cheng *et al.* (2002) presented a case study of

conditional probability distribution for blade tip deflection (influenced by wind speed). Four distribution functions were used in their study to estimate the posterior probability. These included Gumbel distribution, three-parameter Weibull distribution, log-normal distribution, and generalised extreme value (GEV) distribution. It was observed that after plotting the probability of deflection using each of the distribution functions, the three-parameter Weibull distribution and GEV distribution were the best fitted models to the input deflection data. The authors argued that the accuracy of the results would improve when well-fitted conditional distributions are used to estimate the maximum deflection of wind turbine blades. The authors estimated 100-year deflection probabilities using different distribution functions and compared the results with those calculated by Bayesian analysis. The blade tip deflection was found to be larger when a deterministic method is used. This was mainly because the Bayesian approach accounted for data uncertainty and distribution model uncertainty.

2.4.7 Case studies in O&M planning

In a case study that compared the efficiency of CBM strategy with risk-based maintenance (RBM) strategy, Florian and Sørensen (2017) used BN updating to model the degradation of wind turbine blades subjected to fatigue cracking. Random input variables were generated for the BN model for a period of 25 years (the expected lifetime of a wind turbine system). The maintenance decision-making parameters included: the time to first inspection, time interval between inspections and the repair threshold. MCS was used to generate the cost estimate distribution, taking into account different factors. The simulation procedure entailed identifying the maintenance strategies based on different inputs and then estimating the probabilities of failure and the associated repair/replacement costs. The expected number of blade failures under a CBM strategy was evaluated and the crack categories with the highest potential impact were identified. The number of preventive repair required during the blades lifetime was also calculated. The total lifecycle cost was estimated using a pre-posterior Bayesian decision tree, assuming that an inspection is carried out only when the risk of failure is high. The RBM strategy, on the other hand, was studied

with a risk-based model to determine the inspection plan and the optimal repair policy after each inspection. Two hundred simulations were run to determine the average annual cost of O&M. The maintenance strategies, namely, CBM and RBM resulted in different number of preventive repairs for wind turbine blades. CBM showed that 96% of the wind turbine blades required a preventive repair during their expected lifetime, whereas this percentage under RBM strategy was 62%. This led to a reduction in total lifecycle cost by 23%.

Dinwoodie (2013) presented a case study on an offshore wind farm consisting of 60 wind turbines installed at 45m water depth. The failure rate distributions for wind turbine components such as gearbox, generator, blade and bearings were calculated. Three decision points during the lifecycle were considered: (*i*) early life strategy, (*ii*) strategy at year seven, and (*iii*) strategy for the remaining lifetime. In the case study, the uncertainties upon which the BN was built were primarily the failure rate and the electricity price. The analysis relied on both the inspection data as well as subjective expert opinions. A risk profile was also generated and the variables causing the highest risk were identified.

Table 2-1 presents the case studies on different wind turbine components that have used Bayesian statistical methods in the reviewed literature. As can be seen, amongst the wind turbine components, the blade has been studied the most (13 papers). This is followed by gearbox with 11 papers, pitch system and generator with 8 papers, and support structure with 7 papers.

Table 2-1 Case studies in BN for different wind turbine components (note: some components have been studied in more than one paper)

Component	References
Bearing	Asgarpour and Sorensen (2018a); Asgarpour and Sorensen (2018b); Herp et al. (2018); Reder et al. (2018)
Support structure	Mardfekri and Gardoni (2013); Kougioumtzoglou and Lazakis (2015); Stutzmann *et al.* (2017); Asgarpour and Sorensen (2018a); Lazakis and Kougioumtzoglou (2019)

Gearbox	Chen and Hao (2011); Plumley *et al.* (2012); Kougioumtzoglou and Lazakis (2015); Jin and Liu (2017); Nabdi *et al.* (2017); Ding *et al.* (2018); Reder (2018); Lazakis and Kougioumtzoglou (2019); Zhong *et al.* (2019)
Sensors	Fernandez-Canti (2015)
Pitch system	Chen *et al.* (2012); Fernandez-Canti (2013); Nielsen *et al.* (2014); Fernandez-Canti (2015); Kougioumtzoglou and Lazakis (2015); Nabdi *et al.* (2017); Uzunoglu (2018)
Blade	Sorensen and Toft (2010); van Buren *et al.* (2012); Lee *et al.* (2013); Kougioumtzoglou and Lazakis (2015); Florian and Sorensen (2017); Nabdi *et al.* (2017); Nielsen and Sorensen (2017); Reder (2018); Lazakis and Kougioumtzoglou (2019)
Converter	Nabdi *et al.* (2017)
Nacelle	Nabdi *et al.* (2017)
Control systems	Mahmoud and Oyedeji (2018)
Tower	Kougioumtzoglou and Lazakis (2015)
Generator	Wang *et al.* (2013); Fernandez-Canti *et al.* (2015); Kougioumtzoglou and Lazakis (2015); Nabdi *et al.* (2017); Reder (2018); Song *et al.* (2018)
Rotor	Fernandez-Canti *et al.* (2015)
Cables	Kougioumtzoglou and Lazakis (2015);
Yaw system	Kougioumtzoglou and Lazakis (2015); Reder (2018)
Hub	Kougioumtzoglou and Lazakis (2015)
Main frame	Kougioumtzoglou and Lazakis (2015)

2.5 Results and discussion

Table 2-2 presents the classification of reviewed literature according to their application areas, including: structural analysis, reliability, wind power forecasting, wind speed forecasting, noise emission, O&M, fault diagnosis and prognosis, and risk assessment. All the classifications are centred around a common theme: *improving the reliability of offshore wind turbine structures*. The main areas of reliability improvements that have been the focus of the research community can be broken down further as seen below.

As can be seen, the field of fault diagnosis and prognosis has received the most attention in the literature. This is closely followed by wind power generation forecasting, reliability analysis, O&M planning, and structural analysis. The fields of risk assessment and acoustic noise emission estimation, with respectively two and one publications, have been researched the least. An increasing research trend is witnessed towards the use of BNs in fault diagnosis and prognosis, power forecasting capacity, O&M and reliability. The largest number of publications has appeared in the years 2017 and 2018, where fault diagnosis and prognosis, O&M planning, wind power forecasting and reliability analysis with respectively 10, 8, 7 and 6 publications had the highest contributions.

In what follows, the results of the literature review for some of the most addressed application areas are briefly discussed.

2.5.1 Wind speed forecasting

Wind speed forecasting is useful for determining the potential wind energy production. However, due to the stochastic nature of wind, it is difficult to estimate accurately a wind farm's energy output. For this reason, it is required to design and develop short- and long-term wind speed forecasting tools. One of the ways to forecast the wind speed is by looking into data collected from some geographically similar wind energy projects. In some cases, there is no historical data available for deepwater locations; thus, it is important to use tools through which wind farm managers can update their initial decisions when some information becomes available. This makes the case for the use of probabilistic models such as BNs. BNs have the capacity to learn based on new information inputted into the model and may be used in the BN classifier. Bayesian classifications help to determine the most probable value amongst a set of variables such as wind speed profile at a particular location. Beyond that, BNs also allow multiple locations to be accounted for in the estimation of wind speed and direction within the model.

Table 2-2 Classification of BN applications in the wind energy industry

Reference	Year	Structural Analysis	Reliability	Wind power forecasting	Wind Speed Forecasting	O&M	Fault diagnosis and prognosis	Risk Assessment
Cheng et al.	2002	√						
Garbatov and Soares	2002		√					
Rangel-Ramírez and Sørensen	2009	√				√		
Sørensen	2009					√		
Li and Shi	2010				√			
Nielsen and Sørensen	2010a					√		
Nielsen and Sørensen	2010b					√		
Sloughter et al.	2010				√			
Sørensen and Toft	2010	√						
Blonbou	2011			√				
Carta et al.	2011			√				
Chen and Hao	2011						√	

Nielsen and Sørensen	2011					√		
Toft *et al.*	2011		√					
Toft and Sørensen	2011	√						
Chen et al.	2012						√	
Li and Shi	2012			√				
Plumley et al.	2012						√	
Fernández-Cantí et al.	2013						√	
Lee et al.	2013	√						
Mardfekri and Gardoni	2013		√					
Van Buren et al.	2013	√						
Wang et al.	2013		√					
Nielsen and Sørensen	2014					√		
Su and Fu	2014		√					
Ashrafi et al.	2015							√
Bracale and De Falco	2015			√				
Fernández-Cantí et al.	2015						√	

Kougioumtzoglou and Lazakis	2015							√
Li et al.	2015		√					
Mardfekri and Gardoni	2015	√						
Pan et al.	2015			√				
Sinha and Steel	2015						√	
Cai et al.	2016						√	
de Bessa et al.	2016							
Herp et al.	2016					√		
Pattison et al.	2016			√				
Ciobanu et al.	2017			√				
Florian and Sørensen	2017					√		
Galanis et al.	2017				√			
Jin and Liu	2017		√					
Jing et al.	2017						√	
Nabdi et al.	2017	√						
Nielsen and Sørensen	2017		√					
Park et al.	2017					√		
Pobočíková et al	2017				√			

Tatsis et al.	2017	√						
Wang et al.	2017			√				
Yang et al.	2017			√				
Afshari-Igder et al.	2018			√				
Asgarpour and Sørensen	2018a						√	
Asgarpour and Sørensen	2018b						√	
Ding et al.	2018		√					
Han et al.	2018				√			
Herp et al.	2018					√		
Joshuva and Sugumaran	2018						√	
Kumar and Sahay	2018				√			
Mahmoud and Oyedeji	2018					√		
Reder and Melero	2018		√					
Song et al.	2018		√					
Uzunoğlu	2018b					√		
Du	2019				√			

Lazakis and Kougioumtzoglou	2019		√					
Moghaddass and Sheng	2019						√	
Otero-Casal et al.	2019			√				
Valeti and Pakzad	2019		√					
Wang et al.	2019a			√				
Wang et al.	2019b				√			
Xie et al.	2019			√				
Zhong et al.	2019						√	

Although BN results were seen to be superior to the use of linear regression (LR) and vector regression (VR) models, it is still inconclusive as to whether this holds true when different correlation coefficients are considered. Thus, we have found that more research is needed in the accuracy of BN models if different correlation coefficients are considered (Carta *et al,* 2011).

Wind speed forecasting can also be useful for predicting periods of energy shortfall, so as to have measures in place to compensate for low energy output from wind turbines and given that BNs were used as a training tool, there is huge potential for use in a wide range of hybrid applications. Generating a probability distribution of weights is valuable for probabilistic modelling; but one key reservation regarding the applicability of this model lies in the fact that the prediction is expected to operate in real-time. However, its behaviour and performance were evaluated using pre-recorded wind speed and wind power data and evaluated offline. Additional research needs to be conducted on the real- time impact of BNN prediction scheme. Also, since the power predictions can only be reliable when there are no abrupt changes, it is difficult to state how ready this technology is to be applied to real scenarios outside of the modelling environment. If this can be improved, assumptions need to be validated for accurate results in practical terms for O&M managers (Blonbou, 2011).

BNs are useful for short-term probabilistic wind power forecasting and are also suitable for optimising model parameters when other tools are used to forecast the wind speed. The reliability of distribution systems is predicated on accurate wind forecasts. As wind speeds are random in nature, the use of a probabilistic tool like Bayesian models to predict wind speeds required for more reliable wind power distribution. Bayesian models can easily incorporate both unimodal and bimodal wind regimes if a suitable PDF is used. One key predictor of Bayesian model adoption is its improved computational efficiency, which may promote an increase in its applicability to wind energy systems. The authors made a case for applying BN methods because a wind farm can have turbines with varying cut-in and cut-out speeds. The main limitation with its application is that to maintain computational efficiency, there is a trade-off in the power curve used in the

estimations. The use of deterministic power curves is the only way to make BNs more computationally efficient. This reasoning is flawed, however, the technologies using BNs have not been developed to manage the problem yet and more research needs to be conducted in this area. It was not unusual to find that the authors used Bayesian methods for optimisation. The question thus is: if optimisation is a main application for Bayesian reasoning, what ways will it be most applicable, how and why will it be justified for use? (see Bracale and De Falco, 2015; Wang *et al.* 2017).

2.5.2 Risk assessment

Risk assessment is at the heart of reliability and availability of wind turbines as wind turbines can only be efficient and available if they maintain high reliability and safety levels. Risk assessment is carried out in order to estimate the likelihood of occurrence and severity of hazards that may damage the integrity of wind farms or cause harm to the life of personnel. A number of tools and techniques are used for risk assessment, e.g. FMECA, HAZID, etc. In order to carry out risk assessments, it is more suitable to use a HBN, which has the capability to model dynamic states within nodes. Some particular properties of BNs as they relate to risk assessment are as follows (Ashrafi *et al*., 2015):

- Additional information and data about the maintenance activities can be implemented in BN and expanded. This will be useful when there is a need to include other parameters that have to be analysed for risk assessments.
- BNs can be used for both the forward (top-to-bottom) and backward (bottom-up) risk assessment approaches.
- Risk analysis can be performed to quantify the system's reliability conditioned on the impacts of environmental factors, human activities, and the selected maintenance strategy. This shows how different factors will impact the others and provides optimal strategies for resource deployment by risk analysts and O&M planners.
- The BN tool also allows for updating the system's reliability when there is an improvement in any of the factors considered in the network.

- Depending on the parameters to be quantified, a continuous or discrete node may be used.
- BNs can be used to represent and quantify conditional probabilities with considering different situations.

The argument for using BNs with other risk analysis tools (as a hybrid method), since deterministic methods are limited in being able to incorporate human and organisational factors in the risk assessment and analysis. The study in Ashrafi *et al*. (2015) shows that it was possible to use certain variables as discrete inputs (environmental, organisational and human reliability). Although these factors are subjective in nature, a closed system is needed to capture these factors within the nodes, increasing the subjective nature of the BN in an attempt to increase objectivity. Thus, care must be taken in application to real applications as to how many possible child nodes can be incorporated for each variable (parent node).

In the BNs, factors like the organisation factors can practically only inputted as binary inputs (best modes or worst modes), because it takes a long time for changes in these factors to take effect. This may be a limitation in the BN application in reality because organisational/cultural changes are gradual and not easily measurable. This may, therefore, be good in theory but there remains a reservation for its usefulness in risk assessment accuracy in practice. Since the organisational factors cannot be modelled by distributions, as they do not have physical behaviours that can be forecasted like wind speed, for example; an attempt to include the organisational factors may not provide any particular information for improved decision-making.

2.5.3 Fault diagnosis and prognosis

Depending on the wind turbine subsystem being analysed, different failure mechanisms may be involved. Using BNs, these failure mechanisms can be represented by nodes along with their probability of occurrence, considering other nodal probability distributions. Improved fault diagnosis and prognosis will have a positive impact on wind farm maintenance since the available resources can be effectively deployed to address any concerns based on continuously updated

information. Some of the advantageous properties of BNs related to fault diagnosis and prognosis include (Chen *et al*, 2012; Plumley *et al*., 2012):

- BNs can be used to effectively determine the fault position (location).
- Component/system faults can be detected once the posterior probabilities of nodes are calculated. It is helpful to model the most critical stochastic parameters that are required for performing fault diagnosis and prognosis on the wind turbine subcomponents.
- BN is a flexible tool for online fault diagnosis and prognosis, for which the O&M planners aim to embrace in large-scale wind farms in the future. This shows the potential for real-time updating capacity of the Bayesian methods.
- BNs have the potential to lower O&M costs in the long term as they can help wind farm asset managers quantify different variables and their relationships so as to make risk-informed O&M decisions.
- BNs can be used to develop real-time condition-monitoring systems, which can be useful for PM planning across the wind farm.
- Data regularisation can be used to train prediction models and improve their accuracy, and this can be achieved using HBNs. Also, if updates are carried out at a higher frequency, fault diagnosis and prognosis can be improved.
- The components that have been studied for fault diagnosis and prognosis in the reviewed literature include gearbox, pitch system, bearing and support structure.

2.5.4 Reliability assessment

High reliability of wind turbines ensures continuous system operation for energy production to meet the growing demand and lower the LCOE. When performing reliability assessment, there might be some unknown parameters or parameters with little to no prior information involved in the analysis. Reliability assessment can benefit from the Bayesian updating approaches in cases where there are unknown parameters, uncertain assumptions or latent variables. In such

situations, the estimations can be obtained using the pre-obtained data from SCADA or experimental data (Mardfekri and Gardoni, 2013). Depending on the number of parameters to be involved in the reliability assessment, the BNs may be sufficient to accurately compute the overall conditional probability. When the problem becomes too complex, the BNs can be used in combination with other models for reliability studies. BNs can also be used as a validation tool for other reliability assessment techniques. Since the main limitations in using the BNs are based on the presentation of the nodal relationships and model uncertainties, one of the key improvements required in BNs tools are related to the GUI (graphic user interface) of the modelling tool. In terms of the computational capacity, the BN is believed to have capacity for updating, which should be an addition for its use in reliability assessment (Li *et al.*, 2015). The Bayesian reasoning can show any weak connections within the subsystem when calculating reliability at a design stage. The weak connections are identified by the BNs' backward reasoning capability (see Jin and Liu, 2017). Besides using BN as a verification tool, other tools and techniques such as FMECA can be used to verify BN results. The BN model will be updated when there is new information that can be inputted to show the most accurate state of the system, thus informing better maintenance plans. Even though BNs have the capacity to update, on the operations side, there has to be more efficient means of data collection and updating for the BN capacity to be maximised. (Lazakis and Kougioumtzoglou, 2019). The components that have been studied for reliability assessment in the reviewed literature include generator, blade and gearbox.

2.5.5 O&M planning

Improving the O&M practices is vital to optimise wind farm availability and maximise wind power output. Many tools are used by wind farm asset managers to optimise O&M strategies, but Bayesian methods have shown potential for improvement in O&M planning. Some of the properties that make BNs attractive for use in O&M planning include (see Cheng *et al.*, 2002; Nielsen and Sørensen, 2010b):

- Both logical and stochastic nodes can be incorporated in BNs. This results in a more robust O&M planning model.
- Continuous nodes can be included in BNs when an approximate inference is used (e.g. discretisation of distribution parameters).
- Condition monitoring data and inspection outputs can be incorporated into the BN structure in order to update the O&M decisions when needed.
- Bayesian learning approaches can be used to incorporate different parameters such as defect (crack) size in the estimation of propagation rates. This informs O&M planners about the optimal time to repair or replace the failed parts, especially in deepwater locations where accessibility is restricted.
- Besides being able to model stochastic processes with limited information and very minimal data points, an approximation tool such as Bayesian Ascent algorithm can model complex relationships within a system, and when more information is obtained, more data points can be added for improving the estimation accuracy.
- Annual probability of failure estimates will be lower if observations are incorporated into the model. Thus, a strong case is made for when monitoring results are included in a model, as it will increase the confidence levels of failure predictions.

BN-based O&M planning tools can be useful for more accurate RUL estimation using real-time updates of critical subsystems. This will result in reduced cost of repairs as well as improved availability of wind turbines. As BNs have the capability to process limited data and to update the results when new information becomes available, they prove to be very useful for deepwater sites where floating wind farms will be developed in the future.

A detailed analysis of the reviewed studies in terms of their model inputs, outputs, specifications, challenges of the solutions, advantages and limitations is presented in Table A-1 of the Appendix section.

2.6 Conclusion and future work

Wind energy systems often operate in highly dynamic and ever-changing environments; thus, their condition may change rapidly over time. In such environments, reliability is more difficult to achieve for several reasons and thus, different areas in wind farm management must be improved or adapted for complex and dynamic conditions. It is crucial for wind farm managers to update their decisions and actions continuously, taking into account changes in operational/environmental conditions and/or newly collected data. The new data is usually provided from the inspection reports, Supervisory Control and Data Acquisition (SCADA) systems or the sensors fitted to different parts of the wind turbines.

Among all the Machine Learning (ML) tools and techniques that allow for updating, Bayesian networks (BNs) are the most promising method for real-time planning. This is because BNs can be used to quantify uncertainty when solving a decision-making problem, based on recorded or prior knowledge about the system dynamics and their resultant effects. They are useful in situations where there is limited information about a complex system and the environment, which is the case for wind energy systems, and the network can be updated when additional information becomes available.

In this paper, we conducted a systematic literature review on the use of BN models in the onshore and offshore wind energy industry. Several documents were identified and analysed for the purpose of this review. It was found that the major applications of BNs in the wind energy industry include: wind speed forecasting, wind power generation forecasting, risk assessment and management, fault diagnosis and prognosis, system reliability studies, structural analysis, and operation and maintenance (O&M) planning. An overarching theme was observed in all those applications: *the need for improved reliability.* If wind speed and power forecasting is improved using an updating method like BNs, there will be more reliable grid supply data to adequately meet energy demand. Also, improving risk assessment and management will ensure improved system availability and better planning and decision-making. Improved fault diagnosis

and prognosis, structural analysis, O&M are central to wind system reliability. A detailed review of the publications, thus, shows that the areas of fault diagnosis and prognosis, reliability analysis, O&M planning, wind power generation forecasting, and structural analysis have been the most researched areas. One of the reasons maybe is that if fault diagnosis and prognosis can be improved by a tool with the ability of real-time updating, the reliability of wind turbines as well as O&M practices will also be improved. This eventually will result in an increased O&M efficiency as well as reduced LCOE in the wind energy industry. This literature review revealed that BNs, albeit an efficient tool in OW applications, has not been applied in the decommissioning/end-of life phase. Thus, warranting research into Bayesian Network applications for the decommissioning phase of the OWF Asset lifecycle.

In spite of various applications of BN modelling in the wind energy industry, future work is needed to improve the prediction performance of BN algorithms, particularly the newly developed cyclic Bayesian approximation models. BNs and their approximation models have the potential to help wind farm asset managers move towards ‘real-time’ predictive analytics. The uncertainties lying within the system performance, stochastic environmental conditions and model can be quantified and subsequently modified with field information to facilitate improved decision-making processes. Hybrid models like the Bayesian-Kalman filtering, sparse Bayesian learning, etc. were more common in different studies, in order to compensate for the current limitations of BNs. A common trend in Bayesian method applications are seen in its use because of its good optimisation and model averaging properties during wind forecasting, to improve the confidence levels of posterior probability outputs. Although BNs have the capacity to combine different complex combinations of wind turbines’ structural, electrical, mechanical, natural, political and social environmental factors, the GUI development of BN tools have not improved at the same rate.

The uncertainty caused by the selection of the inspection technique can also be incorporated into BNs, which shows a usefulness of the method, especially because not all inspection method has 100% detectability in every instance. BN

model demonstrated good health state monitoring capacity and because the reliability of BN method depends on the input data, Bayesian updating will help manage issues arising due to insufficient data. An advanced reliability and RUL prediction tool like BNs will be able to take advantage of the real-time data from condition monitoring improvements in the wind energy industry. The potential that Bayesian updating can have on decision-support optimisation for improved system structural analysis, RUL and reliability predictions has also been discussed; this can address issues in predictions caused by insufficient data. When data can be updated using BNs, it will be easier to estimate with higher confidence levels the reliability, risks/safety associated with the wind turbine structures and operations. Some areas that show potential for future research direction include:

- More models need to be developed using BN algorithms in order to make tools more robust, reliable and efficient for different wind energy applications.
- Damage growth models using Bayesian statistics still require improvements, especially, for small size damages in wind turbine structures.
- A future outlook in fault prognosis and diagnosis application is expected to bring application improvements when real-time data is collected for wind system fault diagnosis and prognosis.
- Bayesian inference techniques must be improved in order for models to combine corrosion effects along with fatigue deterioration in reliability studies.
- BNs can be used as a decision support tool for modelling life extension strategies in wind farms (for more see Shafiee and Animah, 2017).
- Because wind power predictions with BNs to-date are reliable when there are no abrupt changes, the technology readiness is difficult to state for application in real scenarios outside of the modelling environment. For this to be improved, assumptions for wind power predictions using BNs need to be validated for accurate results in practical terms for O&M managers (Blonbou, 2011).

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3 An economic analysis model for decommissioning of offshore wind farms using a cost breakdown structure

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Abstract

Purpose As wind power generation increases globally, there will be a substantial number of wind turbines that need to be decommissioned in the coming years. It is crucial for wind farm developers to design safe and cost-effective decommissioning plans and procedures for assets before they reach the end of their useful life. Adequate financial provisions for decommissioning operations is essential, not only for wind farm owners but also for national governments. Economic analysis approaches and cost estimation models therefore need to be accurate and computationally efficient. Thus, this paper aims to develop an economic assessment framework for decommissioning of offshore wind farms using a cost breakdown structure (CBS) approach.

Methods In the development of the cost breakdown structure (CBS), the cost elements and their key influencing factors are identified from literature and expert interviews. Similar activities within the decommissioning process are aggregated to form four cost groups. Some mathematical models are proposed to estimate the costs associated with activities and to identify the most critical cost-drivers in each activity group. The proposed models include all cost elements within each decommissioning phase for more robust cost assessment.

Results and discussion A case study of a 500MW baseline offshore wind farm is proposed to illustrate the models' applicability. The results show that the removal

of wind turbines and foundation structures is the most costly and lengthy stage of the decommissioning process due to many requirements involved in carrying out the operations. Although inherent uncertainties are taken into account, when more information becomes available, cost estimates can be easily updated using our approach. Additionally, more decommissioning cost elements can be captured allowing for sensitivity analysis to be easily performed.

Conclusions Using the CBS approach, cost-drivers can be clearly identified, revealing critical areas that require attention for each unique decommissioning project. The CBS approach promotes adequate management and optimisation of identified key cost-drivers, which will enable all stakeholders involved in offshore wind farm decommissioning projects to achieve cost reduction and schedule optimization, especially for safety-critical tasks.

Keywords: Wind energy; Decommissioning; Life-cycle costing; Cost Breakdown Structure (CBS).

3.1 Introduction

Offshore wind energy has been gaining a lot of attention in the renewable energy sector in recent years. A large number of offshore wind turbines have been installed recently due to more stable and steady flow of wind as well as less noise and visual impacts at sea than on land (Markard and Petersen, 2009; Bilgili *et al.*, 2011). By the end of 2017, the total global installed capacity of offshore wind power was 18.8 gigawatt (GW). Of all the regions in the world, Europe is the leader in offshore wind development and is home for the largest operational wind farms for both bottom fixed and floating foundation technologies. WindEurope (2019) reported the total installed offshore wind capacity of 18,499 MW from 4,543 offshore wind turbine (OWT) units across 11 countries including: United Kingdom, Germany, Denmark, Belgium, Netherlands, Sweden Finland, Ireland, Spain, France and Norway.

Along with increasing the number of wind turbine installations globally, there will be a substantial number of assets reaching their end-of-life (EOL). There are three EOL strategies applied to wind farms including: life extension, repowering

and decommissioning (Ortegon *et al.*, 2013; Shafiee and Animah, 2017), which are shown in Figure 3-1. All assets will eventually be decommissioned, irrespective of the EOL strategy adopted; hence, this paper focuses only on decommissioning (Shafiee and Animah, 2017; Topham and McMillan, 2017; Hou *et al.*, 2017). Decommissioning includes all the activities performed before, during, and after dismantling of wind turbines and their supporting assets and equipment. The wind farm assets are disconnected from the grid, dismantled, items left-in-place are buried or marked, and the site returned to its original state (Bezbradica *et al.*, 2016; Rubert *et al.*, 2016; Animah and Shafiee, 2018; Department for Business, Energy and Industrial Strategy, 2018; Ziegler, 2018).

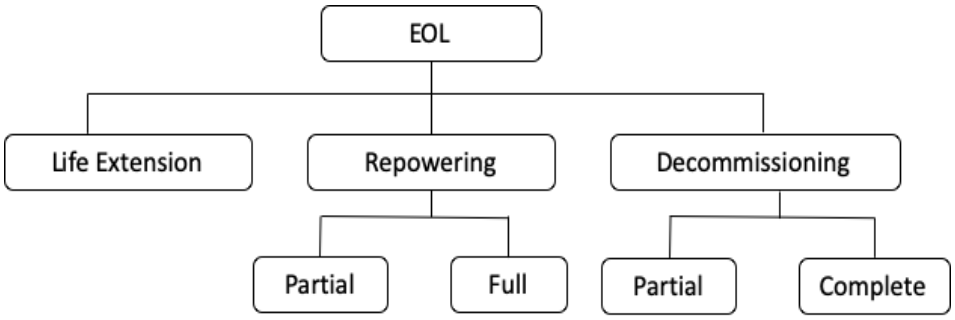

Figure 3-1 End-of-life (EOL) strategies for offshore wind farms (Luengo and Kolios, 2015; Shafiee and Animah, 2017)

Although the decommissioning decision is often influenced by several factors such as time to end of leasing permit, cost/benefit factors for operating and maintaining the asset, availability of spare parts, age of the asset, etc. all wind farm assets are required to be decommissioned by law. Offshore wind turbine decommissioning is still in its infancy around the world and only a few regions have begun decommissioning activities. There is limited data available about the decommissioned wind farms within the wind energy databases. Seven offshore wind farms have been decommissioned in Europe to date ranging from 8 to 23 years in operation. Table 3-1 gives details about these seven offshore wind farms including the type of their foundations. Some of the wind farm assets were decommissioned before the usual lifespan of wind turbines.

Table 3-1 Decommissioned offshore wind farms in Europe (4C Offshore, 2019)

Country	Wind Farm	Farm Capacity	Operational Years	Decommissioned Year	Foundation Type
Denmark	Vindeby	4.95 MW	26	2017	Gravity-based
Germany	Hooksiel	5 MW	9	2016	Tri-pile
Netherlands	Lely	2 MW	23	2016	Monopile
Sweden	Utgrunden I	10.5 MW	19	2018	Monopile
	Yttre Stengrund	10 MW	15	2015	Monopile
UK	Blyth	4 MW	13	2019	Monopile
	Beatrice Demonstration	10 MW	8	2016	Jacket (piled)

The total decommissioned capacity in Europe as at 2019 is 46.45 MW, and the contribution of five main countries is presented in Figure 3-2 (4C Offshore, 2019). In a few years, the amount of decommissioning activities in Europe will increase exponentially and the wind industry will be better off preparing for the financial liability, production deficit in the grid, removal options and strategies and environmental remediation. In order to ensure that decommissioning costs are well managed, the highest cost drivers and the priorities for industry need to be identified in a safe and efficient manner. Therefore, the financial implications are the main focus of this study; including the cost and implications of different tasks and activities and the cost of production deficit in the overall energy supply. Although in the energy industry, offshore wind farm decommissioning will be different from the oil and gas or nuclear industry, some elements may provide some experience in this sector. Hence, estimation of the potential costs to operators and regulators is crucial to quantify so as to make provisions early on in the life of the wind farms and make adequate resource planning.

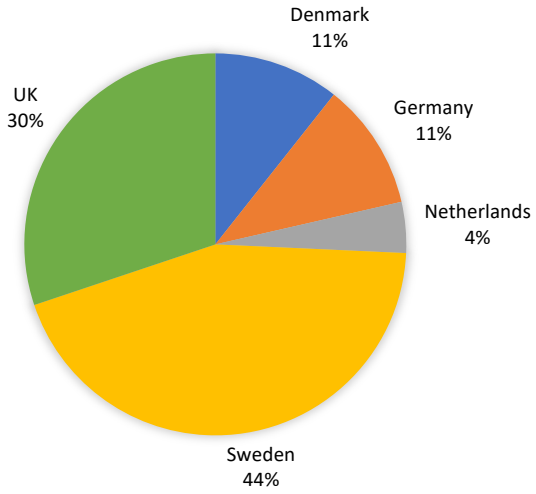

Figure 3-2 The contribution of five countries in the Europe's wind farm decommissioned capacity between 2015 and 2019 (4C Offshore, 2019)

It is crucial for wind energy operators and regulators to design efficient and cost-effective decommissioning plans and processes for their assets before they reach their end of life. The cost estimation of the entire decommissioning process is subject to numerous uncertainties. Attention has to be paid at the early stages of wind turbine decommissioning to close the knowledge gap and foster improved procedures and processes in the wind energy industry. The estimated cost of decommissioning is usually accounted for at the early developmental stages of a wind farm project so as to calculate the cost of energy more accurately. The cost of energy depends on improved accuracy in estimation even though future outlooks are based on assumptions of many uncertain parameters. These decommissioning estimates are laden with many assumptions as the cost is dependent on different factors like the decommissioning year (before, during or after planned asset lifespan), cost and supply of vessels at the time of decommissioning, foundation type, location (water depth and distance from port), the cutting and removal time, tools and techniques at the time of the project initialisation, learning experience, etc. It is safe to say these estimates, although they make provisions for the initial investment costs required, will be a gross underestimate at the time of decommissioning. To date the estimated decommissioning cost is said to account for about 3% of the overall project cost

of a 240MW capacity wind farm; based on highlighted factors, the cost estimates are not true representations of the actual (Topham and McMillan, 2017).

To date, there has been very limited research about decommissioning of offshore wind farms and the associated cost factors. To fill this research gap, we aim to study the decommissioning activities and their influencers in the offshore wind sector, especially with regards to cost reduction. The methodology includes to construct a decommissioning cost breakdown structure (CBS) and then develop mathematical models for estimating the cost of activities. This method will provide a clear identification and analysis of factors that influence wind farm decommissioning projects in order to help reduce their associated costs. Further to this, our method ensures that the most critical cost factors are evaluated by all stakeholders and major areas of focus for efficient decommissioning project execution and cost control are identified. A case study of a 500MW baseline offshore wind farm is used to illustrate the method applicability.

The following sections are organised as follows. Section 3.2 presents an overview of wind farm decommissioning activities, the decommissioning standards, guidelines and best practices and the different strategies that can be adopted. Section 3.3 presents an introduction to decommissioning cost estimation and the research studies available in that area. Section 3.4 describes the breakdown of the decommissioning phases and their cost elements in detail; showing cost factors and relationships between different cost elements by means of process flowcharts. Section 3.5 presents a case study applying the cost models to a baseline offshore wind farm project. Section 3.6 discusses the results, and the concluding remarks and section 3.7 presents the future outlooks on offshore wind energy decommissioning cost estimation.

3.2 Overview of the decommissioning process

The decommissioning process is almost similar for all wind turbines; however, it can be tailored on a case-by-case basis and depending on the peculiarities of the wind farm such as the type of wind turbine substructure, water depth, wind turbine capacity and weight. Decommissioning tasks/activities are presented in regulatory reports, guidelines and recommended practices for different regions,

for example, see: Department of Energy and Climate Change (2011) and Department for Business, Energy and Industrial Strategy (2019). The decommissioning project activities will be executed by different stakeholders and there must be a coordination of all the tasks assigned to them to ensure the project is executed on time, within budget and in line with the standards required (Kerkvliet and Polatidis, 2016). The standard processes are from planning to component waste management and the process is assessed for potential risks that may arise (Gjødvad and Ibsen, 2016).

3.2.1 Decommissioning activities

Wind farm decommissioning projects are composed of a number of activities and depending on the scale of the wind farm and the size of the wind turbines, the workflow may be adjusted on a case-by-case basis. These activities, from the planning and documentation phase to the post-decommissioning phase, are all shown in Figure 3-3.

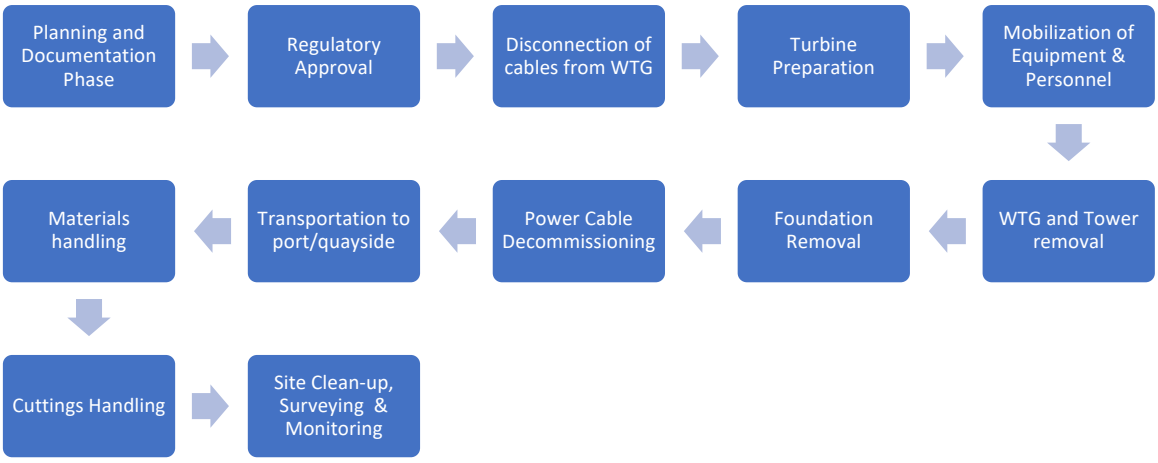

Figure 3-3 Decommissioning task workflow (Department of Energy and Climate Change, 2011; Gjødvad and Ibsen, 2016).

The decommissioning activities must be planned for, as much as reasonably practicable, well in advance before the offshore wind farm is commissioned at the initial phase of the project lifecycle. The transportation methods during decommissioning should be factored into the engineering design, especially for possible transportation mechanisms of removed components (Castro-Santos,

2016). Due to the time gap between commissioning and decommissioning, different factors relating to the engineering and regulatory plans, cost, time to decommission, and disposal options are likely to change, and the models used for the initial estimations must be flexible enough to accommodate those changes. A report by the U.S. Department of Energy (2012) discussed the environmental impacts of offshore wind farm decommissioning activities. Gjødvad and Ibsen (2016) developed a decommissioning process optimisation tool called the ODIN-WIND to assist in decision-making of the necessary activities for a typical decommissioning project in order to develop an appropriate workflow and make changes whenever needed. In a study by Topham and McMillan (2017), a general decommissioning process breakdown for offshore wind farms was presented and the decommissioning activities were divided into three categories including: project management, planning and procurement (PPP), operations, and post decommissioning.

Before a wind farm project is approved for commissioning, a plan for all lifecycle phases including the decommissioning phase must be submitted to the appropriate regulatory body for approval. The decommissioning programme is then revisited and reviewed at scheduled times within the project lifecycle, the last being about two years before decommissioning is to take place, depending on the specificities of the wind farm project. At these scheduled times, a number of cost elements are subject to change, as expected due to different factors like vessel hire rates, capacity and availability, weather windows, and other elements that may be affected by inflation, etc. (Irawan *et al.*, 2019).

3.2.2 Decommissioning strategies

The appropriate decommissioning strategy chosen is dependent on financial, safety, socio-economic, environmental, and technological factors. The current decommissioning strategies include removal (complete or partial) for reuse, recycling, and repurposing (e.g. reef) of the entire wind turbines or the components (Statoil, 2014). Partial removal involves removing some components and leaving some others in place like the foundation piles and the cables. Due to regulations in place, however, only certain components can be left in-place

because of peculiar reasons like excessive cost to decommission and potential environmental impacts. Within these strategies, removal options also need to be determined like single lift or piece-meal removal, which are done with different types of vessels and cranes like lifeboats, jack up barges, self-propelled installation vessels (SPIV), etc.

3.2.3 Decommissioning standards, guidelines and recommended practices

The regulatory standards, guidelines and best practices for offshore wind farm decommissioning are based on existing standards for the marine environment or some adopted from other industries like the oil and gas industry, including United Nations, 1982; Department of Trade and Industry, 2006; OSPAR Commission, 2006; Januário *et al.*, 2007; Statoil, 2014; Smyth *et al.*, 2015:

- International Maritime Organisation (IMO) guidelines
- Standards for removal of offshore installations and structures on the continental shelf and in the exclusive economic zone (1989)
- Convention on the prevention of marine pollution by dumping of wastes and other matter, 1972
- United nations convention on the law of the sea (UNCLOS) 1982
- Convention for the protection of the marine environment of the north-east Atlantic (OSPAR) decision 98/3 guidance notes
- Best practicable environmental option (BPEO)
- OSPAR guidance on environmental considerations for offshore wind farm development 2008-3 (OSPAR OWF guidance)
- Review of the current state of knowledge on the environmental impacts of the location, operation and removal/disposal of offshore windfarms, OSPAR commission (2006)

Regional standards, guidelines and best practices are listed as follows Department of Trade and Industry, 2006; OSPAR Commission, 2006; Department of Energy & Climate Change, 2011:

EU

- Environmental impact assessment (EIA) directive (85/337/EEC)
- Habitats directive (92/43/EEC)

UK

- Decommissioning of offshore renewable energy installations under the Energy Act 2004: Guidance notes for industry, Department of Trade and Industry (DTI) (2011)
- UK Department for Energy and Climate Change guidance on waste management
- Health, Safety and Environment (HSE)

USA (Kaiser and Snyder, 2012):

- Code of federal regulations (CFR) (Title 30, part 285, Subpart I, 285.900-913)
- European Union waste legislation (Cherrington *et al.*, 2012):
- Landfill Directive (1999/31/EC)
- End of life vehicles (ELV) Directive (2000/53/EC)
- Incineration of waste Directive (2000/76/EC)
- Waste electrical and electronic equipment (WEEE) (2002/96/EC)
- Waste Framework Directive (2008/98/EC)

3.3 Decommissioning cost estimation

3.3.1 Overview of decommissioning cost estimation literature

Decommissioning cost estimation includes the quantitative assessment of all the likely costs involved in decommissioning of a project. In offshore wind farm projects, although estimated decommissioning costs are accounted for in the application document before any approval is granted at the early stage of a project, this does not present an accurate picture of the true cost at the end of life of the wind farm assets. This is because cost estimates are based on a number of factors including the time at which estimation is done and the amount of information available. One major factor is the uncertainty of several elements surrounding decommissioning such as the uncertainty about the time that

decommissioning is anticipated to take place, the decommissioning process, the weather window for execution, options available for decommissioning, etc. Although many countries ensure that the decommissioning liability rests on the asset owner, both the asset owners and the government need to know how much of a liability the assets will be at the end of their asset lifecycle. Regulators require that asset owners/operators have the capacity to meet the financial obligations for decommissioning. In order to ensure the financial security is adequate, reliable decommissioning cost estimates have to be submitted.

Many companies keep their proprietary information about the cost of their projects and there is no standardised method for decommissioning cost estimation (Ferrell and DeVuyst, 2013). If the remaining useful life of wind turbines is very uncertain, accounting for when decommissioning is required to take place will also be very uncertain. Other reasons for uncertain costs include the time value of money, changes in initial assumptions used in the cost estimate, changes in demand and supply of resources required for the decommissioning campaign, changes in technical and technological capabilities in industry, etc. The project lifespan of wind turbines is often between 20-25 years. Some wind farms are decommissioned earlier or later depending on the availability of parts to repair or repower the wind turbines. The lifecycle cost estimation for a project determines the investment necessary and the levelized cost of electricity (LCOE) during operation. The cost of decommissioning is first estimated at the initial phase of the project planning before operations. The lifecycle cost includes the initial estimated decommissioning costs so that financial provisions can be adequately planned for using the profits from the projects over the number of years in operation. The study by Shafiee *et al.* (2016) was the first publication which included detailed decommissioning cost estimates in lifecycle cost analysis of bottom-fixed offshore wind farms. Another study by Ioannou *et al.* (2018) presents a lifecycle model for offshore wind farms. The study presents mathematical models for different modules including the capital expenditure (CAPEX) module and the operating expenditure (OPEX) module considering decommissioning and disposal costs.

The overall decommissioning cost is estimated on a case-by-case basis and the costs are incurred from the moment planning begins because the buy-in of all stakeholders is crucial. The cost effectiveness of the procedures and practices used to maintain aging facilities and any strategies adopted at the EOL of offshore assets is critical to the overall decommissioning cost. A number of documents were reviewed in this study to gain a broad perspective of the processes and activities involved in decommissioning of offshore wind farms. Studies by Kaiser and Snyder (2011, 2012b) used a bottom-up model to estimate decommissioning costs, which were seen to make up about 3% to 4% of the CAPEX. The removal cost of the wind turbine, foundation, cables, substation and met tower, scour protection, site clearance and material disposal were calculated, and a case study was used to present the application of the cost estimation models. The approach used in the study was based on the associated cost for each task. The models did not consider the costs associated with regulatory approval, insurance and some other costs. Decommissioning costs are presented as a percentage of installation cost in Myhr *et al.* (2014) when estimating the LCOE from offshore floating wind turbines.

Gjødvad and Ibsen (2016) presented a tool called ODIN-WIND tool for decommissioning cost estimation in offshore wind farms. The decommissioning cost estimates included different activities including: planning and engineering, decommissioning design, contingencies and other major processes usually carried out in decommissioning. The study, however, did not present the procedure for estimation. A more recent publication by Hinzmann *et al.* (2018) discusses the current methods for decommissioning of bottom-fixed offshore wind farms and proposes a number of solutions. The adoption of these improved methods may result in a decrease in decommissioning costs; however, the study did not focus on effects of procedure improvements on overall decommissioning costs. The impacts of decommissioning and some of its cost implications - like the option to remove cables or keep them in place – were discussed briefly in a study by Januário *et al.* (2007).

A study by Castro-Santos and Diaz-Casas (2014) used a cost breakdown structure (CBS) methodology to estimate the lifecycle cost for an offshore floating wind farm. Although this study did not focus on bottom-fixed structures, it captured dismantling costs, which informed some cost elements considered in this study. The total cost of each major dismantling activity was grouped into port, transportation and removal costs. The study, however, left out overhead costs like planning and regulatory permitting costs, which make up a significant portion of decommissioning costs. Another study by Castro-Santos *et al.* (2018) captured the available lifting methods and installation strategies that may be used during decommissioning for removal, transportation and port handling in offshore deepwater locations. Different criteria for selecting the alternative options for decommissioning methods were presented in Kerkvliet and Polatidis (2016). It included economic criteria, which encompassed the removal cost, monitoring and maintenance costs of the items left in place. They evaluated economic criteria (for both partial and complete removal) as well as environmental and social criteria.

In another study by Irwan *et al.* (2019), a wind farm schedule optimisation model was developed with the aim of reducing decommissioning costs, with time and costs being the most critical project constraints. Also, after the EOL strategy has been decided upon, the decommissioning method is proposed to be selected using a multi-criteria decision analysis (MCDA) technique by taking into consideration all economic, technical, safety and social criteria (Kerkvliet and Polatidis, 2016). Therefore, all cost assumptions and risks must be adequately managed during the decommissioning phase. The qualitative descriptors of an installation project are the wind farm power output/capacity, turbine capacity and distance from site to port/shore; whereas, the qualitative descriptors for a decommissioning project are the water depth, weight of turbines, distance to port, vessel capacity and availability, and the transportation strategy (Kaiser and Snyder, 2011).

The cost estimation of decommissioning activities is majorly based on the cost of the vessel and the vessel strategy adopted for removal and transportation. The

optimal strategy selected may be based on different criteria like the types of vessels available from suppliers, type of contract signed for vessel hire (voyage, time or bareboat charter agreements). The type of contract will influence the cost estimates for the vessel dependent activities as some include the cost of mobilisation, vessel operating costs, fuel, crew, voyage costs, etc. Other factors for vessel selection considered in that study include vessel specifications depending on the water depth, weather conditions for the vessel to carry out removal operations as seen in the study by Dalgic *et al.* (2015). Another research on transportation cost reduction is conducted by Faiz (2014), which estimates transportation and installation time using a developed model, which may be translated into decommissioning cost.

The waste management methods used for decommissioned components of offshore wind farms have been explored in some studies in the past. All the removed components need to be adequately disposed of in the most regulatorily efficient manner. Although many components which are made out of steel can be easily recycled, wind turbine blades are difficult to manage; in particular as because they are primarily manufactured from composite materials. Even with the EU legislations surrounding waste management, disposal alternatives for composite materials are difficult to adopt due to the cost and market restrictions on the by-products obtained from recycling composite materials. The cost associated with recycling of components can be challenging to estimate due to market changes that make prediction of components' salvage value, landfill costs, and labour costs more uncertain. The rule of thumb for blade recycling cost is 6% of the total waste management cost. On the other hand, the landfill costs will be based on the regional landfill tax laws (Pickering, 2006; Guezuraga *et al.*, 2012; Cherrington *et al.*, 2012). Uncertainty in the market value of scrap components makes the salvage values difficult to estimate during decommissioning cost analysis (Ferrell and DeVuyst, 2013).

The waste management is the main activity that many studies have considered in decommissioning environmental impact assessment. However, our review shows that very few studies have focused on the environmental footprint of the

entire decommissioning process. With potential changes to marine legislations to reduce the carbon footprints from shipping/marine operations, some of the costs involved in decommissioning may be impacted. This is because the vessel owners will likely transfer the costs to the asset owners, who will have to pay more than the estimated costs for hiring the vessels. Demir and Taskin (2013) studied the environmental effects of wind turbines throughout their lifecycle. A Lifecycle Cost Analysis (LCA) was performed for 15 different wind turbine alternatives based on their hub height and power output capacity. The evaluation was grouped into two categories for manufacturing and operation, and decommissioning and recycling management. The authors assumed that only 90% of steel will be recycled while the other 10% of metals, concrete and other materials are landfilled, using this to estimate the energy payback throughout the lifespan of the wind farms. In a study by Kaiser and Martin (2009), the cost of site clearance is estimated for the Gulf of Mexico offshore continental shelf (OCS). The study details the factors that may affect site clearance costs during decommissioning, including the nature of debris at the site, location, weather influences, equipment and removal methods used, etc. Overall, the cost of alternative clearance techniques determines the method selected by the asset owners. The authors presented a simple mathematical model for estimating the total cost of site clearance and calculated its duration using regression models from historical clearance data in that location. The authors observed that the highest cost contributors to the site clearance included the vessel hire cost, crew cost, and type of trawling net selected. Although this was applicable to offshore oil and gas fields, a similar method may be used for offshore wind farm applications.

Overall, the decommissioning cost is highly influenced by the operators' current focus on time-efficient methods due to rigid regulatory requirements to decommission within the same time window (2 years after receiving the consent to decommission) regardless of wind farm size. A focus on time-efficiency while ignoring cost-efficiency will lead to higher costs than necessary. Newer alternatives for wind turbine and foundation removal have been proposed using the felling method and the float-tow method, respectively. The cost of cutting the

recyclable components (e.g. steel) needs to be weighed against the salvage value to be obtained (Kaiser and Snyder, 2012). An optimisation tool called Mermaid® was developed in a study by Morandeau *et al.* (2013) to reduce the time for marine structures installation. The cost is estimated based on the vessel costs, accommodation costs and port fees. The tool is applicable to tidal wave installations but has the potential to be adopted for offshore wind energy decommissioning purposes.

3.3.2 Decommissioning cost estimation techniques

There are several cost estimation tools and techniques including expert judgement, analogous estimating, parametric modelling, bottom-up analysis, three-point estimating, data analysis, project management information system and decision making by voting (Project Management Institute, 2017). Each decommissioning activity incurs a direct or indirect cost and in order to meet all the decommissioning project criteria, these cost elements must be analysed and managed appropriately. A Department for Business, Energy and Industrial Strategy (2018) report developed by ARUP was based on confidential operator data. The report presented a decommissioning framework in order to determine the assumptions for which uncertainty can be reduced. Some of the key cost factors identified include: the cost of removal workboat, execution time and the number of turbines to be removed. In the report the decommissioning costs have varying ranges because of the uncertainties associated with the different activities involved. However, the transmission assets were excluded from the decommissioning cost estimates.

In another study by Topham and McMillan (2017), a decommissioning process breakdown framework was presented and the duration and cost for decommissioning activities were estimated. The study only considered removal of wind turbine generators (WTG) and foundations and excluded transmission assets, overhead costs (planning and regulatory approval costs), waste management and post-decommissioning costs. The study focused on determining the optimal transportation approach by comparing three methods for transporting removed components, including the use of a removal vessel and two

combinations of removal and transport vessels. It was concluded that using two wind turbine installation vessels simultaneously would result in the most cost-effective transportation approach for the wind turbine decommissioning. In the near future, increasing turbine capacity will lead to bigger turbines, which will make transportation a lot more difficult in the coming years. Therefore, attention must be paid to providing state-of-the-art logistics solutions to the offshore wind industry.

In Shafiee *et al.* (2016) and Kaiser and Snyder (2011, 2012b), lifecycle cost (LCC) analyses were performed, accounting for costs that are incurred during the decommissioning phase. Shafiee *et al.* (2016) addressed the primary decommissioning cost elements within the analysis including port rental, removal, waste management, site clearance and post-decommissioning costs. Kaiser and Snyder (2012b) used empirical studies to estimate the cost of decommissioning for offshore wind turbine projects using a bottom-up approach. The authors proposed that since decommissioning costs are uncertain, if the contributing uncertain parameters can be better understood and studied, there will be an opportunity to reduce the cost of the most sensitive factors/parameters. The study detailed cost models for wind turbine and support structure removal considering different vessel logistics strategies, cable removal based on installation rates adjusted for inflation, substation and met tower removal based on the vessel costs, scour protection removal based on the cost/m^3, site clearance cost, and disposal costs (based on salvage value, processing, landfill, and transport costs). Each cost element was estimated using different case studies; however, no case study was used to estimate the expected planning and regulatory approval cost, work contingencies like equipment breakdown. The authors recommended analysis that refrains from decommissioning cost estimations per wind turbine or MW capacity, since many factors like wind turbine physical properties may influence the engineering approach for removal. Nonetheless, the authors conclude that the decommissioning cost estimation is still fundamentally uncertain.

3.4 Cost breakdown structure (CBS)

A CBS for the decommissioning process is developed based on the work breakdown structure (WBS) in order to highlight the main cost issues that need to be focused on during project execution in a systematic manner. One main difference between cost estimate for a decommissioning project and those of other engineering construction projects is that decommissioning is not primarily intended for profitability. Thus, since it is not income-generating, care must be taken to minimise cost whilst ensuring safety and environmentally conscious execution.

The aim of this study is to identify and analyse the cost elements to determine all factors influencing decommissioning project costs for offshore wind farms and to identify the factors critical to cost reduction. It is used to present each phase within the decommissioning process that contributes to the total decommissioning cost estimate. The costs can be direct or indirect, fixed or variable. Direct costs are costs accrued as a direct result of the activities or tasks performed; whereas indirect costs arise from other overheads necessary to cover expenses in a project. Fixed costs are those that remain unchanged regardless of amendments during the project execution; whereas variable costs are flexible due to the influence of different factors like the market demand or labour costs. The major cost drivers can be updated in the model so as to take into account the changes in decommissioning cost factors at the time of project execution. As illustrated in Figure 3-4, the wind farm decommissioning project consists of four primary phases which are broken down into subtasks. The cost information of phases and subtasks are used to develop the CBS. The total decommissioning cost for an offshore wind farm equals summation of the costs of planning and regulatory approval phase, execution phase, logistics and waste management phase, and post-decommissioning phase. Therefore,

$$\sum_{t=0} C_{decom-total} = \sum C_{P\&RC} + \sum C_{EX} + \sum C_{Lo\&W} + \sum C_{POST-D} \quad , \qquad \textbf{3-1}$$

where $C_{decom-total}$, $C_{P\&RC}$, C_{EX}, $C_{Lo\&D}$ and C_{POST-D} represent the total decommissioning cost, cost of planning and regulatory approval, execution, logistics and waste management, and post-decommissioning, respectively. As

the execution of offshore wind farm decommissioning projects may take some time, the Net Present Value (NPV) method can be used to incorporate the time value of money. The NPV equation is expressed as follows:

$$NPV = \sum_{t=0}^{T} \frac{R(t)}{(1+r)^t} \quad , \qquad \textbf{3-2}$$

where $R(t)$ is the net cash flow of the decommissioning project in a given year t, r(>0) is the discount rate and T is the time to complete the decommissioning project.

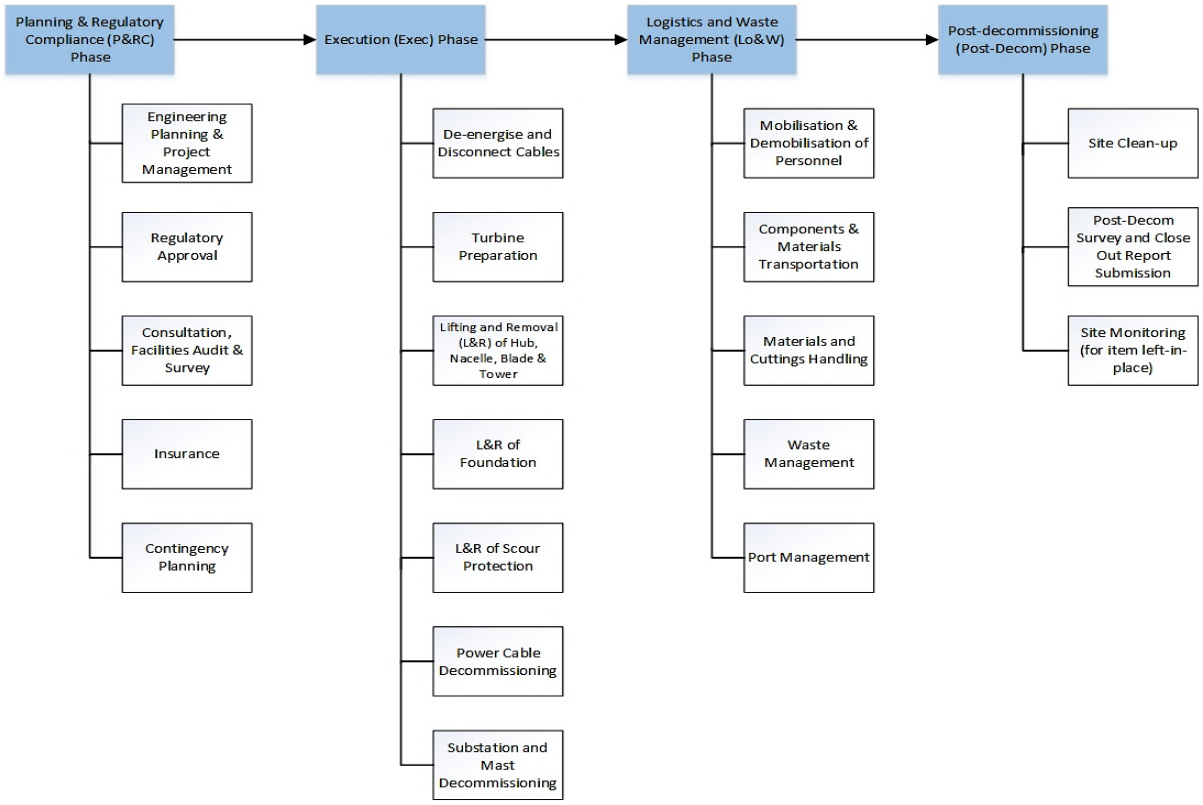

Figure 3-4 Cost breakdown structure (CBS) for decommissioning of offshore wind farms

Table 3-2 summarises the cost elements that were identified for different decommissioning activities. Some cost functions may be fixed or variable, and some may be subject to changes due to policy changes or market fluctuations.

Table 3-2 The cost elements involved in wind farm decommissioning process

Decommissioning activity	**Cost elements**
Engineering planning, project management and documentation	Engineering designs, contractor and vendor fees, time-to-execution, EIA studies required, A_{WF}, r_{survey} (survey radius), $N_{consult.}$ (marine agency/organisation, vendor consultation, other groups/workshops), insurance premium, facility structural integrity and engineering works required before execution, project management percentage, contingency provisions (based on scale of project).
Regulatory approval	A_{WF}/ N_{WT}, $N_{revision}$, $N_{permits}$, $N_{consult.}$,
De-energise and disconnect cables from the wind turbines	N_{OSS}
Turbine preparation	N_{WT}, N_{OSS}, N_k , N_{WB}, type of vessel support (helicopter, workboat)
Mobilisation of equipment and personnel	Type of vessel contract (turnkey or day rate), N_V, N_k, types of equipment required
Wind turbine, tower and transition piece removal	$t_{removal}$, N_V, transportation strategy
Foundation removal	Time for removal, type of foundation
Power cable decommissioning	Burial/removal rate, burial depth, seabed soil type, length of cables
Transportation to port/quayside	D_{port}, v_{speed}, N_V
Materials handling	Recycling facility availability, crap rate/tonne of materials
Cuttings handling	waste processing facility, waste processing cost/tonne
Site clean-up and surveying	$r_{clear.}$ (clearance radius), r_{survey}, N_V, $N_{personnel}$, types of equipment required
Monitoring	number and nature of facilities left in-place

Each of the decommissioning phases are explained in the following subsections:

3.4.1 Planning and regulatory compliance phase

3.4.1.1 Engineering planning and project management

Engineering planning involves the organisation of all the leasing, technical, purchase and contractual requirements for the decommissioning project. Project management will continue throughout the decommissioning project in order to create and monitor all project tasks and ensure that milestones are met on schedule to the required standards and are within the designated budget. Provisions for engineering planning and project management are critical as the risks posed by the project execution may be identified and duly addressed, contracts agreed, tasks scheduled, and costs assigned to all stakeholders. Engineering planning also involves performing environmental risk assessments and the identification of risk responses required during execution, where the risk management approaches are reviewed for cost-effectiveness (Association of Project Management, 2019; Statoil, 2014). In many cases, project management costs are calculated as a percentage of the overall decommissioning cost. Since a decommissioning project involves inputs from different contractors, suppliers and vendors, the project team ensures that task execution is well managed for delivery. The project management plans for the scope, resources, cost, schedule, quality and risk are inputted into the cost estimations and then used to update the project documents. The contracts for different work phases and equipment and vessel hires have to be accounted for. The project management cost is expressed by the following equation:

$$C_{PM} = \beta \cdot C_{decom-total} \quad , \qquad \textbf{3-3}$$

Where: C_{PM} is the project management cost and β represents the planning and project management percentage of the total decommissioning cost. In this study, it is assumed to be 6% of the total decommissioning cost based on the Statoil (2014) report, but it may be subject to changes depending on conditions.

3.4.1.2 Regulatory compliance

There have been a number of guidelines related to decommissioning activities in the renewables sector at both international and national levels. Some of these regulations refer to offshore marine installations in general. In a study by Smyth *et al.* (2015), the regulatory decommissioning framework for different decommissioning options are presented. In the UK, the Department for Business, Energy and Industrial Strategy [formerly known as the Department of Energy and Climate Change (DECC)] published guidance notes for the decommissioning of offshore structures (Department of Energy and Climate Change, 2011). This guideline clearly spells out the responsible parties for wind farm asset decommissioning. The local and international legislation must be strictly adhered to by the asset owners and regulatory approval for a decommissioning programme obtained from the DECC through a 7-stage process. It is recommended that decommissioning discussions begin at the initial planning and consenting stage for installation during which the programme draft and the environmental impact assessment are submitted to the Secretary of State. There is a model framework for the initial decommissioning programme and inputs from all stakeholders are necessary to avoid problems during the decommissioning execution phase. The stakeholders include the fishing industry and other sea users, the maritime and coast guard agency, environmental protection agencies, etc. Notifications must be made to other agencies like the mariners and fishermen's organisations to inform them of the upcoming decommissioning activities and to receive their inputs. All necessary permits for use of the sea will need to be processed for all the activities planned. Regulatory approval applications for decommissioning campaigns vary from region to region and must include details about the assets to be decommissioned, the proposed schedule of activities, removal techniques and procedures, resources required, an Environmental Impact Assessment (EIA) and the assumptions used in all work schedules, safety and cost estimates. If approval is not granted by the regulator when the decommissioning programme is initially submitted, revisions will have to be made before resubmission for approval. Figure 3-5 illustrates the flowchart

for the planning and regulatory compliance phase presented for the first time in this study.

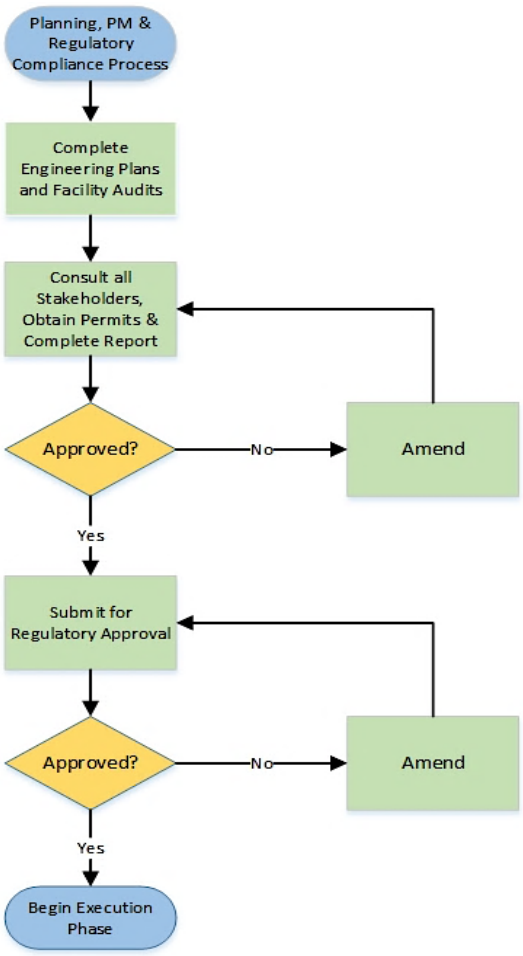

Figure 3-5 A flowchart for planning and regulatory compliance phase of the decommissioning process in offshore wind farms

The cost elements associated with planning and regulatory compliance phase are expressed as follows:

$$\sum C_{P\&RC} = C_{E-Plan} + C_{PM} + C_{Conting.} + C_{Consult} + C_{Audit} + C_{EIA-Survey} + C_{amend.} + C_{RA} + C_{Permit} + C_{insure} \quad \textbf{3-4}$$

where C_{E-Plan}, $C_{Conting.}$, $C_{Consult}$, C_{Audit}, $C_{EIA-Survey}$, $C_{amend.}$, C_{RA}, C_{Permit} and C_{insure} are the costs of engineering planning, contingency, consultation, facility

audit, EIA survey, amendment expenses, regulatory approval, permit and insurance, respectively.

The regulatory approval fee guidelines for approving and revising oil and gas asset decommissioning programmes are publicly available, but no regulatory approval fee is currently paid for wind farm asset decommissioning in the UK but it may change in the future (Offshore Petroleum Regulator for Environment & Decommissioning, 2013; Department for Business, Energy and Industrial Strategy, 2019b). Using the oil and gas fee structure, it can be assumed that wind farm decommissioning fees are also structured in either of the following forms:

$$C_{RA} = (K * N_{WT}) + C_{revision} \quad \textbf{3-5}$$

$$C_{RA} = (K * A_{WT}) + C_{revision} \quad \textbf{3-6}$$

where K is an indicative fee for different wind farm sizes (adapted for OWF fee structure and payment from Offshore Petroleum Regulator for Environment & Decommissioning (2013)), N_{WT} is the number of wind turbines or the wind farm capacity, $C_{revision}$is the cost of revision and $A_{WT}$is the area of the wind farm.

3.4.1.3 Contingencies

Contingency planning is required in order to allow for changes in the schedule or any additional work that was not previously accounted for. Since offshore wind farm decommissioning is a new activity relative to oil and gas decommissioning, the contingency estimates cannot be roughly estimated yet for different wind farm capacities. As wind farm operators and contractors become more experienced, less contingency allocations may be required due to some reduced uncertainty. It may be grouped into work contingencies and wait-on-weather (WoW) to make allowances in the event of changes in vessel spread costs, workflow modifications, and bad weather conditions. When estimating costs, the work contingencies often make up about 10% of total decommissioning cost depending on the type of wind turbines and the distance from shore. The WoW makes up around 20% of the total decommissioning cost, both are calculated with excluding the mobilisation and demobilisation costs. Thus, the contingency cost

is estimated to be around 8% to 30% of the base cost of decommissioning as a guide (Statoil, 2014; Kaiser and Liu, 2015), which can be determined on a case-by-case basis based on future industry experience. In this study, the contingency cost is expressed as:

$$C_{conting} = \alpha \times C_{decom-total} \quad \textbf{3-7}$$

where α represents the percentage of WoW and other work contingencies related to schedule changes and unplanned works.

3.4.2 Execution phase

After the reviewed decommissioning plan is approved and all contractual and legal documentations are signed, the activities will then be executed by all necessary parties. Project management will be ongoing at this stage to ensure that tasks are safely completed to budget, schedule and standard requirements. The contingency plan and budget will also be continuously revisited at different milestones at the execution phase. Some activities are spaced out months apart, depending on the schedule and the availability of removal facilities. The activities at this phase may be carried out a few years before structure removal. The cost of this stage is sum of the cost of activities involved. Therefore, the execution cost is represented by the following equation:

$$C_{EX} = C_{Disc.} + C_{prep.} + C_{L\&R} + C_{OSS-decom} + C_{cable\ decom} \quad \textbf{3-8}$$

where $C_{Disc.}$, $C_{prep.}$, $C_{L\&R}$, $C_{OSS-decom}$ and $C_{cable\ decom}$ are the cost of disconnection of wind turbines from the grid, cost of wind turbine preparation for removal, cost of lifting and removal of wind turbines, tower, support structures, foundations and scour protection, and cost of cable decommissioning (inter-array and export), respectively. These costs are explained in details in below subsections.

3.4.2.1 Disconnection of wind turbines from the grid

Disconnection of wind turbines from the grid is the first activity in the decommissioning execution phase. It ensures that transmission of power from the wind turbines to the substation is stopped, the turbines are deenergised and

electrically isolated, and the inter-array cables are disconnected. This task involves personnel cost and offshore workboat cost.

3.4.2.2 Preparation of wind turbines for removal

The wind turbines are prepared for removal by extracting the lubricating fluids and other harmful materials from the wind turbines' nacelle. This waste will be transported to shore for adequate handling to specified standards. The activities carried out are done to make the removal process as safe as possible; hazards are identified, and preventive actions are taken to address them at the decommissioning stage. Other preparation activities include rotor reorientation, ventilation of airtight platform, removal of the elevator in the tower, removal of marine growth on the foundation structures or scour mattresses, draining the substation of the oils or resins contained and fitting or welding lift point fixtures on the monopile, substation topsides and masts, and installation of navigational lights and markings (this will ensure that obstructions during and after decommissioning are visible to prevent navigational hazards) (Statoil, 2014; Topham and McMillan, 2017). The cost of preparation of wind turbines for removal is given by:

$$C_{prep} = (N_i * C_{i/day} * t_{prep}) + \left(C_{fixt./unit} * N_{fixt}\right) + (N_k * C_{k/day} * t_{prep}) + C_{Nav-mark} + C_{eqt/day} \quad \textbf{3-9}$$

where N_i is the number of vessels required (*i*=1: workboat, *i*=2: jackup, *i*=3: helicopter, *i*=4: other vessels such as heavy lift vessels (HLV), offshore support vehicles (OSV), barges, etc.) (GL Garrad Hassan, 2013), $C_{i/day}$ is the daily rental rate of each vessel, t_{prep} is the time taken to complete all subtasks such as draining the lubricating fluids ($t_{WT-drain}$), marine growth removal ($t_{MG-remov.}$), offshore substation draining ($t_{OSS-\,drain}$) and the pre-decommissioning survey ($t_{pre-survey}$), $C_{fixt/unit}$ is the cost of fixtures required for each unit (wind turbine or support structure), N_{fixt} is the number of fixtures, N_k is the number of personnel, $C_{k/day}$is the labour cost per day, $C_{Nav-mark}$ is the cost of navigation markings (similar to installation) and $C_{eqt/day}$ is the equipment cost per day.

3.4.2.3 Lifting and removal of wind turbines

Lifting and removal of the wind turbines require cutting and lifting of all components including the blades and hub, nacelle, tower, support structure, foundation, and cables. Lifting and removal methods include single lift and piece-wise lifting. A decision will be made on the transportation strategy (single vessel which is known as pendulum method and the multi-vessel/collector option). This decision will inform the number of vessels, type of vessels and equipment (e.g. cranes) required, and the lift method will be chosen based on the most time and cost-effective option. The disassembly of wind turbine blades, the hub, nacelle and tower and the deconstruction of the transition pieces require different types of vessels with different capacities depending on the size (capacity and weight) of the wind turbines to be decommissioned, number of wind turbines and the water depth. Unlike the nuclear or oil and gas facilities decommissioning, the wind turbines require the lifting and removal of many more components. Thus, efficiency gains in this process will have a positive impact on the costs related to this activity. An in-depth study of possible efficiency gains in lifting and removal will be beneficial. Currently, the strategies for lifting and removal include: single vessel or multi-vessel methods (Kaiser and Snyder, 2012; Statoil, 2014; Topham and McMillan, 2017).

The types of vessel for removal include tug boats, lift barges, mechanical dredges, HLV, OSV, jack up vessels or SPIVs, etc. (Uraz, 2011). The vessel types will be decided based on the transportation strategy, which is a function of the most ideal removal option, distance to the port (D_{port}), number of lifts (N_{lifts}), estimated total weight (W_{total}), weight per lift (W_{lift}), vessel capacity required ($V_{capacity}$), number of vessels required (N_V), number and duration of trips to and from port - including loading and offloading time (N_γ and t_γ), and activity durations (t_j). The lifting and removal vessel and equipment cost is based on fixed vessel rental costs and daily hire rates ($C_{i/day}$) and the above-mentioned cost functions.

Cutting methods include internal or external abrasive water jetting, oxy-flame cutting, diamond wire cutting, explosives, laser cutting, “felling” of the wind turbine structures by using internal or external cutting methods (which reduce or remove

the need for a specialised vessel), etc. There are also different lifting and removal options that can be adopted from the wind turbine installation methods like the bunny ear and tower in one piece, hub and tower in one piece, etc. (Kaiser and Snyder, 2012; Gjødvad and Ibsen, 2016; Paterson *et al.*, 2018; Castro-Santos *et al.*, 2018). The total lifting and removal cost for the lifting and removal activity and transportation of removed components is represented by the following equation:

$$C_{L\&R} = (N_i * C_{i/day} * t_j) + (N_\gamma * C_{i/day} * t_\gamma) + (N_k * C_{k/day} * t_j) \quad \textbf{3-10}$$

where N_i is the number of vessels required, t_j is the time taken to complete all subtasks, N_γ is number of trips required to shore and t_γ is the distance to and from shore. The time required to complete all lifting and removal tasks (t_j) is expressed by Equation 3-11 as below:

$$t_j = t_{L\&R-WTG} + t_{L\&R-B\&N} + t_{L\&R-T\&TP} + t_{L\&R-found.} + t_{cable-decom} + t_{L\&R-misc.} \quad \textbf{3-11}$$

where $t_{L\&R-WTG}$ is the time required for lifting and removal of wind turbines, $t_{L\&R-B\&N}$ is the time required for blade and nacelle removal, $t_{L\&R-T\&TP}$ is the time required for tower and transition piece removal, $t_{L\&R-found}$ is the time required for foundation removal, $t_{cable-decom}$ is the time required to decommission inter-array and export cables, and $t_{L\&R-misc.}$ is the time required for lifting and removal of miscellaneous components like concrete mattresses, scour protection, rocks, etc.

Some durations involve further subtasks. For example, $t_{L\&R-WTG}$, $t_{L\&R-B\&N}$, $t_{L\&R-T\&TP}$ involve time to set-up, lift, jack down (if jack-up is used) and time to move to another wind turbine. $t_{L\&R-found}$ involves time to stabilise, pump, cut and lift foundation, and time to move to another foundation.

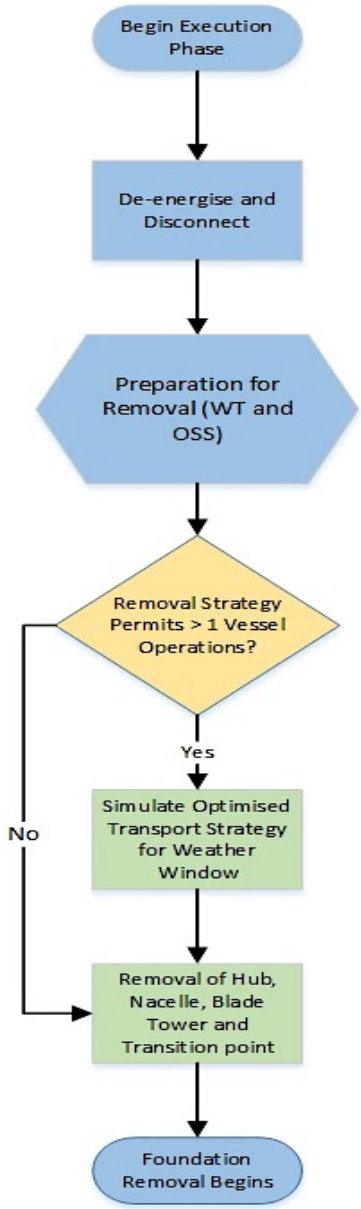

Figure 3-6 A flowchart for execution phase of the decommissioning process in offshore wind farms.

Depending on the type of logistics strategy, one or more vessels will be used for the lifting and removal activities and this decision is shown in the workflow chart in Figure 3-6. This must be analysed to determine the most cost-efficient strategy to use when more than one vessel is used. The total lifting and removal cost and time will depend on the size of the wind farm (A_{WF}) and the number of wind turbines (N_{WT}). Therefore, the contracts and procurement department has the responsibility to make well-informed decisions for the optimal vessel charter

contract for reduced cost and time. One way to do so is to use software in determining the weather window for operations.

The type of foundation is a major consideration when planning the removal of foundation. There are different foundation types used for offshore wind farm installations. There are either fixed-bottom (such as monopile, tripod, jacket, concrete gravity-based structure (CGBS)) or floating (such as tension-leg platform (TLP), spar-buoy and semisubmersibles). The type of foundation and its weight are usually correlated with the water depth and they determine whether the foundation will need to be completely or partially removed. The fixed-bottom structures must be cut to the regulatory-required depth (4.6m/15 ft). The floating foundations can be detached from the mooring lines (which attach them to the seabed) and transported to shore. Different foundation removal concepts are introduced in Gjødvad and Ibsen (2016). The water depth (WD) and installation method can be a good guide to decide on the foundation removal method to use. Removal of the foundation and offshore substation piles requires different methods similar to the cutting techniques as mentioned above (like internal or external cutting) or other removal techniques like vibration, internal dredging, external water jetting, pressurised air technique, and the use of buoyancy forces (Hinzmann *et al.*, 2018).

The flowchart for foundation removal is presented in Figure B-1 (A) of the Appendix section. As seen in Table 3-3 the foundation removal method may be the cut-lift-carry (CLC), lift-float-tow (LFT) or detach-tow (DT) method. Monopiles are mostly removed partially, using jack-up (JU) barges or HLVs and cranes for lifting and removal operations and tow boats for transportation. For complete removal, dredging vessels may be required (Ontario Ministry of the Environment and Climate Change, 2016).

Table 3-3 Removal options and methods for different types of wind turbine foundations (Ontario Ministry of the Environment and Climate Change, 2016; Gjødvad, 2016)

Foundation type	Typical removal option	Removal method
Monopile	Partial/complete	CLC/LFT

Tripod	Partial/complete	-
Jacket	Partial/complete	CLC
Suction bucket	-	LFT
CGBS	complete	LFT
Floating	complete	DT

3.4.2.4 Offshore transmission owner (OFTO) assets

Offshore transmission owner (OFTO) assets include the offshore substation platform and the inter-array and export cables. These assets are quite complex and therefore estimating their decommissioning costs is not an easy task. The offshore substation is the collection point of the power generated on the wind farm before it is transferred to the grid. This is typically made up of the topsides and the foundation and may be one or more per field depending on the size of the wind farm. The masts are put in place for signalling transmission and to notify other sea users of the installations in place. The flowcharts for removal of the assets in this group are presented in Figure B-2 (A) of the Appendix section.

3.4.2.4.1 Offshore substation decommissioning

Offshore substation (OSS) decommissioning includes the removal of the topsides and foundation and the transportation of the modules to the port. The factors that can affect the offshore substation decommissioning costs are the vessel requirements, water depth, distance to port, pile diameter and wall thickness, duration of removal activity, need for navigational markings during decommissioning, etc. The offshore substation platform (OSS) foundation pile is decommissioned in a similar way to the wind turbine foundation and is cut below the seabed level to ensure it causes no obstructions for other users of the sea. Markings must be put in place and communicated to other sea users via the most appropriate and relevant channels in order not to pose any risk (See Figure B-1 (B) of the Appendix section). The Greater Gabbard offshore wind farm decommissioning programme listed a number of criteria used to make the selection of the complete or partial offshore substation removal, including: safety, other sea user needs, environmental impact, sustainable development, polluter-pays principle, reuse maximisation, commercial viability and practical integrity

(Greater Gabbard Offshore Winds Limited, 2007). A list of offshore substation components to be decommissioned are provided in the Diamond Transmission Partners BBE Limited Programme (2018). The offshore substation preparation cost is accounted for in the preparation activities of the entire wind farm. The total offshore substation decommissioning is obtained by Equation 3-12:

$$C_{OSS-decom} = (N_i * C_{i/day} * t_{OSS-decom}) + (C_{i/day} * t_\gamma * N_\gamma), \quad \textbf{3-12}$$

where all parameters are similar to that of the wind turbines but specific to the offshore substation topside and pile removal. $t_{OSS-decom}$ is the time for offshore substation removal.

3.4.2.4.2 Power cable and met mast towers decommissioning

The other sets of assets in the OFTO group include the power cables (inter-array and export cables), which are either completely removed or decommissioned in-place by burial to a specified depth. In more recent installations, the cables are very well arranged in wind farm layouts; therefore, mapping the cable locations on the seabed is straightforward. Cable installation methods require installation vessels or cable-laying vessels equipped with remotely operated vehicles (ROVs) and it is assumed that these vessels and equipment will be used for decommissioning also. However, this will be determined based on the decommissioning option (partial or complete). There must be a decision point for the selection of the removal option and method, vessel selection, which will incur varying cost implications. The factors that will affect the total cable decommissioning cost include: time, vessel day rate, equipment day rate, transportation strategy, removal option, dredging time, intra-field movement time, weather window, vessel capacity, speed, water depth, distance to port and removal/burial rate. The vessels used for cable installation are self-propelled vessels, barge-tug systems and OSVs (Kaiser and Snyder, 2011). The vessel day rates may include the cost of ROV equipment, otherwise this may be hired from an independent contractor. This has to be considered when estimating the vessel and ROV costs. Regulatory standards to date do not require all cables to be removed and in practice most cables are simply buried below the seabed level.

It is difficult to accurately estimate the cable removal rates as there is little data openly available. The next best approach was developed using the adjusted installation rates (Kaiser and Snyder, 2012). This technique may be the best when there is limited data but still remains a bogus metric and must be reviewed as more data becomes available. One of the reasons that this technique may not be the most ideal is because not much care is taken to remove the cables as is required during installation. Also, there is terrain-related specifics for removal as seabed movement over the years of installation may have buried them or exposed them at different locations within the wind farm area. Thus, an additional cost factor is the wind farm area/radius. If cables are removed, the chosen waste management method will be recycling as there is a relatively ready market for the copper from long meters of cables. If they are left in-situ, having a lifespan of 50 years, they may be reconnected for reenergising if the seabed soil settles and can be reused. Based on the installation data, the cable length during removal will be known. Hence, some uncertainty is eliminated regarding the length and the reeling equipment that may be required. The vessel storage capacity, winch, ROV and hydraulic sheer equipment capacity can also be determined. If the cables are cut and buried, mattresses or concrete covers/rocks may be used to cover the cable ends and these may be reused from recovery elsewhere or costs incurred to make provisions for those items (Kaiser and Snyder, 2011). The masts/meteorological towers used during operation will also be decommissioned at this stage. The met tower is usually cut and lifted at once or cut before lifting depending on the capacity of the vessel used. The most cost-effective option is to bury the power cables and monitoring them in perpetuity. This is done both for the inter-array and export cables. In the case where the cables are not cut but buried, the cost estimation model will be:

$$C_{cable-decom} = (N_i * C_{i/day} * t_{cable-decom}) + (N_\gamma * C_{i/day} * t_\gamma *) + (N_k * C_{k/day} * t_{cable-decom}) + C_{eqt/day} \quad \textbf{3-13}$$

Where $C_{cable-decom}$, $t_{cable-decom}$, and $C_{eqt/day}$ represent the cost of cable decommissioning, time for cable decommissioning, and the cost of equipment per day, respectively. The workflow of cable decommissioning depends mostly

on the decommissioning option which is selected based on financial, environmental, risk, technical and social factors. The duration of cable decommissioning depends on the time to cut, de-bury and reel cables onto the ship. The safety/risk factors include any potential interference to other marine activities by other users.

3.4.3 Logistics and waste management phase

Depending on the removal options used for the offshore wind farm installations, the removed components will be transported to a port where some preparations are carried out for component reuse, recycling, incineration or scrapping (e.g. disposal in a landfill). The components may be sorted into different categories like metal (aluminium, steel, copper from cables, etc.), electrical components, mechanical components, hydraulic waste, concrete waste, etc. This systematic approach makes it possible to manage all components economically, safely and environmentally. The major "inventory" considerations during decommissioning include steel, concrete, plastic, non-ferrous (e.g. carbon fibre, concrete), drill cuttings and hazardous substances. Each inventory must have a pre-approved mode of transportation and disposal. The costs incurred at this phase include logistics cost and waste management cost. Therefore,

$$C_{Lo\&WM} = C_{logistics} + C_{WM} \quad \textbf{3-14}$$

where $\boldsymbol{C_{logistics}}$ and $\boldsymbol{C_{WM}}$ represent logistics and waste management costs, respectively. Logistics costs are market sensitive, therefore their estimation is usually subject to uncertainty until it is closer to the time when decommissioning programme is executed. The flowchart for the logistics phase is shown in Figure B-2 (B) and

Figure B-3 (A).

3.4.3.1 Logistics

Logistics planning for offshore wind operations is critical to the success of the entire decommissioning programme and it makes up a large chunk of

decommissioning costs. It involves the resource flow for all activities required for movement, transportation, storage and processing throughout the decommissioning process. The logistics system used for different activities must be considered in the planning and decommissioning stage as it spans across nearly all decommissioning activities. Movement and transportation of resources during an offshore wind farm decommissioning project is a financial, technical, organisational, and safety critical challenge. In a study for wind farm installations, Lange *et al.* (2012) argue that there is a need for the wind energy industry to embed their logistical processes within the maritime supply chain requirements. The need to do this will become more urgent as an increasing number of wind farm assets approach their end of life in the coming decades. The authors proposed a campaign-based supply chain simulator for the wind energy industry that can be used for logistics service providers, which can account for changes in weather windows and equipment or vessel breakdowns/failures. This simulation programme was developed by the Institute of Shipping Economics and Logistics in University of Bremen. Sarkar and Faiz (2017) assumed the total duration for transportation to be a function of the wind turbine's rated power output and chosen pre-assembly method. The authors performed a sensitivity analysis for different learning rates (through increasing experience) and their effects on transportation and installation costs.

For decommissioning activities, Topham and McMillan (2017) proposed a decommissioning approach based on a model that estimates the time and cost per megawatt (MW) for different transportation strategies in order to select the most cost-effective and time-optimal strategy. This model was implemented in MS Excel. The contract signed with a vessel supplier is usually based on a fixed daily rate or turnkey contract when vessels are to be hired. The same vessel can be used to perform different functions to remove, store and transport the components to the port or multiple vessels can be used to perform the different functions. Different transportation strategies can be used, including self-transportation/pendulum strategy, barge method and multi-vessel/collector method (Lange *et al.*, 2012; Kaiser and Snyder, 2012b). The self-transportation/pendulum strategy involves using the same vessel for wind turbine

removal and transportation to shore and back to the site. This will only be cost-effective for a small-scale wind farm. The barge method or multi-vessel/collector method involves the use of a vessel for removal and a barge or other vessels for transportation to shore. The number and types of vessels required must be considered and the type of vessel to be used depends on the cutting method, transportation method, the size and number of components, and water depth. During the installation of offshore wind turbines, the transportation cycle can be seen in Sarker and Faiz (2017).

The types of vessels that may be hired for use include: tugs, barges, lift vessel, mechanical dredges, JU vessels, removal vessels, SPIV, OSVs, heavy-lift vessel, clean up vessels, etc. Logistics software tools like the ODIN-WIND can be used to determine the number and types of vessels required for the lifting and removal phase (Gjødvad and Ibsen, 2016). The factors involved in logistics costs are distance to and from port, port fees, port capacity, port upscale requirement, storage and processing capacity of port, permit durations, mobilisation/demobilisation costs (vessels and personnel), water depth, number of vessels, number of personnel/crew, accommodation and feeding costs, duration of activities, number of vessels required (and different vessel class mixes), selected transportation strategy, weather windows (uptime and downtime), vessel capacity, and weight and dimensions of the items to be transported, crane capacities, probability of failure of equipment/vessels and the duration of failure/time to replace, etc. (Kaiser and Snyder, 2012; Lange *et al.*, 2012; Topham and McMillan, 2017; Sarkar and Faiz, 2017; Gjødvad and Ibsen, 2018). The cost of vessels has been accounted for in different execution activities for ease of calculation; hence, that is left out in this subsection to avoid double counting. The logistics cost can be expressed as:

$$C_{logistics} = (N_i * C_{i/day} * t_j) + (N_k * C_{k/day} * t_j) + (C_{i/day} * t_\gamma * N_\gamma) + C_{accom} + C_{port/annum} \quad \textbf{3-15}$$

where N_i, $C_{i/day}$, t_j, N_k, $C_{k/day}$, C_{accom}, $C_{port/annum}$ represent the number of vessels, daily rate of each vessel, the time taken for execution (to set up,

complete all subtasks and in-field movement), number of personnel, labour cost per day, accommodation cost and port rental fee per day, respectively.

Besides the transportation cost, the costs of making the ports fit for purpose must be accounted for, daily or contractual port fees. The major factors involved in port selection are the distance from the offshore wind farm site, vessel access, port laydown area and storage capacity, nearness and access to processing facility, environmentally sustainable procedures and regulatory compliance (Ontario Ministry of the Environment and Climate Change, 2016). The regulatory compliance for ports varies by jurisdiction and it is up to the decommissioning project planners to obtain the most favourable port for separation and further onshore processing. They must also ensure that it has the required capacity to meet and surpass regulatory requirements. The transportation routes on sea are limited and it is important to obtain all permits required before any activity commences. The vessel pool available for offshore operations is not specific to the wind energy industry as the oil and gas industry has equal, if not greater demand for the vessels for decommissioning offshore assets. This demand and supply of vessels has impacts on the cost of vessels. A decision-support tool that can determine the best combination of factors to calculate optimum completion time, vessel fleet and optimum cost and can update the decisions based on changes in weather window for decommissioning activities will be beneficial to decommissioning managers.

3.4.3.2 Waste management

Waste management is a topic of interest in decommissioning because regulations across several regions prohibit the disposal of wastes in the sea and require adequate sustainable practices for disposal onshore. Waste management methods include waste handling processes adopted at the final stage of decommissioning activities where the recovered components reach the end of their current lifecycle. The different materials handling methods include reuse, recycling, repurposing (e.g. as artificial reefs), refining and hazardous materials handling, mechanical processing, incineration for energy recovery, disposal to landfills, etc. The waste hierarchy must be used to prioritise the final method that will be used for the different components (Department of Energy and Climate Change, 2011; Kaiser and Snyder, 2012; Gjødvad and Ibsen, 2016; Jensen,

2019). After unloading at the port, the components have to be separated, sorted, cut, crushed or packaged for transfer for further processing. Components like composite blades are challenging to dispose of and have little to no salvage value. Concrete may be reused as secondary construction material. A flowchart for wind farm decommissioning waste management is presented in

Figure B-3(A) of the Appendix section**.**

With increasing capacities of offshore wind turbines in deep waters, there will be an increase in the decommissioning waste in the future. Studies show that components like blades are challenging to recuse or recycle because they are made out of composite materials (for improved stiffness-to-weight ratios and reliability), which are difficult to manage during the waste management stage. Thus far, the most practical method of waste management for blades is energy recovery through incineration. Their recyclability, therefore, requires more research compared to other components. Some non-recyclable wastes include lubricants and coolants, power electronics and composite materials (Januário *et al.*, 2007; Cherrington *et al.*, 2012; Topham *et al.*, 2019). There are different EOL legislations in place to ensure that waste is manged in a sustainable manner. For example, there is a chargeable landfill tax in the Landfill Directive 1999/31/EC imposed based on the nature of the materials and their weights. These taxes are a government-imposed levy aimed at reducing landfill waste and ensure that other waste management methods higher up in the waste hierarchy are used before the components are disposed of in a landfill. Some factors that affect waste management costs are dependent on the port location, labour and local transportation costs (Cherrington *et al.*, 2012). Some additional component waste management studies can be found in Liu and Barlow (2017), Sudaia *et al.* (2018) and Jensen (2019). In Table 3-4 wind turbine components and the current waste management methods for each are presented.

The waste management cost can be expressed as follows (Shafiee *et al.*, 2016):

$$C_{WM} = C_{w-proc} + C_{w-OTransp} + C_{port} + C_{landfill} - SV\ , \quad \textbf{3-16}$$

$$C_{w-proc} = C_{w-proc}{}_{/unit} * Wt_j\ , \quad \textbf{3-17}$$

$$C_{w-OTransp} = C_{truck/km} * \left[\frac{\sum Wt_j}{W_{truck}}\right] * t_\gamma * N_\gamma\ , \quad \textbf{3-18}$$

where C_{w-proc}, $C_{w-OTransp}$, C_{port}, $C_{landfill}$, SV, $C_{w-proc}{}_{/unit}$, Wt_j, $C_{truck/km}$, and W_{truck} represent waste processing cost, onshore waste transportation cost if it will be transported elsewhere for processing, port fees, landfill costs, salvage value, unit cost of waste processing, weight of materials (recyclable and non-recyclable), truck cost and capacity of trucks, respectively.

Table 3-4 Wind turbine components and waste management methods

Component	Waste management method
WT foundation	recycle
WT tower and transition piece	recycle
Blades	Energy recovery (incineration), landfill
Hub	reuse, recycle
Nacelle	reuse, recycle, incineration, landfill
Scour protection	recycling, landfill, leave-in-place*
Power cables (inter-array and export)	recycle
Substation topsides	reuse, recycle
Substation foundation/jacket	recycle
Rocks	leave-in-place*
Platforms and ladders	recycle
cables	recycle
Miscellaneous e.g. concrete mattress, rubber, plastics, PVC, etc.	recycle, incineration, landfill, reuse in construction
Oils	Chemical waste treatment (refined and upcycled)
Marine growth	use as sludge

The recyclable materials include all the materials that are not disposed of in the landfill. All recyclable materials will be managed in a way so as to obtain maximum residual value. Therefore, the salvage value is calculated by **Equation 3-19** (Shafiee *et al.*, 2016):

$$SV = \sum W_j^R * SV_{per\ unit\ wt}\ , \qquad \textbf{3-19}$$

where W_j^R and $SV_{per\ unit\ wt.}$ represent the weight of recyclable materials and salvage value per unit weight of each material, respectively.

3.4.4 Post-decommissioning phase

This phase is the last phase of the decommissioning process and consists of all the activities carried out to ensure that the offshore wind farm condition is returned to its original state as much as is possible. The cost elements will include the cost of surveying, cost of cleaning up the site, vessel and personnel/crew cost, and equipment cost. During decommissioning activities, there will be seabed upheaval due to the removal operations; the seabed soil will be allowed to settle naturally. Also, any items left-in-place (e.g. buried cable ends and pile ends will be monitored in perpetuity. It is difficult to quantify the cost of post-decommissioning monitoring as it will be dependent on the types and number of items left in place. This becomes a liability of the government if the former operator goes out of business, or the liability is not transferred to the new business owner if sold. This stage involves perpetual monitoring and management of the wind site. Other activities that are categorised under miscellaneous include notifying the appropriate bodies for map updates within the regulatory requested period. In the UK, a minimum of six weeks is required in advance for notifying the Hydrographic Office (UK Hydrographic Office, 2020) about any map updates. Some post-decommissioning standards for wind turbine decommissioning programmes can be found in Department of Energy Climate Change (DECC) Guidance (2011).

A flowchart for the post-decommissioning phase is illustrated in

Figure B-3 (B) of the Appendix section. There are several factors affecting the cost of post-decommissioning. For example, the distance from shore is a critical factor for the logistics related activities/tasks. Other factors like length of mooring lines, size of anchors, length of cables also need to be considered. The cost of post-decommissioning is expressed by the following equation:

$$C_{P-Decomm} = C_{surv} + C_{Sc} + C_{Sm} + C_{rem} + C_{misc} \quad , \qquad \textbf{3-20}$$

where $C_{P-Decomm}$, C_{surv}, C_{Sc}, C_{Sm}, C_{rem}, and C_{misc} represent the costs of post-decommissioning, site surveys, site clearance, site monitoring, site remediation (if required) and miscellaneous, respectively.

3.5 Case study

In this section, the proposed cost estimation models are applied to estimate the decommissioning cost of a hypothetical baseline offshore wind farm, which consists of 100 5MW wind turbines based on datasets presented in Table B-1, Table B-2, Table B-3 and Table B-4 of the Appendix section (data with references to “Datasets” were based on a confidential dataset). This hypothetical baseline case has been studied in some papers in the last years (see Myhr *et al.*, 2014; Shafiee *et al.*, 2016). The water depth at the wind farm site is assumed to be 45 m because bottom-fixed wind turbines are in water depths of up to 50 m (The European Wind Energy Association, 2013). The foundation which is more suitable for such water depth is jacket foundation. The method for foundation removal is the cut-lift-carry (CLC). During the decommissioning process, all the wind turbines are removed and the jacket foundations are cut 4.6m (15 ft) below the seabed. The wind farm has one offshore substation. The export cables are assumed to be left in place at the end of the life of the project. It is assumed that different removal vessel classes and barge(s) are used for the decommissioning operations. However, the capacity of the vessels remains unchanged throughout the process.

3.5.1 Planning and regulatory approval phase cost

The costs for the planning and regulatory phase are calculated based on the current UK legislation. The planning and regulatory approval cost is made up of the engineering planning base cost, legal permit costs, environmental impact assessment cost, facilities audit cost, consultation, contractor and vendor fees, insurance premiums and contingency planning costs.

3.5.2 Execution phase cost

The execution phase is made up of the costs calculated for lifting and removal of the wind turbines, foundations, inter-array cables, offshore substation and met masts. The inputs required to estimate the cost for all execution activities are the type and number of vessels to be used, the number and time of trips to shore and cost of transportation spread, and the number and cost of offshore personnel and the time required for the removal activity. It is assumed that there is a transportation spread available at the time of removal for transportation to shore. The WoW is accounted for within the time estimated to complete each activity. The time taken to remove the jacket foundations is assumed to be 80% of installation time, whereas the time for the wind turbine removal is 90% of installation time (based on the discounted removal time estimated to be between 0.75 to 0.99 of the installation time as seen in Kaiser and Snyder, 2012b). The typical wind turbine and foundation removal vessels are jack up and HLVs. The daily rate of jack up vessels is £149,800/day, whereas the daily rate of HLVs is £288,900/day, inclusive of fuel costs using the same rates used in Shafiee *et al.* (2016) dataset. Based on the vessel day rates, the total lifting and removal cost of the wind turbines and their foundations is between £81.72 and £157.31 million when jack up vessels and HLVs are used, respectively based on Equation 3-8. Crew boats are estimated to be on site and the selected modes of transportation for the removed components are barges and tugboats. The number of barges, tugs and crew boats may vary, and the optimal number may be determined depending on project budget and duration. In all projects, the budget must be within the spending limit; therefore, the optimal number of vessels, transport barges and tugs is determined based on appropriate estimates of the desired

project outcomes. This study neither explored fleet optimisation or optimal vessel numbers. The cost of equipment like cutting tools have been included in the overall vessel costs. The time it takes to complete removal activities is primarily dependent on the number of resources allocated, especially removal and transportation vessels.

The cable removal is assumed to include only the inter-array cables as the export cables are cut and buried at the terminating points. The length of array cables to be removed and the weight to be transported depend on the size of the wind farm, type of seabed, type of removal vessel, etc. The cables lied on the seabed surface must be removed in a way so as to avoid concerns for other users of the sea. Most of this information is obtained from the survey done during preparation phase as well as the installation data available in the wind farm. The two vessels used for cable removal include the OSV and a cable-laying vessel, which cost £2,071.51 and £85,600 per day respectively, using the same rates used in Shafiee *et al.* (2016) dataset. The time taken for completing the removal operation will depend on the type of vessel used. A larger capacity vessel can remove more length from cables in a shorter time. Export cables are commonly not removed completely. However, if they are to be removed, a large vessel (cable removal vessel) will be required to lift the burial rocks or structures used to keep the cables in place.

The substation removal involves removing the topsides and foundation. A heavy lift vessel is used to remove the topsides and foundation of the offshore substation, while a smaller vessel like an OSV is used for the removal of met towers. Barges and tugboats will be used in transporting the removed items to shore for processing. The cost of offshore substation and met mast depends on the number of offshore substations and met masts to be removed, the type of vessels used, and the assumptions made during estimations based on the weight of the structure(s). This is subject to the wind farm capacity, which determines the number of units. In the baseline wind farm, it is assumed that one offshore substation and six met masts (with jacket foundations) are removed. It is also assumed that the offshore substation and met mast removal will take 4.5 days

and 2 days, respectively based on mast and substation removal times proposed in Kaiser and Snyder (2012b).

3.5.3 Logistics and waste management cost

The logistics cost includes the cost of personnel accommodation, port rental cost per annum (converted to daily rate) and onshore personnel costs. The cost of vessels used and personnel costs for all decommissioning activities are not accounted here to avoid double counting. Ideally, all vessel day rates and mobilisation/demobilisation costs and personnel costs will be accounted for in this cost group; however, most available data report decommissioning activity costs inclusive of the associated vessel costs. All input data are based on the dataset presented in Table B-3 of the Appendix section. The accommodation and onshore personnel costs are £4,500 and £150 per day, respectively. The total port rental cost per annum is £13.4 million and the duration of the decommissioning execution is estimated to be 543.4 days (it will be completed in the same duration it takes for all activities to be completed; thus, execution duration is used); thus, when port cost is normalised to the duration of the decommissioning project it will be £19.9 million. Mobilisation costs for the JU and HLV are £138,000 and £276,000, respectively.

The waste management cost is made up of the cost of processing each component and onshore transportation from port to processing facility/landfill. These costs are dependent on the weight of materials to be transported and processed, the capacity of the trucks and the cost of processing each of the items. The recyclable items are processed differently from the non-recyclable items. The estimated salvage value of the recycled items is deducted from the waste management cost. The distance from the port to both the processing facility and landfill/scrapyard are assumed to be equal in this case. Table B-3 of the Appendix section provides the input data used to estimate the waste management cost. Recyclable and non-recyclable wastes are assumed to account for 60% and 40% of the total weight, respectively (Shafiee *et al.*, 2016).

3.5.4 Post-decommissioning cost

The post-decommissioning cost is dependent on the cost of surveying a pre-set radius of the wind farm area, site clearance using different methods to ensure no dropped objects or other components from the installation phase remain on the seabed, cost of site monitoring (in the case where assets like export cables are left in place), site remediation and other miscellaneous expenses. The model used in estimating the total cost of post-decommissioning for this case is based on the summation of all the primary cost elements.

In the next section, the results were generated based on the cost model developed and discussed.

3.6 Results and discussion

In this section, the cost estimate outputs from each of the cost groups are presented and the results are discussed. The individual cost contribution of the activities in each phase is illustrated and the total decommissioning cost is given in Table 3-5.

Table 3-5 The cost estimates for different decommissioning phases and activities

Decommissioning Phase	Decommissioning Activity	Cost (£)
Planning and regulatory approval		23,401,966
Execution	Wind turbine and foundation removal	81,716,408 (min) 157,308,912 (max)
	Array cable removal	1,573,005 (min) 22,162,778 (max)
	Substation and met tower removal	1,642,314
Logistics and waste management	Logistics	22,578,722
	Waste management	(5,386,511)
Post-decommissioning		7,274,513
Decommissioning base cost estimate		132,800,417 (min) 228,982,693 (max)

Total decommissioning cost estimate (including 10% contingency)		145,313,417 (min) 241,495,689 (max)

The total decommissioning cost was estimated by adding cost estimates of different decommissioning phases. As can be seen, the decommissioning base cost estimate for the offshore wind farm ranges between £132.8 million and £229 million, excluding contingency costs. The total decommissioning cost estimate is made by adding contingency cost to the base cost estimate. Therefore, the total decommissioning cost will range from £145.3 to £241.5 million. Figure 3-7 represents the contribution of different activities in low-range cost estimate of the decommissioning process. As shown, the top three contributors are: the wind turbine and foundation removal cost, planning and regulatory approval cost, and the logistics cost, making up 62%, 18% and 17% of the total decommissioning cost, respectively. Waste management activities are estimated to generate a profit of £5.39 million. The salvage value of the components (e.g. steel) are estimated with the assumption that 60% of the total removed structural weight is recyclable as in Shafiee *et al.* (2016). Waste management is the cost of processing, on-land transportation to processing sites and landfill costs less the salvage value.

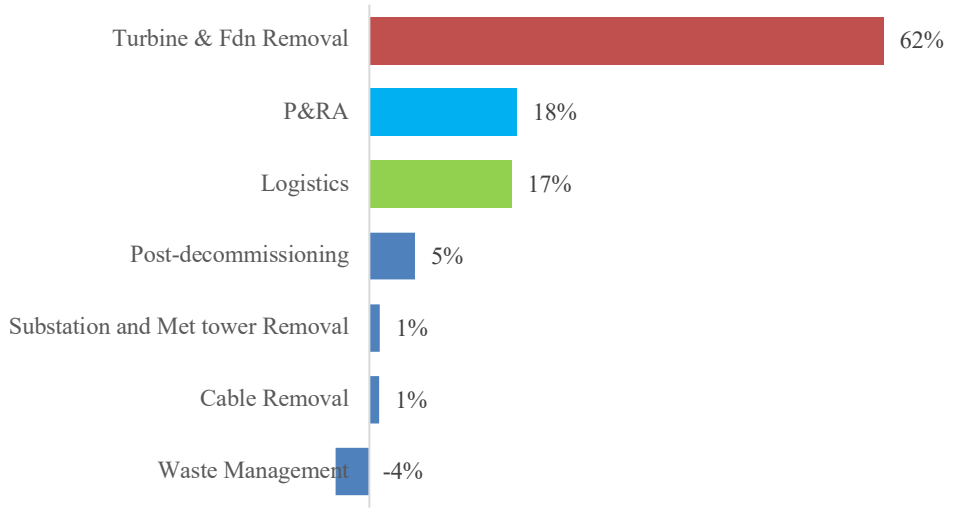

Figure 3-7 The contribution of different activities in low-range cost estimate of the decommissioning process

3.6.1 Planning and regulatory approval cost

The planning and regulatory approval cost is estimated to be about £23.4 million. This phase is the second largest contributor to the total decommissioning cost and is composed of all the overhead costs within the decommissioning project, including the project management costs and environmental impact assessment survey cost. An approach to reduce this cost is to negotiate about the most appropriate contracts with suppliers and contractors; and wherever possible, in-house expertise can be capitalised on. Also, with increased contractor/operator experience, there will be potential cost savings; some research account for this as learning improvement cost savings, but it is excluded in the above estimate. The regulatory compliance cost is usually higher in countries where regulatory fees are required for approval and amendments. Overall, it depends on the wind farm size and regional government policies. In order for regulatory bodies to support the offshore wind industry, regulatory approval related costs can be reduced.

Contingency planning must be well accounted for in order to lower the impacts of unforeseen events on the project success. The potential risks must be accounted for and quantified in the cost estimates for the decommissioning project. The less the uncertainty within a decommissioning project, the less the planning and regulatory approval costs. Development of the most optimal contingency plan is a challenge, and the contingency allowance percentage is dependent on different factors like type of the asset to be removed, distance from shore, potential breakdowns, etc. For example, a concrete gravity-based structure removal may pose more risk than a monopile foundation. The different factors must be taken into account to make sure that the risks are managed properly. In the case study, the main cost drivers identified in this phase are the project management and contingency. Until more data can be collected from different regions about offshore wind farm decommissioning activities, it will be difficult to estimate with lesser uncertainty the cost range that will be most appropriate for planning and regulatory approval provisions.

3.6.2 Execution cost

From the results, it is confirmed that the execution phase is the costliest phase primarily because of the logistical provisions required for offshore marine operations. The execution phase makes up 64% of the total decommissioning cost. The wind turbine and foundation removal costs are the highest contributors to overall execution cost. The most influencing factors in this regard are the vessel requirements and the duration of the activities. Both are variable parameters which depend on the removal and transportation strategy adopted for each subtask. For example, cable decommissioning may be carried out by removal using reverse-installation (reel back unto the vessel), removal and cutting in sections or by burying the cable ends and leaving it in place. The types of vessel contracts must be selected according to the wind farm size and project constraints. Potential efficiency gains within this area can be studied for the best return on investment, as decommissioning is a little to no income generating phase in the asset lifecycle.

Among all execution subtasks, the wind turbine removal has the longest duration. Although the estimations of removal duration are currently based on estimations from the installation times and weather factors (Shafiee *et al.*, 2016; Kaiser & Snyder, 2012b), because offshore wind farms are projected to move into deeper waters, decommissioning project duration for future offshore turbines are not projected to scale linearly. Thus, further work can be done to collate data for decommissioning activities in deeper waters. Some suggestions for the key variable data that can be collated methodically for decommissioning projects are highlighted below.

3.6.2.1 Duration of decommissioning activities

The duration to complete decommissioning activities is one of the most important factors in execution costs. There is likely to be a correlation between the duration of removal activities, the wind farm size/capacity and foundation type. This may be explored in further research. An optimisation of task execution time, even by a few minutes, will accumulate into notable cost savings.

3.6.2.2 Number and weight of wind turbines

The number and weight of the wind turbines will influence the duration of cutting, lifting and transportation operations. The weight of each wind turbine will also influence the capacity of the vessel to be used for transporting the materials recovered from the site. In this study, the 100 wind turbines weigh a total of 55,250 tonnes took a total of 543.44 days for removal. Based on the number and weight of the removed components, the deck space required can be directly estimated for different arrangements.

3.6.2.3 Water depth and distance to shore

The water depth and distance to shore can have a significant impact on decommissioning costs. These factors influence the type of foundation structure and the length of transmission cables to be decommissioned. Although correlations of these factors have not been considered for the results in this study, the water depth of 45m, distance to shore of 10km, jacket foundation type and cable length of 133.11km took a total of 543.44 days for removal (Shafiee *et al.*, 2016). Future decommissioning data can be obtained to determine how the different factors are correlated with total removal duration.

3.6.3 Logistics and waste management

Logistics cost contributes significantly to the overall decommissioning cost – making up 17% of the total costs, excluding the costs included in the execution phase. Logistics is the third most critical cost-driver in the decommissioning project as it has a major influence on lifting, removal and transportation costs. The logistics phase cost elements span across activities in both onshore and offshore environments. Any efficiency gain in logistics will contribute significant savings in the overall cost of decommissioning. The key cost drivers in this phase are the vessel requirements, activity durations, and the number of wind turbines/size of wind farm. With accommodation, onshore personnel and port rental costs at £4,500, £150/day and £13.37 million per annum, the mobilisation and demobilisation cost at £138,000 for jackup vessels and £276,000 for heavy lift vessels. The port rental cost has the highest opportunity for cost reduction. Port rental costs will depend on the location and capacity of removed components

to be processed. For this case study, the logistics cost is £22.6 million. Waste management can be optimised by improving the recycling percentage from 60% to 85% and above. Opportunities for reuse or recycling can be explored for other industries outside the maritime industry. The cost of waste management is a negative cost of £5.39 million, showing profit. The cost is made of the cost of waste processing, transportation, landfill, which are £9.8 million, £464,000 and £1.07 million less the scrap value of £16.75 million.

3.6.4 Post-decommissioning

Post decommissioning costs are made up of the survey, site clearance, site monitoring, site remediation and miscellaneous costs. The cost of site clearance is the largest cost element in this activity group. Site surveys will be done using ROVs at the offshore marine sites at £36,750. The cost of remediation was excluded in this study under the assumption that any seabed upheaval will settle with time. The site clearance cost is a product of the cost of site clearance per area (£51,542/km^2) and the wind farm area (70.14 km). Site monitoring per day was obtained from Shafiee *et al.* (2016), which is £3.6 million/annum, which is expected to be different depending on the items left in place at the wind farm site. Miscellaneous costs are £7,500 to account for any unaccounted activity. The total post-decommissioning cost estimated is £7.27 million.

3.6.5 Sensitivity analysis

In this subsection, we investigate the effect of the above-mentioned key factors on the overall decommissioning cost. Therefore, a sensitivity analysis is carried out based on the decommissioning cost estimates. The analysis is performed by changing four parameters, including: the number of resources, vessel rental costs, activity durations, and contingency provisions.

3.6.5.1 Changing the number of resources

In order to show how an increase in the number of resources will affect the total decommissioning cost, a sensitivity analysis is performed. The resources considered in this analysis include the number of removal vessels, transportation vessels, personnel and equipment (such as cranes). An increase in the number

of removal vessels is observed to increase the decommissioning costs but reduce the duration of activities. The number of manpower required is variable from an activity to another and can be increased or decreased depending on the nature of skills required. The analysis shows that an increase in personnel has a notable impact on the overall decommissioning cost. Personnel cost for decommissioning activities can rise in two ways: an increase in the *number of personnel per activity* or an increase in the *cost per offshore/onshore personnel*. The first analysis of increased personnel cost on total decommissioning cost involved increasing the number of personnel per activity. When the *number of personnel* was increased by 50%, the total decommissioning cost increased by 0.42% (£667,000). The *cost per personnel* was increased by 20% and 30%, increasing the total decommissioning cost by 0.18% and 0.27% (£287,630 and £431,446), respectively. Thirdly, depending on the equipment required (e.g. heavy cranes, cutting equipment, ROVs, generators, etc.), an increase in equipment costs can have a significant impact on the total decommissioning cost. To estimate the influence of increased equipment cost, a conservative assessment using the mobilisation/demobilisation cost of a heavy crane. If the cost is increased by 20% or 30%, the total decommissioning cost increases by 0.03% (£55,200) or 0.05% (£82,800). The transportation vessels used for decommissioning the baseline offshore wind farm are one tug and one barge. It is observed that when the number of tugs and barges increases to two each, the cost of planning and regulatory approval as well as removal activities will increase significantly. Figure 3-8 shows the effect of an increase in the number of transportation vessels on the total decommissioning cost. As can be seen, doubling the number of transportation vessels increases the total decommissioning cost by 0.02%, while tripling the number of transportation vessels increases the costs by 0.04%. This additional expenditure on transport vessels is insignificant compared to the time savings it provides. Based on this analysis, it is recommended that employing more than one transportation vessel will be beneficial to the project. The additional cost due to an increase in the number of transportation vessels is less than the overall cost saving based on its positive impact on reduced project

duration. Hence, this should be a primary consideration for industry as a time saving mechanism over several other options.

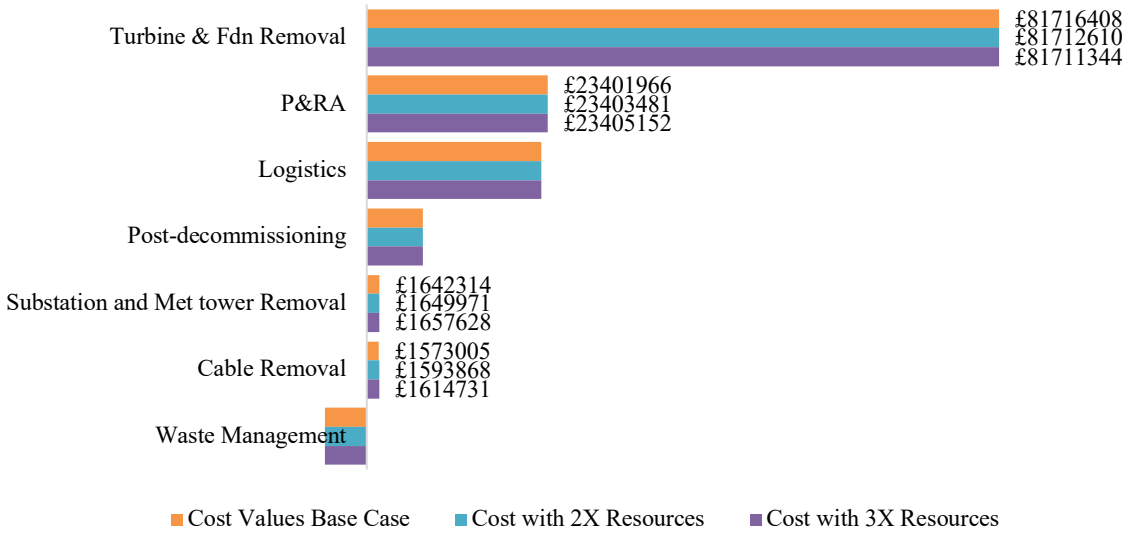

Figure 3-8 Decommissioning cost with increased number of transportation vessels

3.6.5.2 Changing the vessel rental charges

The impact of a 20% increase and decrease in removal vessel rental charges on the total decommissioning cost is analysed and the results are shown in Figure 3-9. As can be seen, when the removal vessel rental charge increases by 20% the wind turbines and foundation removal cost increases by 3%. This increases the total decommissioning cost by £17.6 million. This is a significant increase, although the estimate is conservative in nature. The effects, however, have a high impact on the decommissioning expenditure. Future market trends are uncertain and difficult to predict and depend on the value of money at the time of decommissioning. Therefore, inflation must be managed adequately by exploring potential hedging mechanisms.

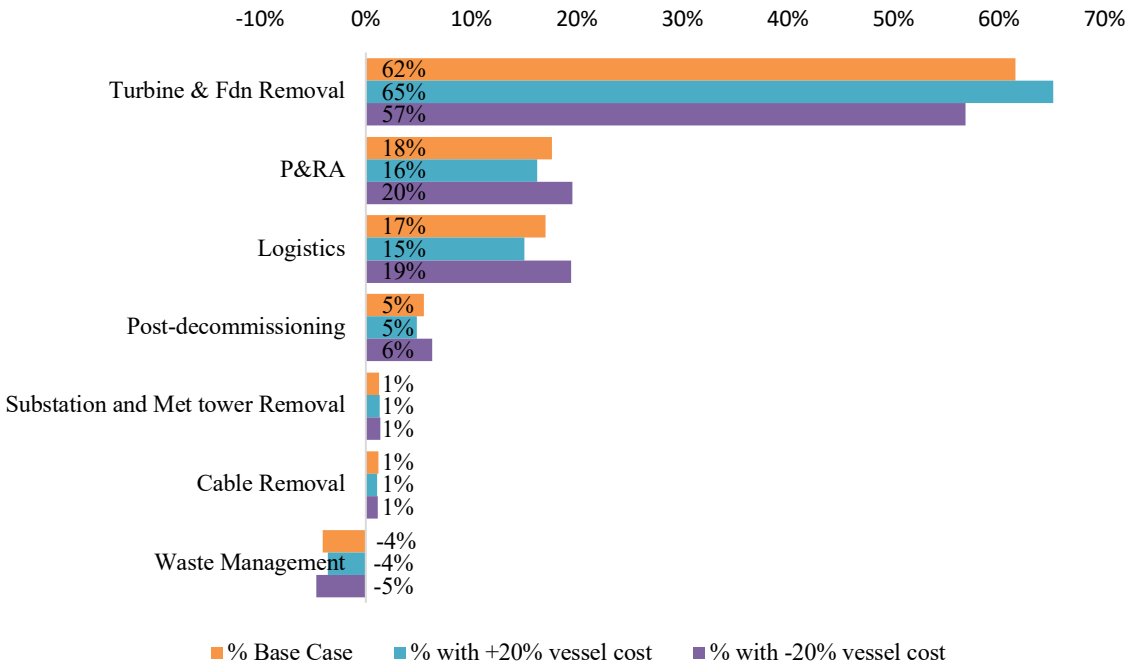

Figure 3-9 Decommissioning cost changes with increased and decreased vessel rental charges

3.6.5.3 Changing the duration of decommissioning activities

Regulators require the wind farm owners to decommission their assets within a certain period. The implications of decommissioning duration will critically impact the total cost. The impact of a 20% increase and decrease in duration of activities on the total decommissioning cost. The base duration of activities during planning and regulatory compliance, execution (preparation, lifting and removal, OSS removal and cable removal) and logistics (Equation 3-4, 3-8 and 3-15) were increased and decreased by 20%. The results are shown in Figure 3-10. It was observed that if the duration of activities decreases by 20%, the total decommissioning cost will decrease by 17%-18% (£22.3 to £41.6 million). Research into decommissioning operation efficiency should therefore be prioritised. Some factors have been identified to have the largest impact on the decommissioning duration. These include: removal and transportation time (including mobilisation and demobilisation time), removal method, cable burial/removal rate, and the transportation strategy.

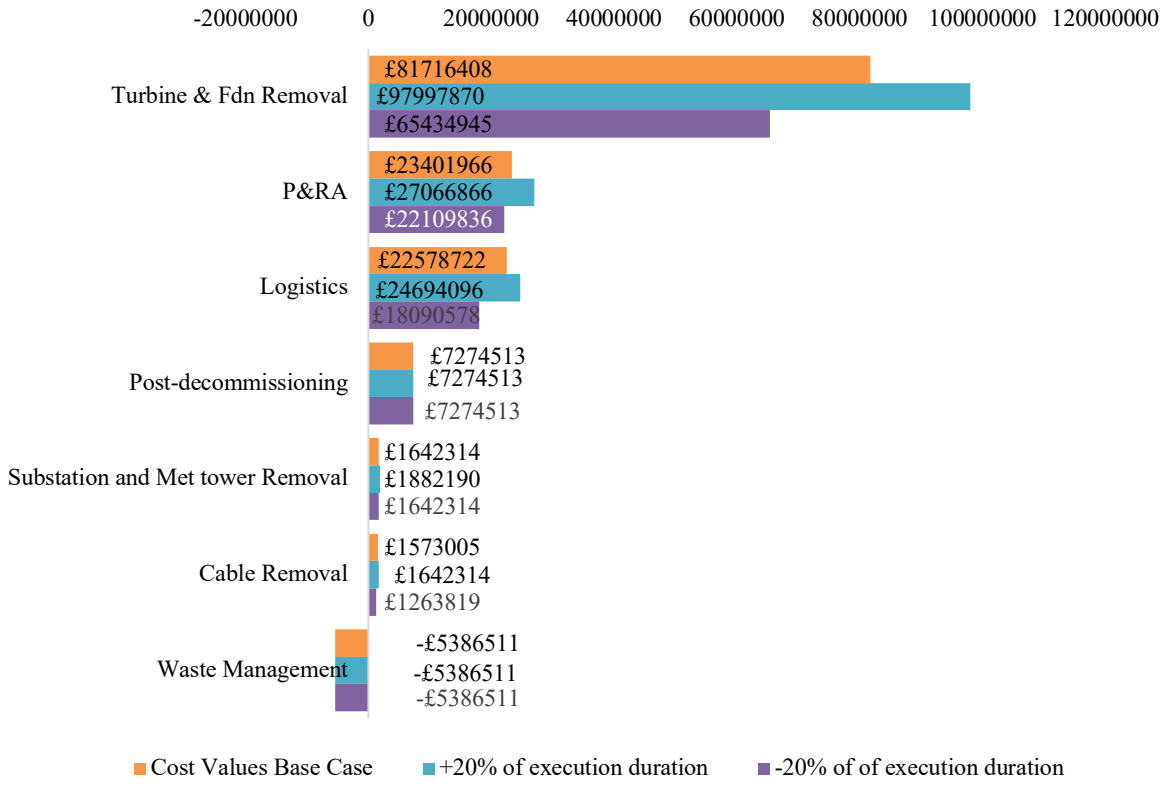

Figure 3-10 Effect of the duration of decommissioning activities on total cost

3.6.5.4 Changing the contingency allocation

Offshore wind farm decommissioning activities are susceptible to uncertainties related to schedule, finance, weather and other potential unforeseen circumstances. Hence, it is important to evaluate the cost implication of increased or decrease contingency. The risks of a project have to be reduced to as low as reasonably practicable (ALARP) and provisions must be made to account for risks. Contingency allocation serves as a potential avenue for decommissioning cost reduction, especially if risks can be adequately identified, quantified and mitigated. To evaluate the effect of contingency allowances on the overall decommissioning cost, different contingency percentages are considered. The total decommissioning cost was estimated for two cases of 10% and 20% contingency allocations. This increase was done by changing only the planning and regulatory cost ($C_{P\&RC}$); estimated by calculating the total decommissioning cost and then adding a 10% and 20% contingency cost, respectively. The results are shown in Figure 3-11. From the figure, it can be seen that the percentage

allocation changes for the other cost elements decrease when the planning and regulatory compliance costs increase. This is because the contingency is added after the total decommissioning cost has been estimated. Thus, the proportion of each cost element is updated based on the contribution to the total decommissioning. If a lower risk is expected, 10% may be allocated as the benchmark contingency cost. However, if higher risks are expected, the contingency of 20% may be allocated.

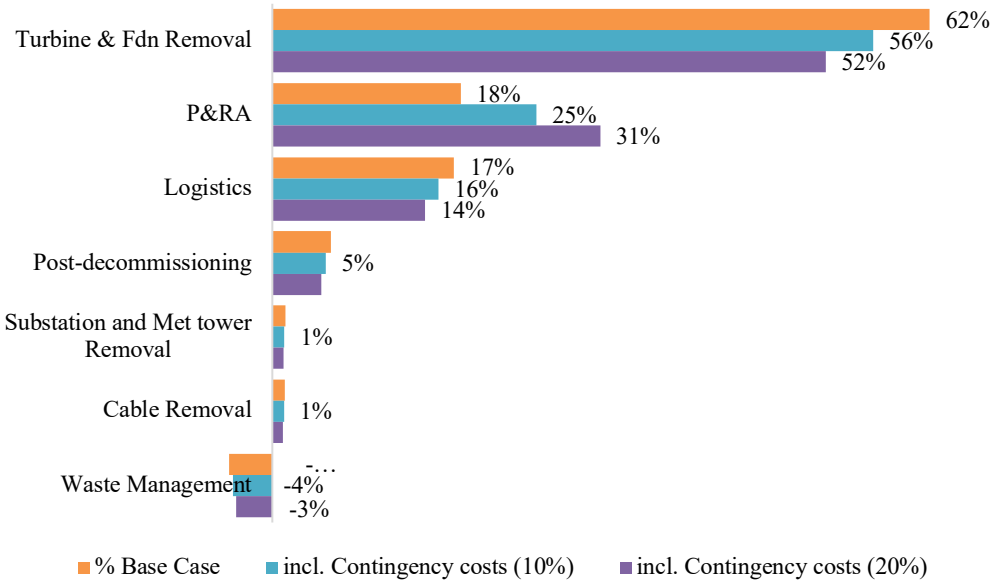

Figure 3-11 Effect of the contingency allocations on total decommissioning cost.

As can be seen, a 10% increase in contingency allocation increases the decommissioning costs by £12.5 million. This cost affects the different cost contributions because of the increase in the planning and regulatory compliance cost.

3.6.6 Verification of the results

In order to check the cost estimates for the baseline offshore wind farm decommissioning, the results of this study are compared with the decommissioning estimates in Shafiee *et al.* (2016). The authors also applied a cost breakdown structure in developing a whole life cost estimation, including detailed decommissioning costs in the estimate. The authors also used a similar

baseline case of 500MW wind farm. The comparison is shown in Figure 3-12. The average decommissioning cost estimated in this study equals £196.7 million, compared with the £202.4 million estimated in Shafiee *et al.* (2016). The decommissioning cost estimates are not exactly the same because not all cost elements were accounted for in Shafiee *et al.* (2016). The cost comparison shows that although decommissioning had been studied previously, this study presents a more detailed breakdown of cost elements that can aid asset manager decision making. This study takes into account the cost associated with planning and regulatory approval, and contingency allocations. This is because that the overheads, administrative and regulatory compliance costs must be captured in a way that can easily be modified by operators on a project-by-project basis. In order to ensure that the most critical cost components in different activities are monitored, classifying the cost elements in the appropriate cost group will help asset managers to optimise costs within particular cost groups. If the planning and regulatory cost is included in the removal costs, it will be more challenging for factors such as process optimisation to be factored into potential cost reduction avenues.

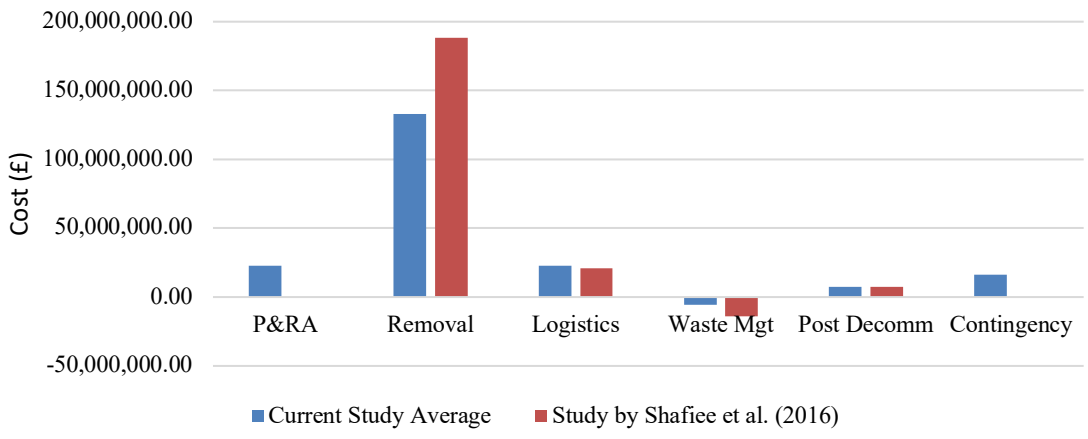

Figure 3-12 A comparison between the decommissioning costs estimates in this study and Shafiee et al. (2016)

3.7 Conclusion and future outlooks

The wind energy industry will have an increased number of wind farms to be decommissioned in the coming years. Therefore, it is crucial for wind farm

owners/operators to identify the high-cost areas and establish the opportunities and priorities for cost savings. The lifecycle costing (LCC) has been applied as an effective method to assess the total cost of wind farm development with taking into consideration all expenditures over the entire life cycle from the initial investment costs to subsequent maintenance and operating costs through to salvage and resale value. This paper performed a LCC analysis for offshore wind farm decommissioning projects using a cost breakdown structure (CBS) approach. Our analysis enables the wind farm owners/operators to identify the critical cost factors and evaluate the effects of any improvements on the total decommissioning cost. The decommissioning activities for offshore wind farms were grouped into four key phases, including: planning and regulatory approval, execution, logistics and waste management, and post-decommissioning, and some mathematical models were proposed to estimate the costs associated with activities involved in each phase. The total decommissioning cost for a 500MW baseline offshore wind farm was estimated including contingency cost provisions.

The key findings from the decommissioning cost estimation were that the removal of wind turbines and foundation, logistics, and planning and regulatory approval activities accounted for the largest proportion of the total decommissioning cost. The key cost drivers included the vessel rental charges, duration of activities, contingency cost allocations and potential market changes. These identified cost drivers should be the primary focus for the wind energy industry in order to reduce decommissioning costs for future deepwater wind farms. A sensitivity analysis was also carried out to understand the effect of any changes in different key cost drivers on the overall decommissioning cost. The impact of the number of resources, vessel rental charges, decommissioning activity duration, and contingency allocations on the total decommissioning cost were analysed.

Future areas of research include optimisation processes that can help to reduce the duration of decommissioning activities, improve the efficiency of transportation vessel schedule, mitigate the contingency/financial risks, and improve the materials recycling methods to increase income from waste management. Improvements in logistics, contingency planning, and removal

methods are possible avenues of research in the future, with the aim of making the decommissioning process a more sustainable part of the renewable energy systems lifecycle.

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4 Offshore wind farms infrastructure: risk analysis of decommissioning operations

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Abstract

Renewable energy generation has gained significant traction in recent years. In the offshore wind farm (OWF) project lifecycle, risk assessment research of the decommissioning phase has received little attention to date. OWF installation has been stressed as the most risk-critical phase in the project lifecycle in the past. This study argues that OWF decommissioning is equally a risk-critical phase; thus, it makes a case for OWF decommissioning safety focuses for industry, particularly in lifting and loading activities. The study adopted standardised qualitative and quantitative risk analysis methodologies to identify and quantify the health and safety concerns related to OWF decommissioning, highlighting a need for increased safety research into the critical factors. Potential hazards are identified and assessed using well-established approaches including hazard identification (HAZID), fault tree analysis (FTA), event tree analysis (ETA) and risk matrix were applied to better understand the key risk-drivers in the decommissioning phase of the project lifecycle. Four consequence classes/indices were considered in the analysis for the risk ranking. It was found that lifting and loading operations are the most safety-critical tasks during OWF decommissioning, and therefore, will require specific attention for safety management improvement. Collision, vessel damage and crane failure risks were analysed, and the failures related to crane operations were observed to have the highest risk profile compared to collision/contact and vessel damage. The four-class risk evaluation provides a granular insight into the possible risk mitigation scenarios. Thus, specific

areas of safety management practices that need to be improved in terms of project management, personnel protective equipment, administrative, engineering or mitigation methods were presented. The study output will support decision-makers (operators, independent service providers and asset owners) in focusing mitigation/control efforts on critical risks posed during decommissioning activities and reduce them to as low as reasonably practicable (ALARP).

Keywords: Offshore wind; decommissioning; risk analysis; safety; as low as reasonably practicable (ALARP).

4.1 Introduction

Offshore wind farm decommissioning operations have been increasing in Europe over the past few years with seven offshore wind farms decommissioned to date as presented in Table 4-1. Except the Vindeby offshore wind farm, the other six wind farms were decommissioned prior to the end of useful service life of 20 to 25 years. The early decommissioning of offshore wind farms might be due to technological reasons (such as outdated technology) and/or economic reasons (such as expensive repair costs).

Table 4-1 Decommissioned offshore wind farms (4C Offshore, 2020)

Country	Windfarm	Actual Year of Decommissioning	Estimated year of decommissioning based on design life
Denmark	Vindeby Offshore	2017	2011
Germany	Hooksiel	2016	2028
Netherlands	Lely	2016	2017
Sweden	Utgrunden I	2018	2020
	Yttre Stengrund	2015	2021
UK	Blyth	2019	2020
	Beatrice Demonstration	2016	2026

With sustainable offshore wind construction as a backdrop, the estimated wind farm capacity to be decommissioned between the years 2021 and 2038 is presented in Figure 4-1. The rapid growth in decommissioning activities has necessitated the need to prepare comprehensive risk management strategies for the decommissioning phase of the asset lifecycle. Several factors influence decommissioning operations in offshore wind farms, such as the weight/capacity of the wind turbines, the number of wind turbines on the farm, available vessels (for lifting and transportation) and their capacity, weather conditions, etc. Decommissioning is often viewed as reverse installation. However, because of the age of structures this may be an oversimplification. For instance, lifting points on the wind turbines may have defects, which therefore will cause the structure to have lower strength at later age. The structural integrity must be ascertained through visual inspections as the project plan is being developed. Offshore wind farm decommissioning is not as mature as offshore oil and gas decommissioning. However, in the context of safety management, there are standards and regulations that duty holders in both sectors take into account. Some examples are the International Maritime Organisation (IMO) FSA regulations, Health and Safety Executive (HSE) guidelines, DNVGL recommended practices for location-specific projects, etc. For more information readers can refer to HSE (2002); Danish Maritime (2017); International Maritime Organisation (2018) and BSI (2018, 2019a, 2019b, 2020).

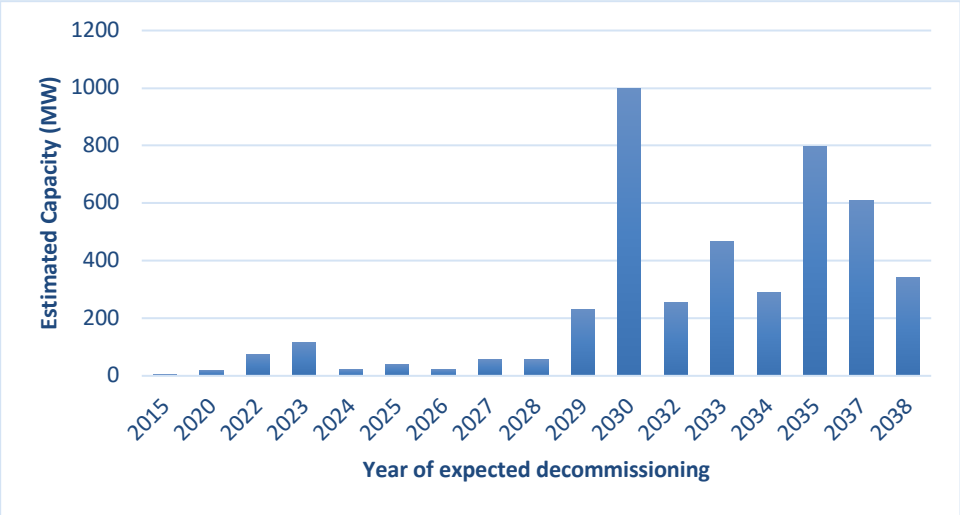

Figure 4-1 Estimated offshore wind farm decommissioning (Hamburg Institute of International Economics, 2019)

Offshore wind energy risk management literature has predominantly focused on the early and mid-stages of wind farm development (design, installation, and operation and maintenance (O&M)). A summary of some of the most important studies are presented. For the planning/concept phase, Mehdi *et al.* (2019) proposed a novel real-time, manoeuvring-based dynamic risk assessment method to improve navigation safety around wind farms and prevent collision. For the design phase, Kahrobaee and Asgarpoor (2011) proposed a risk-based failure analysis method using cost priority numbers (CPN) as the metric to reduce the costs associated with risk of offshore wind turbine failures. For the installation phase, Kim *et al.* (2020b) studied the risk of collision in offshore wind turbine installation vessels and identified the most influencing factors. Lazakis and Kougioumtzglou (2019) proposed the use of Failure mode, effects and criticality analysis (FMECA), hazard identification (HAZID) and Bayesian Network (BN) for evaluating the risks associated with installation and O&M. Gintautas *et al.* (2016) proposed a risk-based decision support tool to incorporate the cost risks associated with assembly, transport, installation, and O&M in the asset lifecycle. For the O&M phase, Dai *et al.* (2013) presented a novel risk analysis framework for the collision of service vessels and offshore wind turbines. The study used fault tree analysis (FTA), event tree analysis (ETA) and BN for estimating the likelihood of occurrence and ANSYS for consequence assessment. Shafiee and Dinmohammadi (2014) proposed an FMECA-based risk assessment method to mitigate the operational risks related to asset failure in offshore wind farms. Shafiee (2015a) proposed a fuzzy analytic network process (FANP) to determine the most appropriate risk mitigation strategy for offshore wind farms. Adedipe *et al.* (2020) presented a review of studies that applied the BN to risk assessment. The authors proposed BNs as a tool to overcome the limitations of classical risk assessment techniques. For further reading, readers can refer to Jha *et al.* (2010), Rangel-Ramirez and Sørensen (2012), Serrano Gonzalez *et al.* (2013), Ekici *et al.* (2016), Cheng *et al.* (2019), Leontaris *et al.* (2019), Mendoza and Kohler (2019), Shiokari *et al.* (2019), Shafiee *et al.* (2019) and Kim *et al.* (2020a).

Safety should be prioritised at *all* stages of the asset lifecycle; thus, this study stresses the importance of more research into end-of-life risk management. As seen from the brief review of the state-of-the-art of offshore wind lifecycle risk management,

no study investigated the OWF decommissioning phase risks. To the best of the authors' knowledge, this is the first study that contributes to risk management and analysis of the offshore wind farm decommissioning activities. Four classes/indices of hazard consequence are considered in the analysis, providing a more granular insight into the possible mitigation/controls required. The specific area of safety management practices that need to be improved in terms of project management, personnel protective equipment, administrative, engineering or mitigation methods were determined. This study will support risk management decision-makers (operators, independent service providers and asset owners) to focus mitigation/ control efforts on critical risks to reduce them to as low as reasonably practicable (ALARP).

The organization of this paper is as follows. Section 4.1 introduces OWF decommissioning trends and some OWF risk management research to date. Section 4.2 presents the research background, detailing the decommissioning phases and some tools and techniques for decommissioning risk assessment. Section 4.3 presents the risk assessment for offshore wind farm decommissioning using the HAZID, FTA, ETA and risk matrix techniques. Section 4.4 presents the results obtained from the assessment: the HAZID result, frequency analysis of the top event, minimal cut set, importance ranking, basic event sensitivity analysis, consequence analysis and risk matrix. It also discusses the most safety-critical tasks during lifting and loading operations and some mitigation measures are proposed. Section 4.5 concludes the study with proposals for future work in offshore wind farm decommissioning safety research.

4.2 Research background

4.2.1 Lifecycle phases in offshore wind decommissioning

Decommissioning is the process of planning, removing, transporting, waste management and post-decommissioning of wind turbines and support structures to return the wind farm site to as close to its original condition (Adedipe and Shafiee, 2021). In each phase, risk factors/hazards must be considered. However, OWF decommissioning has not been a focus in safety engineering research to date. The main decommissioning activities are described briefly.

4.2.1.1 Planning and consenting

This stage involves task scheduling (accounting for weather and other environmental conditions), stakeholder consultation, procurement, (sub)contracting, transportation planning, selection and chartering of vessel fleet, obtaining licenses and certifications to execute, developing a lift plan, etc. (Acero *et al.*, 2016). During planning, the duty holder is responsible for engaging all relevant regulatory bodies. The lift plan informs decisions on the vessel fleet to be chartered and the number of personnel to be deployed for operations. In Morandeau *et al.* (2013), the Mermaid software was proposed as an economic risk management tool to reduce the cost-associated risks by improving the project schedule in planning.

4.2.1.2 Wind turbine preparation

This involves disconnecting wind turbines from the substation/grid, disconnecting the cables, removing hydraulic fluids and other toxic substances from the nacelle, removing the elevator from the tower, removing excess marine growth, fitting/welding lift points on the turbine if required (Topham *et al.*, 2017; Adedipe and Shafiee, 2021). This is a repetitive activity for all the wind turbines on site. The risks associated with this activity involve drop from height, asphyxiation due to confinement for extended periods, etc.

4.2.1.3 Lifting and loading (including unbolting and cutting of WTG and foundation)

This involves unbolting, cutting, disassembly, lifting and loading onto the transportation vessel, and vessel repositioning. Operation durations depend on factors including lift configuration, environmental conditions during operations, wind farm size and number of vessels. Vessels that may be used include jack-up barges, floating cranes, shear-leg crane barges, heavy lift vessels (HLV), installation vessels, etc. (Zhao *et al.,* 2018; Liebherr, 2019). Typical factors involved in crane selection are: height of lift, reach, weight of components, safe working load (SWL) capacity of crane, wind turbine rating, maximum lift capacity of crane, method of nacelle removal, sea states, environmental conditions, etc. Ruud and Mikkelsen (2008) presented the steps involved in a generic offshore lifting operation using cranes, including influencing factors, risk levels and mitigation measures. Safety factors during lifting operations

include: non-exceedance of SWL capacity, adequate prior maintenance and certification, using of appropriate attachment tools, etc. Safety factors during loading operations are related to the loading/arrangement layout, fastening of components, deck loading capacity, and vessel stability/ballasting. The support structure/foundation lift has similar risk factors as the wind turbines removal except the height related factors. For further reading readers can refer to Seyr and Muskulus (2016) and Hinzmann *et al.* (2019).

4.2.1.4 Transportation

After lifting, the components are loaded onto the intended transport vessel based on the transportation schedule and charter plans and pre-planned deck layout. They are transported to shore, and the vessel returns to the site. Goerlandt and Montewka (2015) presented a review of risk management practices in the maritime transportation industry. The decommissioning fleet may be made up of an installation vessel, support barges/vessels and tow tugs. Transport vessels may be subject to mechanical or structural faults or failures, as reported in Abdussamie *et al.* (2018). The authors made a case for relying on qualitative risk evaluations (HAZID and fuzzy risk assessment) because of data sparsity with four consequence classes: personnel, asset (vessel and modules), economic and environment. Transportation alternatives may include the use of one removal vessel like a wind turbine installation vessel (WTIV) or multi-vessel alternative (Topham and McMillan, 2017).

4.2.1.5 Waste management

The removed components transported to port/shore must be disposed of in the most practically sustainable manner and according to local and international waste management regulations like the EU Landfill Directive (1993/31/EC) (United Nations, 1982; OSPAR Commission, 2006; Cherrington *et al.*, 2012). The different waste management methods include recycling, reuse, energy regeneration, scrapping, etc. A number of deepwater ports are used for decommissioning like the Port of Grenaa in Denmark (Port of Grenaa, 2020).

4.2.2 Risk assessment tools and techniques for offshore wind farm decommissioning

According to ISO 31000, risk is defined as the "effect of uncertainty on objectives, expressed in terms of potential events, likelihood and consequences" (BSI, 2018). Risk assessment is used in decision-support to ensure safety of operations. Mathematically, risk may be expressed as seen in Equation **4-1** (Rahman *et al.*, 2020).

$$Risk = \sum_{i=1}^{n} \mathrm{P_i} \times \mathrm{C_i} \qquad \textbf{4-1}$$

where P_i represents the probability of occurrence of the *i*th hazardous event and C_i represents the consequence of the *i*th hazardous event. The probability of occurrence may be obtained from different sources, including: historical data, expert judgement or computerised modelling (Friis-Hansen *et al.*, 2002; Li *et al.*, 2012; Kim *et al.*, 2020b). Some other scholars do not consider that risk should be quantified in absolute values of probability and consequence (Aven, 2015). Most OWF decommissioning risk management practices are adopted from adjacent industries, particularly the offshore oil and gas industry. Risk management involves the identifying and controlling hazards that can hamper operations. Safety is not the absence of risks; it is rather a state whereby as little as possible can go wrong (Aven *et al.*, 2007; Shafiee, 2015). Safety management in construction is studied using different safety indicators like lost time injury frequencies (LTIF) and total recordable injury rates (TRIR) in Winge *et al.* (2019). These indicators also have been adopted in the offshore wind energy industry as reported in G+ Global Offshore Wind Health and Safety Organisation (2020). Some commonly used tools/techniques are described below:

4.2.2.1 HAZID

HAZID (hazard identification) is a tabular, qualitative technique used to identify potential operational hazards/deviations and their possible causes and consequences. A HAZID worksheet lists the different hazards that can occur during operations in an observed system. HAZID can be carried out using workshops, interviews, surveys, etc. During HAZID workshops all or parts of the operation or equipment under control (EUC) can be considered and a log kept of all potential hazards or deviations. The

HAZID is conducted by detailing all likely hazardous events in the particular operation or system being assessed. Secondly, detailed descriptions of the hazards are presented, usually in a tabular form with the possible causes and consequences (Rausand 2013). The asset managers are then notified of the list of potential hazards / deviations, causes and consequences to mitigate, control or eliminate them.

4.2.2.2 Fault tree analysis (FTA)

FTA is an established diagrammatic technique which uses a top-down (deductive) method to identify, model and analyse the relationship between different causal events that can lead to an unwanted system/operational top event (Shafiee *et al.*, 2019). It is used for qualitative or quantitative assessments of the top event based on the use of intermediate and basic events and logic gates. Events are operational/system occurrences that can lead to an unwanted fault/failure during operations. Gates are the symbols that show how the events develop and their relationship to one another. Events are connected by either AND (resulting event occurs only if all input events occur) or OR gates (resulting event occurs if any input event occurs). Some symbols are represented in Figure 4-2. To conduct a fault tree analysis, the top event and boundary conditions will be clearly defined and then the logic tree is constructed level by level with the likely causes of the system/operation failure/event (Rausand 2013). As a widely used technique in safety engineering, FTA is often used in conjunction with other approaches like event tree analysis (ETA), failure modes and effects analysis (FMEA), etc. (Hosseni *et al.*, 2020).

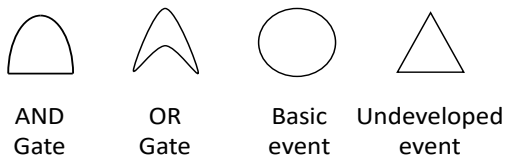

Figure 4-2 FTA symbols

4.2.2.3 Event tree analysis (ETA)

ETA is a bottom-up (inductive) diagrammatic technique that uses reasoning to show escalation/development of a potential unwanted initiating incident/event and different possible outcomes. It shows the safety/hazard promoting factors at each level of the

event tree with each level developing into two branches (one for success and one for failure) for different potential outcomes. The consequences of operational (or system) failure depend on the safety gates at each stage of the tree development. In order to determine an event sequence, the ETA can be performed (Aneziris *et al.*, 2008). The ETA is developed by determining potential scenarios that can result if a hazardous event occurs. Secondly, the barriers/safety promoting factors are identified that can control or mitigate the occurrence or impact of the hazard. Lastly, the consequence as a result of each scenario is then qualified or quantified based on available data input (Rausand 2013).

4.2.2.4 Risk matrix

A risk matrix, also known as the consequence/likelihood matrix, is a technique used to categorise risks into different levels based on the combined likelihood and consequence ranking in order to rate the significance for prioritising mitigation/control actions. It is made up of two axes, with the likelihood on one axis and the consequence on the other axis. Each cell represents a risk rank or rating which is determined for every potential event being assessed. It is used to rate, evaluate and communicate the magnitude of different risks and determine how acceptable they are in order to set risk management priorities. The likelihood or consequence rating can be of three, four or five levels, making a $3X3$, $4X4$ or $5X5$ matrix, respectively (BSI, 2019b).

4.3 Methodology

In this study, semi-quantitative risk analysis approaches are used including HAZID, likelihood of occurrence (frequency) estimation, consequence assessment, and risk matrix in order to prioritise the required risk control/mitigation measures or barriers. A risk assessment is conducted using the HAZID analysis and FTA and ETA methods for the OWF decommissioning activities.

4.3.1 HAZID for OWF decommissioning

The hazards inherent within the decommissioning activities were identified using the HAZID technique. A HAZID study was conducted to obtain different potential hazards or incidents involved in the decommissioning activities. In the study, hazards were identified from the literature and selected based on their potential to disrupt

decommissioning operations. During decommissioning activities, the safety of operations depends on factors such as vessel safety, cranes and other lifting equipment remaining in good working condition, personnel safety, and compliance with regulations.

4.3.2 Fault tree analysis (FTA) - Estimation of likelihood

In this study, the likelihood of occurrence for the top event is estimated for lifting and loading operations to determine the potential threats to safety. The top event (TE) during lifting and loading operations is "suspended/halted lifting and loading operations". The FTA focuses on two types of failures related to lifting and loading activities, including: operational faults/failure and equipment faults/failure. The fault tree diagram (FTD) includes the probability of occurrence of the basic events/causes that could lead to the top event. The intermediate events investigated are collision, vessel damage and crane failure as illustrated in Figure 4-3. FTA can also be used to present the likelihood of occurrence of each of the basic events and the minimal cut sets (MCS), which are the smallest combination of events that can lead to the top event. All datasets used in the fault tree to estimate the likelihood of occurrence can be seen in Table-C-1 of the Appendix section.

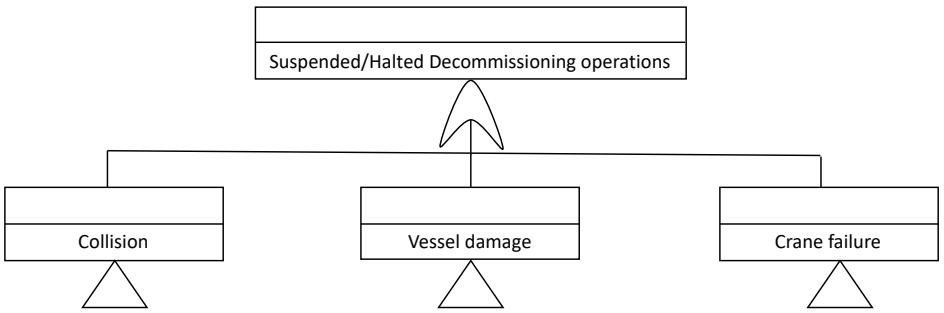

Figure 4-3 Fault tree diagram for top event (suspended/failed decommissioning operations)

They are connected by an OR gate because any one of the intermediate events can result in the top event. There are a host of FTA tools available including PTC Windchill FTA, ReliaSoft BlockSim, MS Excel, Isograph FaultTree+, etc. (Baklouti *et al.*, 2017). The data for constructing the FTDs can be collated from different literature

sources or expert judgement. The probability of occurrence/likelihood ranking used is presented in Table 4-2 below.

Table 4-2 Probability of occurrence/frequency/likelihood index ranking.

Index	Probability
1	$p < 0.00001$
2	$0.00001 \leq p \leq 0.0001$
3	$0.0001 \leq p \leq 0.01$
4	$0.01 \leq p \leq 0.\ 1$
5	$p \geq 0.\ 1$

4.3.2.1 Collision/contact

Collision hazards are a significant concern for the offshore wind energy industry. Collision is often caused by three distinct factors as reported in Antão and Soares (2006) and Dai *et al.* (2013). These are: failure in navigation operations, manoeuvring operations and/or hazard detectability. These basic events and their combination are important to understand in order to make adequate provision for mitigation and control measures. Data on offshore wind collision is available in databases like: G+ Global Offshore Wind Health and Safety Organisation (2020) and Marine Accident Investigation Branch (2020). In Figure 4-4, the collision intermediate event is further developed based on navigation, manoeuvring and detection failures.

Navigation failure is caused by a combination of procedural issues, equipment failures and decision-making errors. Manoeuvring failure is due to human-related errors and equipment failures, and detection failure is most often caused by human errors. Because OWF decommissioning and installation vessel data is not yet as granular as tanker vessels, the data used are taken from collision accident estimations of tankers in Uğurlu *et al.* (2015). The frequency estimates are considered suitable because the probability of failure estimation can be representative for heavy lift / jack up / transportation vessels, which have similar navigation and manoeuvring basic events and thus, applicable only for frequency estimation in collision incidents. The consequence estimation is incomparable, which is not used in this study.

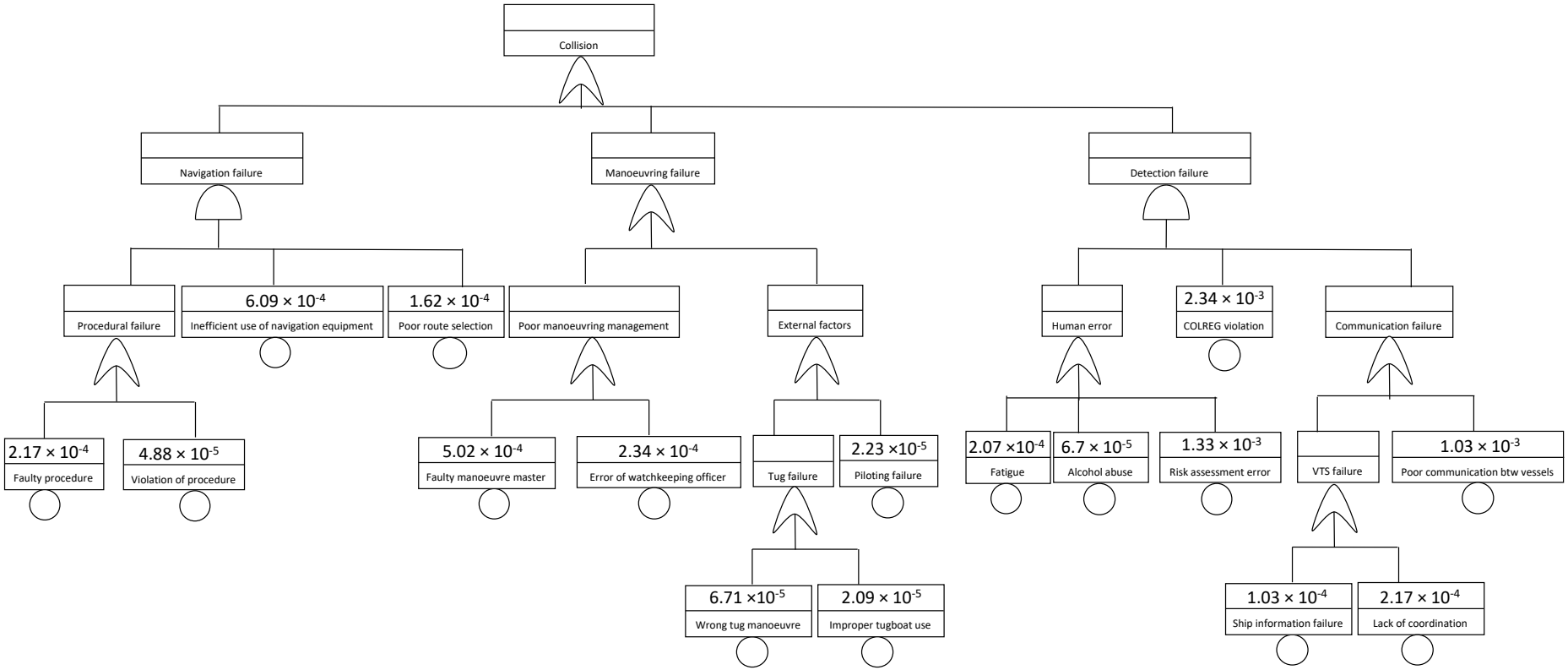

Figure 4-4 Fault tree diagram for collision event (intermediate event)

4.3.2.2 Vessel damage

Vessel operation management is critical for decommissioning and can be costly, especially for operations involving large modules. In this study, vessel damage was considered in place of grounding because there is limited possibility of damage by grounding during lifting and loading operations offshore. Marine vessel damage can be caused by mechanical, structural or human-related failures, and may lead to dynamic changes in vessel response. The fault tree for vessel damage was developed, excluding events that could lead to collision or grounding. Vessel damage can be caused by events like improper cuts, poor payload estimation, an imbalance in the forces acting on the vessel, etc. The failure rate values of each basic event was obtained from Babaleye *et al.* (2018) and Rahman *et al.* (2020) as shown in Figure 4-5.

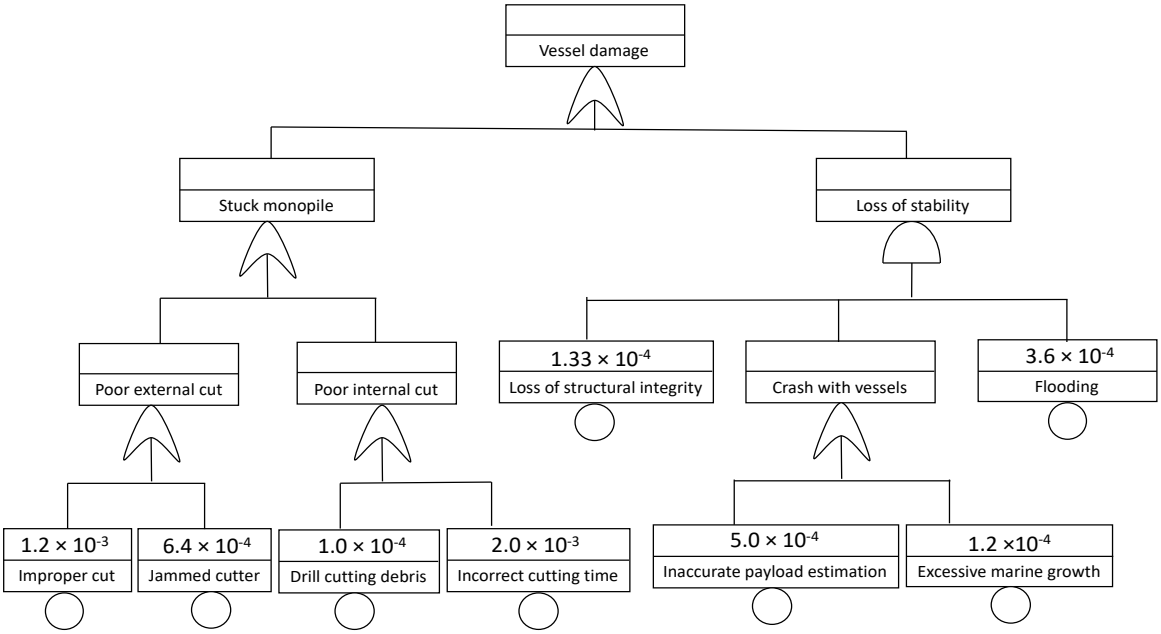

Figure 4-5 Fault tree diagram for vessel damage event (intermediate event)

The operation limits for a lifting vessel are set to ensure that the vessels remain safe (DNVGL, 2015; Luo-Theilen and Rung, 2019). Structural integrity, cutting efficiency, jack up leg/seabed interaction, payload estimation, sea states, etc. are assessed, but failures can still occur if a combination of events takes place. Clean cuts are required to avoid potential operational risks; thus, appropriate severance methods

must be selected (Li *et al.*, 2016; Kaiser and Pulsipher, 2004). Vessel damage can result in sinking or capsize if safety barriers are ineffective or if there is a slow response to incidents that eventually escalate.

4.3.2.3 Crane failure

The crane is the most critical equipment in the lifting operations. Crane overloading must be prevented with due consideration of SWL, load behaviour during all stages of the lift, lifting reach/angles/heights, and the dynamic response of the vessel and crane system in the real time environment. Crane operability must be certified by an independent body such as DNVGL (DNVGL, 2015), however, the duty holders are responsible for ensuring that operational plans and activities are prudent (DNVGL, 2017). Figure 4-6 shows the fault tree of the crane failure event and the basic events and their failure rate values obtained from Bai *et al.* (2012) and Sun *et al.* (2012). Any of the basic events represented can lead to the unexpected motions during lifting and loading, excluding bad weather conditions. There is also a potential for self-induced vibrations like *galloping vibrations* caused by winds acting on the crane (Klinger, 2014) which may be more likely in the offshore operating environment.

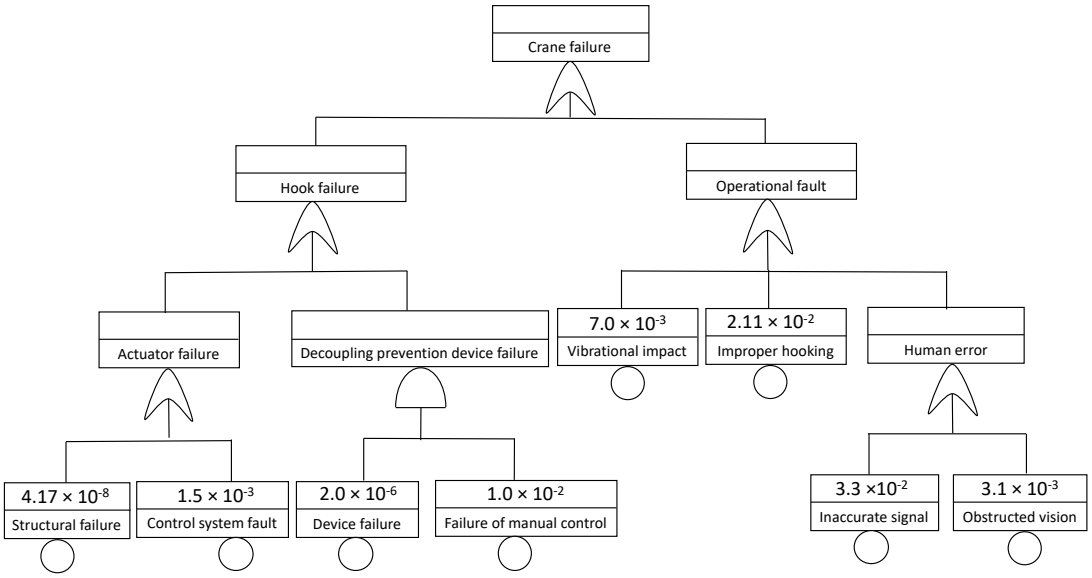

Figure 4-6 Fault tree diagram for crane failure event (intermediate event)

4.3.3 Event tree analysis (ETA) - Consequence estimation using scenario analysis

Event trees are graphical tools used to show how an initiating event can develop depending on the safety/hazard promoting factors for different potential scenario outcomes. The potential consequences of operational (or system) failure depend on the safety/hazard promoting factors at each stage of the tree development. In order to determine the event sequence an ETA can be performed, or a functional block diagram used (Aneziris *et al.*, 2008). Multi-dimensional consequences of the hazards are identified for the events presented for collision, vessel damage and crane failure operational deviations/hazards. The four consequence classes used are offshore personnel safety, asset losses, economic, and environmental consequences. Safety/hazard promoting factors can be evaluated in the event tree to determine where operational/technological improvements may be needed in decommissioning operations. The economic consequence is based on lost days, contingency costs and schedule overruns (Jacinto and Silva, 2010). Consequence data can be obtained from incident reports or computer modelling (finite element modelling). Finite element modelling can be used for collision impact energy estimation to estimate the energy absorbed and structural behaviour of a ship or wind turbine structure (Dai *et al.*, 2013; Kim *et al.*, 2020b).

In this study the consequence ranking is based on the ranking matrix in Figure C-1 of the Appendix section (BSI, 2002; 2019). The ranking is based on the success or failure of the safety/hazard promoting factors, with the letters P, A, E and EN representing personnel, asset, economic and environmental consequences, respectively. The end of each success (S) or failure (F) branch shows the consequence rank for each event/scenario. If an event occurs and does not progress to the next factor/barrier, it follows a success path; if the graduates to the next factor/barrier, it implies a failure (F) and proceeds to the bottom branch of the event tree, until the final event has been reached.

4.3.3.1 Event tree for collision/contact

The event tree for the collision event is presented in Figure 4-7. The safety/hazard critical factors, including vessel hull damage, vessel stability, detached or dropped

load, man overboard and vessel on collision course with another asset are seen above the tree, represented by each tree branch for which failures (F) result in further development of the tree and success (S) results in the expression of the estimated consequence. Collision potential will vary from site to site, largely depending on the wind farm layout. Influencing factors of collision risk include: number of vessels (removal and transportation), number of wind turbines, etc. The risk assessment can further be investigated for the type of collision: vessel-vessel collision (V-V) or vessel-turbine collision (V-T). With more than one consequence class for each branch, the higher ranked consequence was used to classify the chain of events in each tree branch. For example, hull damage and loss of vessel stability, will cause economic and asset-related risks, higher costs in future insurance premiums, remedial action and repair costs - (ranking: 2).

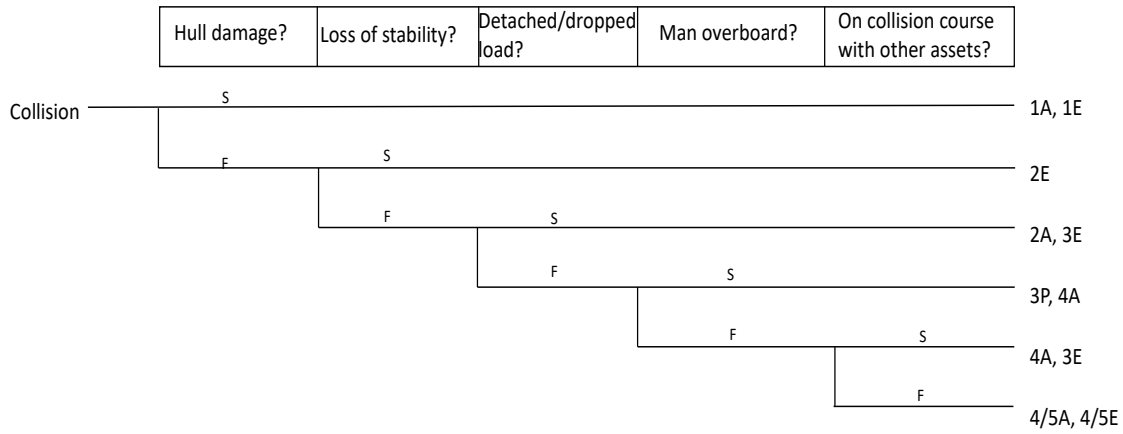

Figure 4-7 Collision event tree

4.3.3.2 Event tree for vessel damage

The event tree for the vessel damage presents the possible consequences as shown in Figure 4-8. The safety/hazard promoting factors are water ingress, flooding, vessel instability, detached cargo, and sink/capsize. If the vessel loses stability, it can lead to detached loads and compound into other failures/incidents. The vessel may be damaged due to swinging/dropped loads or loss of stability. The liability of the removal vessel damage rests with the agreed party within the contract. Regardless of liability, personnel safety must be assured throughout the decommissioning process. If there

is vessel/hull damage with uncontrollable water ingress that leads to flooding, it may cause extensive damages to the vessel and other equipment on board. This will be classed under damage to multiple assets but with no damage to the environment resulting in higher financial/economic liabilities (ranking: 2). If the vessel sinks/capsizes, this is a major loss of asset and potentially multiple personnel injuries (ranking: 5).

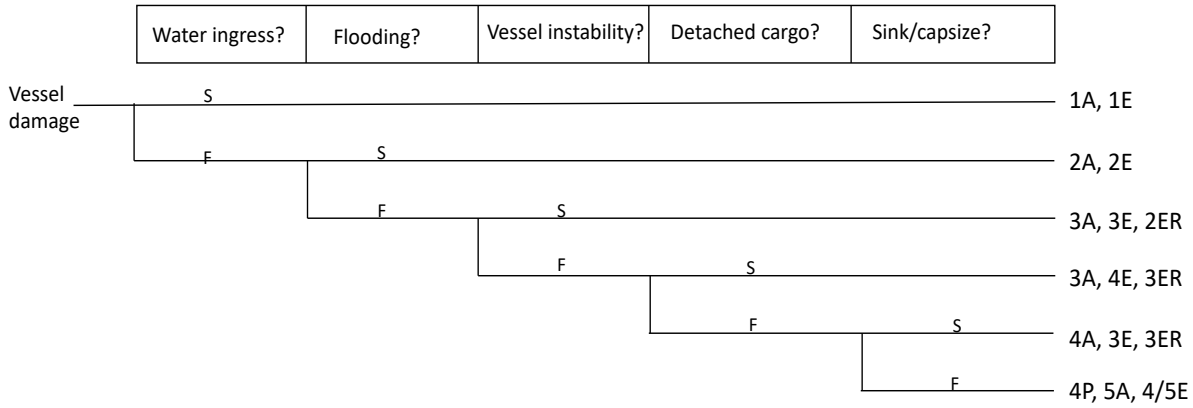

Figure 4-8 Vessel damage event tree

4.3.3.3 Event tree crane failure

Crane failure includes the failures of the crane operations or the load being lifted. The failure of the crane can have minimal or catastrophic consequences that leads to vessel stability compromise depending on the failure extent. It is important that inspections are carried out at set intervals during lifting operations and peculiar project/site factors are taken into consideration. The event tree is presented in Figure 4-9, where the safety/hazard promoting factors are loss of crane/load integrity (the load may lose integrity at the lift points), swinging/dropped load, safe/dangerous zone, loss of structural strength as a result of the swinging load, effectiveness of remedial/corrective action. If crane strength is compromised, this is local asset damage to a single/multiple equipment and moderate economic impact (ranking: 3). If the swinging/dropped load falls within a dangerous zone, there may be multiple personnel injuries and extensive damage without the need for extensive remedial action (ranking: 4).

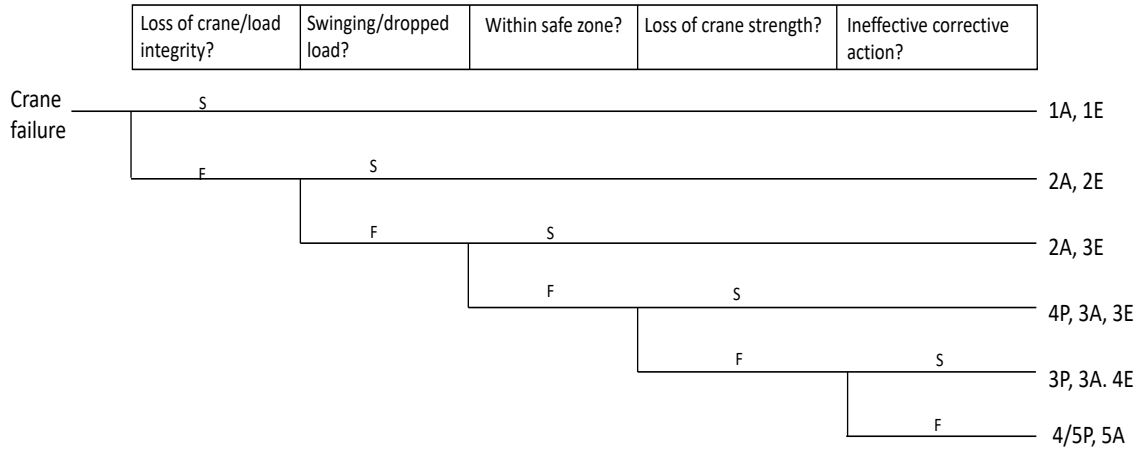

Figure 4-9 Crane failure event tree

Overall, the event trees above consider possible scenarios that could occur if collision, vessel damage and crane failure occur. These different scenarios and their corresponding safety/hazard promoting factors and barrier effectiveness may be further developed using simulations to predict the outcomes presented in order to quantify the consequences. The types of simulations that can be conducted are damage extent, survivability, cargo (WTG components) pollution modelling, and structural response modelling for the different potential outcomes.

4.4 Results and discussion

The results obtained from the HAZID, FTA (including the minimal cut set result), ETA and risk matrix methods are presented in the following subsections. A minimal cut set is determined from the following FTA, a four-class consequence analysis is conducted for the three intermediate events leading to failed or suspended decommissioning operations.

4.4.1 HAZID table

In Table 4-3, the HAZID result is reported for operations involved in an OWT decommissioning project and some guidewords are used to identify the associated operational deviations or hazards.

Table 4-3 HAZID table for OWF decommissioning (literature sources: G+ Global Offshore Wind Health and Safety Organisation (2017); European Agency for Safety and Health at Work (2013); Ontario Ministry of the Environment and Climate Change (2016); Abdussamie et al. (2018); Babaleye and Kurt (2018, 2019).)

Operation	Guideword(s)	Deviation/Hazards	Possible causes	Possible consequences
Planning and regulatory approval	Delay	Schedule delays	Poor weather conditions. Failures or breakdown of decommissioning equipment without backup.	Cost overrun risks.
	Delay	Delay in documentation submission/approval	Delay in obtaining the appropriate permits. Incomplete environmental impact assessment.	Schedule delays and cost overruns.
Preparation activities for removal (removal of hydraulic fluids, marine growth)	Confined space risks	Asphyxiation	Inadequate ventilation in confined spaced.	Personnel harm/fatalities.
		Injuries caused by accreted ice fragments	Extreme weather (cold)	Personnel injuries.
	Electrical hazards	Electrocution	Poor disconnection procedures. Personnel error.	Electrical burns. Other personnel injuries/fatalities.
	Spills	Spill of hydraulic fluid	Poorly secured hydraulic fluid	Additional cost/duration for clean up if above allowable limit.

			receptacle. Poor procedures. Personnel error.	
	Dropped object	Dropped loads	Poorly fastened equipment	Additional cost to retrieve dropped load.
Vessel positioning	Impact	Vessel collision with other assets	Tug impact. Manoeuvre collision.	Vessel damage. Vessel flooding. Vessel capsize/sink. Collision with other assets. Structural damage of other assets.
	Drift	Loss of station-keeping	Faulty dynamic positioning (DP) system. Loss of power in vessel. Extreme environmental conditions (typhoon).	Structural failure. Vessel flooding. Loss of towline. Personnel injury.
	Stability	Loss of stability	Differential sticking of cut monopile. Loss of structural integrity.	Vessel capsizes or sink. Personnel injury/fatality.
	Ascent/Descent	Sinking of removal or transport vessel	Damaged vessel hull. Impact from other vessels. Dropped objects.	Loss of unit. Personnel injury/fatality.
	Ballasting	Ballast system failure	Electrical or mechanical fault. Centrifugal pump failure. Failure of ballast valves.	Delay in ballasting operations. Delay in removal operations.

	Operational fault	Failure of support equipment (tugs)	Mechanical failure. Electrical failure. Barge/tug operational failure.	Schedule delays. Cost overruns.
Personnel transfer/hoisting	Fall	Fall from height. Man overboard.	High winds. Broken hoist cable. Vessel impact. Exposure to dropped object. Spinning of blade when removed.	Personnel injury/fatality.
	Dropped load	Dropped tools/equipment	Poor attachment/fastening of tools.	Additional costs for retrieval.
	Overloading	Lifting crane overload	Inaccurate estimation of payload weight. Presence of significant amount of marine growth on payload.	Structural damage. Loss of vessel stability.
	Structural damage	Damaged lifting point. Hook stabilisation tool failure. Lifting clamp damage. Tugger wire failure.	Inadequate structural integrity inspection. Inaccurate estimates of residual anode thickness. Corrosion thinning at crevice of lifting point. Cyclic loading over the course of the asset life. Inadequate/poor	Dropped objects. Personnel injury/fatality. Collision with nearby vessels or installation.

Lifting and loading operations (blades, nacelle, hub, tower)			inspection of lifting points.	
	Collision	Navigation failure	Loss of control. Faulty procedure. Violation of navigation procedures. Poor use of navigation equipment.	Loss of removal vessel positioning. Financial losses.
		Manoeuvring failure	Loss of control. Poor management of vessel manoeuvre. Failure of tug, barge or other transport vessel.	Collision can lead to damage of nearby assets.
		Detection failure	Poor personnel observation/attention.	Personnel injuries/fatalities.
	Impact	Dropped/swung objects and loads	Extreme weather (high winds). Structural failure. Loss of vessel station keeping. Fastening system not properly installed. Vessel movement during lift. Limited work area on vessel. Other vessel(s) on site. Compromised wire ropes.	Removed component(s) fall over. Personnel injuries/fatalities.

	Stability	Loss of stability	Uneven/poor deadweight distribution during lifting operations. Differential sticking of cut pile.	Impact. Personnel injury.
	Operational fault	Vessel or handling equipment. breakdown. Improper fastening of components.	Mechanical/electrical failure of generator and prime mover assembly. Human error.	Delay in operations.
	Operational fault	Mechanical hazards.	Contact with moving parts.	Personnel injury or fatality.
	Extreme weather conditions	High winds/waves.	Working in winter season.	Fall from height. Collision with tower or other machinery. Personnel injury/ fatality. Dropped objects. Delay in project schedule.
Lifting and loading (foundation, offshore substation (OSS) and masts)	Structural hazards	Stuck pile	Wrong vessel positioning. Soil compaction above estimations.	Vessel damage. Man overboard. Personnel injury/fatality.
	Dropped load	Dropped tools/equipment.	Poorly secured load. Sea fastener failure. Equipment failure. Poor adherence to loading/unloading plan.	Additional cost of retrieval.

Lifting and loading (miscellaneous structures like scour protection)	Dropped load	Dropped structure on nearby assets.	Equipment failure during loading operations. Dropped within dangerous zone.	Additional cos of retrieval. Personnel injury/fatality if in dangerous zone.
Transportation to port	Collision	Collision with other assets/passing vessels	Poor navigation system. Poor weather. Failure of engine.	Vessel damage.
	Drift	Vessel drift	Poor weather. Vessel operational fault.	Collision with other assets.
	Operational fault	Barge operation fault	Electrical/mechanical fault.	Schedule delay.
Waste management	Spills	Fluid spills	Poorly sealed hydraulic fluid receptacles.	Environmental pollution. Additional cost to clean up.
Site clean-up and surveys	Lost equipment	Lost ROV	Murky waters. Poor weather.	Additional cost to charter new ROV.
Post-decommissioning	Monitoring error	Data misinterpretation	Insufficient Environmental hazard identification (ENVID) analysis.	Poor decision-making based on faulty data.

4.4.2 Frequency analysis - Top event FTA

The top event (suspended/halted decommissioning operations) has a probability of failure of 6.9×10^{-2} based on datasets used in the fault tree to estimate the likelihood of occurrence can be seen in Table-C-1 of the Appendix section. It is assumed that the same level of inspections and modifications are used in maintaining reliability/safety of equipment and overall operations. The top three most frequently occurring basic events include: inaccurate signal, improper hooking (during crane activities) and failure of manual control. The least occurring events are crane structural failure, decoupling prevention device failure and improper tugboat use. Of all these basic events, crane-related fault/failure events are estimated to be the highest occurring. Thus, this study suggests that crane-related events are the area of focus for contractors, asset managers and regulators. Existing best practices and guidelines are in place to prevent/control any mishaps/risks. The frequency ranks are presented in Table 4-4, where the frequency index for each intermediate event is shown based on the fault tree analysis from sub-sections 4.3.2.1, 4.3.2.2 and 4.3.2.3 and the overall top event.

Table 4-4 Frequency ranking of lifting and loading incidents

Frequency Index	Intermediate events/top event	Probability
3	Collision	8.46 × 10-4
3	Vessel damage	3.94 × 10-3
4	Crane failure	6.42 × 10-2
	Top event	6.9 × 10-2

4.4.2.1 Collision event frequency of occurrence

The probability of occurrence of collision during decommissioning was estimated to be 8.46×10^{-4}. According to the fault tree, the three highest contributing events to collision risk are COLREG violation, risk assessment error and poor communication between vessels, with probabilities of occurrence of 2.34×10^{-3}, 1.33×10^{-3} and 1.03×10^{-3}, respectively. All these probabilities are based on detection failure (E10 – E16) events,

which is hinged on human errors. Reliable and consistent communication between removal vessels is critical, especially if more than one vessel is to operate on site.

The estimated collision rate in this study assumes activity durations are impacted by decommissioning vessels needing to be repeatedly repositioned by each turbine for removal. The vessels will return to site and be positioned, and this cycle of operations will continue until all modules have been removed and transported. It is uncertain, however, if head-on collision or manoeuvring collision will have a higher probability of occurrence. This study does not classify the collision type. This study anticipated that this would depend on the wind farm size, wind farm layout and number of vessels used for operations. More data will be collected from operators as decommissioning operations increase over time for analysis.

4.4.2.2 Vessel damage frequency of occurrence

The vessel damage frequency assessment yielded a vessel damage probability of failure of 3.94×10^{-3}. The basic events with the highest probability of failure is differential sticking of the monopile during foundation removal operations. This is mostly influenced by the cutting operations as shown in Figure 4-5. There are different cutting techniques, and the selection depends on different criteria including type of foundation, thickness of the material, etc. In an attempt to lower the duration of cutting operations, different methods may be preferred over others subject to operator request. The vessel stability also depends on monitoring different lifting parameters. If the vessel is damaged by flooded members, it can lead to catastrophic vessel sinking or capsize.

4.4.2.3 Crane failure frequency of occurrence

The probability of occurrence of crane failure intermediate event was estimated to be 6.42×10^{-2}. From the FTA it is observed that crane failure or crane related events are mostly due to operational or mechanical failures. In the FTA, inaccuracy in signal, improper hooking of the object and failure of manual control are the three highest contributing events to crane failure. The potential for mechanical faults supports the case for secondary back-up controls fitted on the crane. This study shows that a hazard such as improper hooking may result in falling/swinging loads. Operational

safety thus depends on adherence to proper operating procedures as stated in the guidelines, standards and recommended practices.

4.4.3 FTA outcome - Minimal cut set (MCS)

The minimal cut sets were determined using Boolean logic expressions in the fault tree using the datasets in Table-C-1. The probability of a collision event (intermediate event IE1) was estimated to be 8.46×10^{-4}. The probability of a vessel damage event (intermediate event IE2) was estimated to be 3.94×10^{-3}. The probability of crane failure event (intermediate event IE3) was estimated to be 6.42×10^{-2}. The probability of the top event is estimated to be 6.89×10^{-2}, which presents a baseline case. In calculating the probability of occurrence of top event, the minimal cut set (MCS) is identified. The MCS is presented below.

$$TE = IE_1 + IE_2 + IE_3 \quad \textbf{4-2}$$

$$\begin{aligned} TE = (&E1.E2.E3 + E2.E3.E4 + E5 + E6 + E7 + E8 + E9 + E10.E13.E14 \\ &+ E10.E13.E15 + E10.E13.16 + E11.E13.E14 \\ &+ E11.E13.E15 + E11.E13.E16 + E12.E13.E14 \\ &+ E12.E13.E15 + E12.E13.E16) \\ &+ (E17 + E18 + E19 + E20 + E21.E22.E24 + E21.E23.E24) \\ &+ (E25.E27.E28 + E26.E27.E28 + E29 + E30 + E31 + E32) \end{aligned} \quad \textbf{4-3}$$

where TE is the top event and IE_i are the intermediate events (1=collision, 2=vessel damage, 3= crane failure).

The first order events represent the most critical events for which the top event can occur if only one of them occurs. The third order events are the smallest combination of events that can occur if three of the events occur at the same time.

4.4.4 Importance ranking (risk-critical factors) and sensitivity analysis

In order to improve the operation safety, the importance ranking is calculated to determine the basic events that contribute the most to a failed/suspended

decommissioning operation. This identified where operations need to be improved with respect to the operating system, equipment/vessel and personnel-related decision making. Each activity was analysed to observe how much impact a basic event would have on the overall top event (TE) if that basic event was eliminated. For example, the basic event, improper hooking, is set to zero to show the impact it has on the fault tree while the value (probability of occurrence) of all other basic events remain the same. The top event is calculated subsequently for each basic event set to zero. The output is presented in Figure 4-10, which shows the importance ranking of the basic events, excluding the events that reflected no significant impact. Inaccurate signal, improper hooking and vibrational effects have the highest impact on the top event with 48%, 31% and 10% changes, respectively. Based on this analysis, the crane failure basic events are the most likely to have the highest impact on a failed/halted decommissioning operation. Thus, mitigation and control efforts should make cranes a priority.

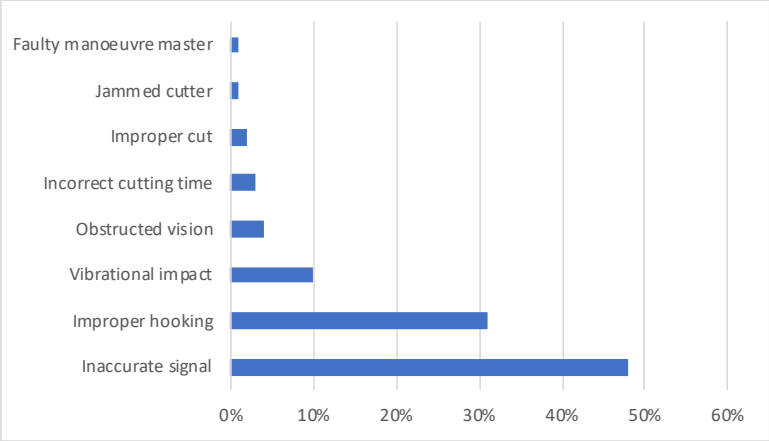

Figure 4-10 Importance ranking of basic events

4.4.5 Sensitivity analysis

In Figure 4-11, the sensitivity of the top event is assessed in order to observe the change in the top event frequency based on each basic event. To compare the sensitivity of each event, each event is set to zero, one after the other, while maintaining the probability of failure values of other basic events. It was observed that inaccurate signal, obstructed vision, improper hooking and vibrational effects shows

the highest sensitivity on the top event when eliminated. This implies that the TE will be most responsive to these events. This means that if those events can be eliminated, then the likelihood of failure of the decommissioning operations will also be reduced. This will be compared against the overall risk ranking determined by the risk matrix.

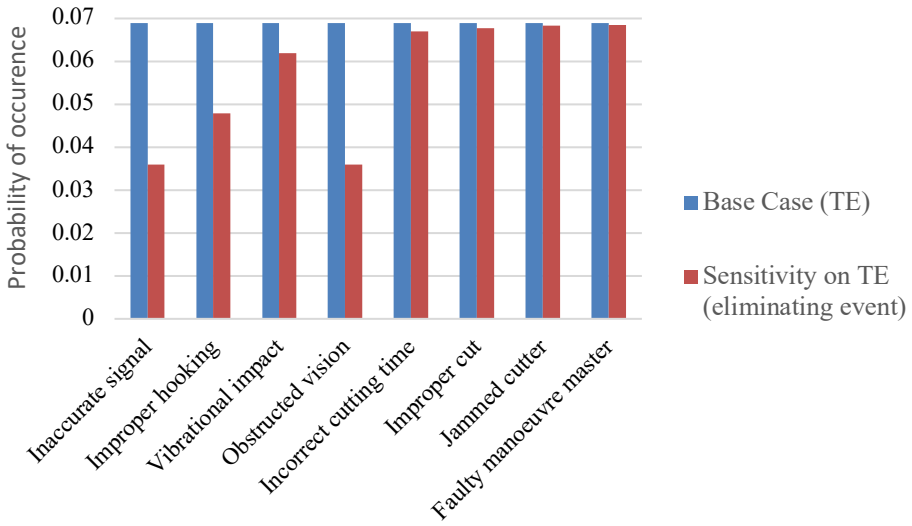

Figure 4-11 Sensitivity of basic events on top event.

4.4.6 Consequence analysis – Outcome ETA

The metrics of each consequence is expressed based on the values as seen in Figure C-1 of the Appendix section.

4.4.6.1 Collision/contact consequence scenario

In Figure 4-12 two scenarios are presented. If scenario A represents a collision event that leads to minor hull damage, the consequence will be asset damage and economic impact from financial loss/increase insurance premium or interest (severity ranking of 1: 1A, 1E). In scenario B where there is loss of stability and dropped/swinging load, this may lead to personnel injury and major damage/loss to the asset(s), and recovery of the dropped load (3P, 4A). There are costs associated with contingencies of these nature; however, more than the amount allocated may be required.

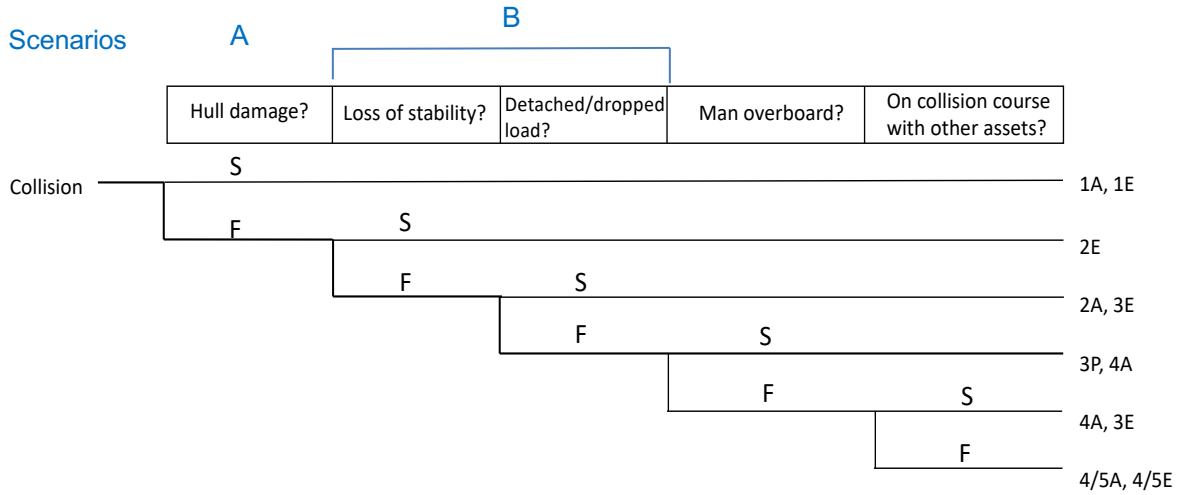

Figure 4-12 Collision consequence

4.4.6.2 Vessel damage consequence scenario

In Figure 4-13 the vessel damage hazard is presented. In Scenario A, if there is only water ingress without flooding or damage to other equipment, this will have a consequence of minor damage to one asset and minimum financial loss/premium/interest (2A, 2E). In scenario B, if after the vessel loses stability, the cargo becomes detached and the vessel capsizes/sinks, depending on the evacuation effectiveness, there may be multiple personnel injuries or fatalities, extensive damage/loss of asset, and maximum financial loss (4P, 5A, 4/5E). The environmental impact will depend on the hydraulic spill/transfer into the sea from the nacelle module. Scenario B shows the event path for the worst-case scenario.

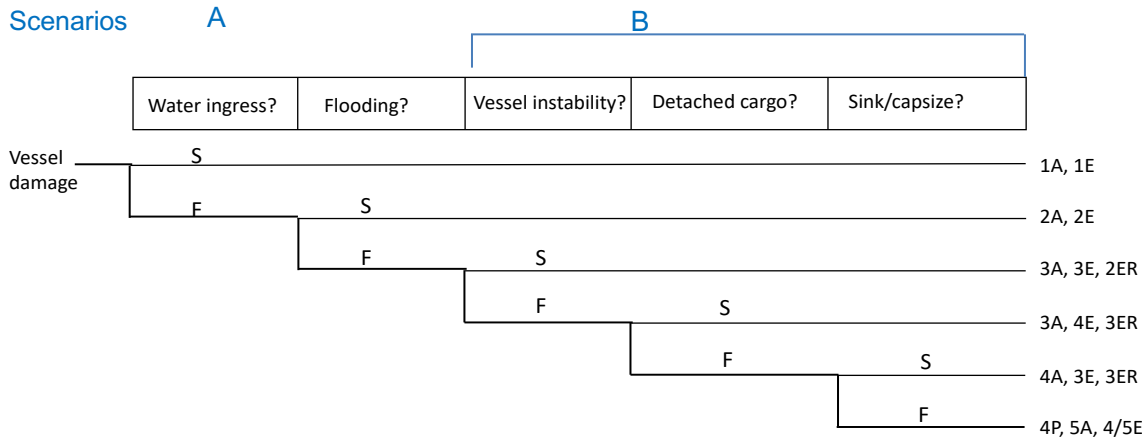

Figure 4-13 Vessel damage consequence

4.4.6.3 Crane failure consequence scenario

During lifting and loading operations, the impact of crane failure on personnel safety is determined based on the zone of occurrence (if it involves swinging/dropped loads), availability of first aid/medical care at the time of the incident. Economic impacts will be based on the exposure of the contractors or duty holders based on the contract liability clause extent of schedule delays. The social impacts depend on the contractors or duty holder's track record in safety; the impact on the asset is defined by the extent of the damage. The environmental damage will be dependent on how thoroughly the WTGs were prepared for removal in the event of a dropped object.

As seen in Figure 4-14, in the scenario A of the crane failure, if there is loss of crane/load integrity without further damage, this will lead to minor/major impact on the asset and minimum financial loss/premium/interest (£), increased contingency cost, and increased schedule delay cost (2A, 2E). In scenario B, there may be multiple injuries/fatalities, extensive asset damage and extensive financial loss/premium/interest (£) (4/5P, 5A).

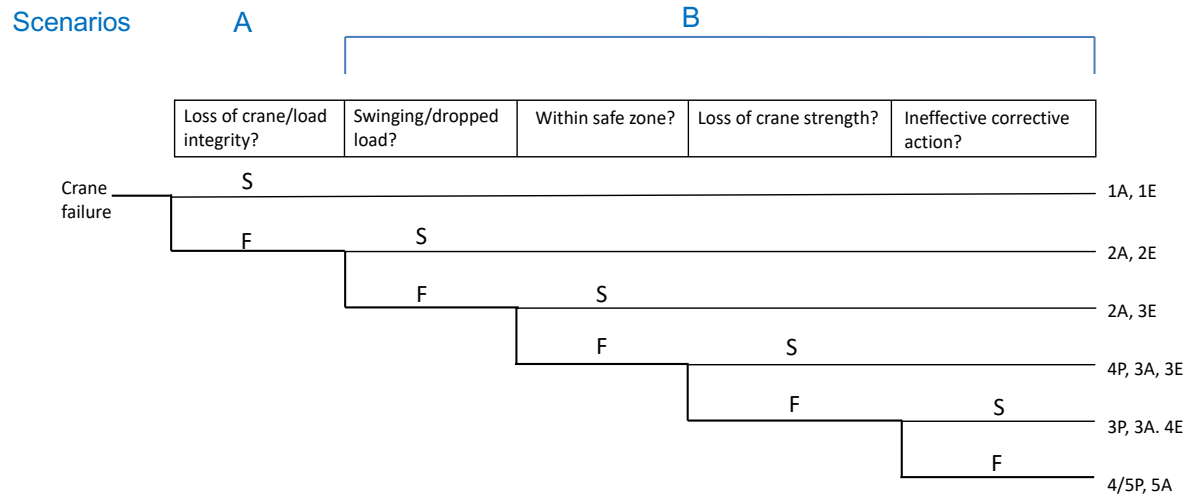

Figure 4-14 Crane failure consequence

4.4.7 Risk matrix for decommissioning operations

The risk matrix shows the risk values for the three intermediate incidents (collision, vessel damage and crane failure). For the incidents studied, the minimum, most likely and maximum consequence scenarios are determined. The risk values are a function

of the probability of occurrence and expected consequence given the safety/hazard promoting factors. The risks associated with each hazard are obtained for different consequence ranking scenarios with different outcomes. For each potential incident, frequency ranks are presented, and the different safety/hazard promoting factors were used to present the four consequence classes (indices) for each event as seen in Table C-3 of the Appendix section. From the risk matrix results, the crane failure has the highest level of risk followed by vessel damage and collision/contact, respectively. From the analysis, it can be seen that the asset and economic impacts are the highest risk classes overall, followed by personnel safety and environmental risks, respectively. The asset and economic risks are closely related. Personnel risk are seen to be unacceptable if crane failure occurred with a dropped object within a dangerous zone, as the punitive damages incurred may be high (medical bills, fatalities and compensation). Long term, insurance premiums may also increase.

4.4.8 The most safety-critical activities in lifting and loading operations

The most safety critical activities during lifting and loading operations are found to be those associated with crane operations. This is consistent with construction project conventions where crane safety is the most important during operations requiring lifting of heavy modules and even more so for offshore marine decommissioning projects. The highest risk drivers identified are related to crane operations such as weight of component in relation to the crane capacity and number of crane inspections per set of lifts. Crane vessels will have been tested for different loads, environmental and vessel response constraints. There is limited research, however, on the operability constraints related to the different types of lifts within wind farm decommissioning projects. In terms of the number of crane inspections per set of lifts, there is a more stringent process required by certification organisations who will usually have representatives present to approve of lifting operations after inspections are conducted. We propose that safety can be improved by lowering the number of lifts per wind turbine, considering crane lifting capacity and vessel type.

4.4.9 Mitigation and control

Reducing the risks involves reducing the likelihood of occurrence of incidents and/or reducing the impact/consequence of the incident to as low as reasonably practicable

(ALARP). To prevent hazards from escalating, barriers are put in place. Records of the barrier/control effectiveness should be kept. Barrier effectiveness can be monitored using maintenance records and inspections, which are closely monitored by regulators. Investment in improvement of barrier effectiveness may not lower the frequency of occurrence failures of the critical events. Therefore, the need for improvement must be considered using cost-benefit or cost-effectiveness analysis as the conventional cost-benefit approach may not always be the most suitable approach (Aven, 2007). Risk control options and some controls may be geared towards reducing the likelihood of occurrence and/or consequence of an event or the manner in which the risk burden is shared amongst all parties involved in the decommissioning project (BSI, 2019a). Mitigation and control measures will be focused to reduce the likelihood of occurrence or magnitude of consequence.

There are a number of mitigation and control approaches to prevent or safeguard against collision errors. Mitigation measures/barriers to reduce the impact of hazardous incidents include: (i) reduction of the level of impact on personnel (ii) ensuring high-quality inspection of the lifting equipment to ensure all standards are met (iii) reduction of marine activity duration (e.g. by using more efficient or robot-assisted methods) (iv) reduction of human-related errors by improved personnel training, modification of tasks or provision of the right personal protective equipment (PPE). Operational research is usually improved by performing human reliability analysis (HRA) (Rahman *et al.*, 2020) and because decommissioning operations are made up of man-machine tasks, human errors are bound to occur or may be caused by poor responses to mechanical errors. When an accident occurs, an investigation will be conducted by an independent body. It is recommended that investigation reports also be made public outside of public enquiries. Some mitigation and control measures are detailed in Table 4-5 below for personnel safety, asset safety, procedures/regulations to be put in place, lifting configuration, contingency planning, reporting and investigation. If a crane failure occurs, barriers should be put in place to control swinging/dropped loads and to prevent further escalations. In order to improve the safety of crane activities, *craneless* and *driverless* technology can be explored for decommissioning operations (Choudhary and Howes-Roberts, 2018).

Table 4-5 Mitigation and control measures for the intermediate events

Intermediate event	Personnel	Asset (Vessel/WF asset)	Procedures/Regulations	Lifting configuration	Contingency planning	Reporting and investigation
Collision	Use of appropriate PPE	Choosing appropriate vessel size for WF access (perhaps standardised criteria)	Safety zone standards should be assessed for decommissioning operations. Where applicable it should be different from WF installation safety zones.	Lifting configuration should be selected based on age of structure and number of removal and transportation vessels available on site.	Financial contingency provisions should be made to address issues that may be caused by hazards.	Collision risks during decommissioning (and installation) operations should be adequately documented, recorded and investigated.
Vessel damage	Depending on causes of event, personnel trainings must incorporate improved methods to improve competence.	Determination of an appropriate accidental limit state. Vessel hardening by design.	Limiting operations during a threshold of environmental conditions.	More research into vessel response during different lifting configurations.	Number of emergency/evacuation vessels should be assessed based on the number of removal vessels and wind farm size/layout.	Investigation reports are made easily accessible for improved learning and development for different stakeholders.
Crane failure	Use of appropriate PPE.	Replace any failed parts considering the cost and	Ensure the appropriate certifications are obtained before each set of lifts.	Removing components in smaller modules depending on	Ensuring the right contract is drawn up for any financial liabilities.	Investigation reports are made easily accessible for improved

	Promptness in response to move personnel into safe zone.	safety optimal level. Inspection records digitised to prevent errors in manual entries.		and factoring in the wind farm size into the chartered lift vessel.		learning and development for different stakeholders.

4.5 Conclusion and future work

This article presented a case to show that OWF decommissioning risk research is also as important as installation risk research and requires more attention in the asset lifecycle. To understand the potential risks better, we explored potential technical and (de)construction risks, particularly in lifting and loading activities. An improved understanding of the risk-critical activities will allow regulators, asset managers and asset owners improve safety operations in offshore wind decommissioning. Based on the G+ Offshore report (G+ Global Offshore Wind Health and Safety Organisation, 2020) the potential hazards throughout decommissioning activities were found to be higher during the lifting and loading operations. Thus, this study focused on lifting and loading operations because operational safety depends on vessels, cranes and other lifting equipment to be in good working condition. In addition, personnel safety must be ensured whilst complying with regulations, standards and recommended practices.

The OWF decommissioning risk assessment presented in this study was conducted using well-established methodologies including HAZID, FTA, ETA and risk matrix. The HAZID was conducted for all the key decommissioning tasks. The HAZID paints a picture of potential hazards involved in the different activities but is not exhaustive. The risks associated with lifting and loading operations were further assessed with FTA and ETA techniques for collision/contact, vessel damage (caused by loss of stability and vessel response) and crane failure incidents/hazards. The corresponding ETA was conducted to estimate the impact of all possible outcomes that can impact on decommissioning operations if hazardous incidents occur. A risk matrix was further used to estimate the level of risk of all potential hazards/incidents.

The crane events were considered to have the highest risk ranking followed by vessel damage and collision, with rankings as high as 20, 15 and 15, respectively. The crane events were caused by navigation faults, manoeuvring failures, hazard detection failures and human errors. The vessel damage, on the other hand, was primarily due to vessel stability concerns and vessel response.

The crane failure was caused by mechanical failures and human errors. The ETA was used to estimate the consequences of each potential incident in four classes, including: personnel, asset (vessel and wind turbines), economic and environmental, and possible scenarios were presented from the least to the highest possible consequence. The risk ranking was presented for the different scenarios. In addition, mitigation and control measures were proposed for personnel safety, asset safety, procedures/regulations to be put in place, lifting configuration, contingency planning, reporting and investigation to reduce the identified loads to as low as reasonably practicable (ALARP). The key risk drivers were identified using importance measures. Based on the analysis, the highest contributing events to the top event are: inaccurate signal, improper hooking and vibrational impact. If industrial HAZID records were to become public, it would be beneficial not just for the offshore wind industry but also for the other sectors in the supply chain.

Beyond decommissioning risks presented in this study, future work can investigate decommissioning operations related to financial risks to the company asset portfolio, transmission asset risk (like cables, piles or foundations removed or left-in-place), design improvements related to lifting points or lifting equipment like cranes, and organisational risks related to a need to improve decommissioning capacity/capability. Risk assessment is paramount to safe decommissioning and four classical risk assessment methods were applied to a baseline offshore wind farm case to identify critical safety factors in decommissioning. However, because these classical methods are limited (due to their static nature and the limited knowledge about OWF decommissioning to date), uncertainties have to be modelled; both as a means to validate and update the risk assessment parameters when new information is obtained. Further investigation into risk can be carried out with the use of methods like advanced fault tree models, probabilistic methods like fuzzy theory, Bayesian network (BN) models. In addition, accounting for the duration of operations in modelling the risks will offer better insight into the impact that the duration of each activity has on decommissioning safety.

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5 Bayesian network model for the probabilistic safety analysis of offshore wind farm decommissioning operations

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Abstract

The risk analysis of different asset lifecycle phases in offshore wind projects has received a considerable attention in recent years. With the accelerated rate of increasing offshore wind farm construction, it is imperative that risk management is planned thoroughly from the concept/planning stage to the decommissioning stage. With the advent of the first wave of wind farm decommissioning, research for the decommissioning phase of the asset lifecycle has become a critical subject. Bayesian Network (BN) has the robustness to be adopted for a safety critical activity like offshore wind turbine decommissioning, with capability of incorporating multiple uncertainties. This article proposes, for the first time, an advanced risk assessment tool based on BNs for offshore wind farm decommissioning. The highest safety-critical incidents are identified, and corresponding critical risk-influencing factors (RIF) determined. The impacts of reducing the likelihood of occurrence of human-error related, procedural and mechanical/electrical risk factors on suspended decommissioning operations are evaluated. This is the first study that applies BNs in risk assessment of the OWF decommissioning phase of the asset lifecycle. The significance of this study is that it is the first study to present safety-critical factors in OWF decommissioning and the potential benefits in improving safety engineering practices if OWF asset operators adopt BNs. In addition, for the most critical factors the corresponding

RIFs during OWF decommissioning were determined, which include visibility, crew fatigue, number of personnel per operation, proper procedures, crane integrity, number of wind turbines on the farm, number of lifts, inspection frequency and good equipment design. Thus, the mathematical descriptors of each critical incident were also determined. The study also shows the capability of BNs to be extended to influence diagrams by including utility and decision nodes, and the impact of treatment of the critical incidents. The results obtained from the influence diagrams report that repairs conducted to reduce the likelihood of crane failure have the highest effect compared with collision and vessel damage. Risk assessment teams can benefit from an advanced and dynamic tool like BN models to also make predictions of anticipated risks in order to improve decision-making of mitigation plans during decommissioning planning.

Keywords: Offshore wind; decommissioning; lifting operations, risk-influencing factors, Bayesian updating, influence diagrams.

5.1 Introduction

5.1.1 Trends in offshore wind decommissioning

The offshore wind energy industry is experiencing an accelerated growth in the number of wind farms installations throughout the globe, especially with commitments to net-zero ambitions. Asset management strategies for these new offshore wind farms (OWF) therefore requires an approach that rigorously incorporates decommissioning in asset lifecycle planning. In offshore wind projects, the decommissioning phase is relatively young compared to the installation phase and there is a need to pay closer attention to decommissioning (Invernizzi *et al.* 2020). Many project management scholars have concluded that there is a dearth of research related to the decommissioning phase of most infrastructure projects and the energy industry is no exception (e.g., see Locatelli *et al.*, 2020; Kaiser and Lui, 2018). Decommissioning is defined as the final phase of the wind farm asset lifecycle. Generally, offshore wind decommissioning operations involve four key phases: planning and consenting phase, transport and logistics phase, lifting and loading phase, and post-decommissioning phase

(Adedipe and Shafiee, 2021). Some motivations for decommissioning include unavailability of spare parts, availability of newer and more efficient wind turbine models, health and safety issues, expensive repair/repowering costs, etc. Safety of decommissioning operations is more critical than that of installation, as aging OWF structures at their end of life (EOL) will have a weaker structural integrity, which may lead to more severe hazards.

Recently, a few offshore wind farms have been decommissioned and there is a need to improve the understanding of project success factors that relate to the risks and costs at the end-of-life of OWF assets. With the increase in the number of wind farms being decommissioned before they reach the end of their designed useful life of 20-25 years, a trend of early asset retirement may continue for many OWF assets installed to date (Topham and McMillan, 2017; 4C Offshore, 2020; Adedipe and Shafiee, 2021). Since the first OWF decommissioning project (the Vindeby offshore wind farm), the trend in **Error! Reference source not found.** shows the estimated OWF decommissioning activities in the coming years calling for an increase in decommissioning capacity (Interreg North Sea Region Decom Tools, 2019).

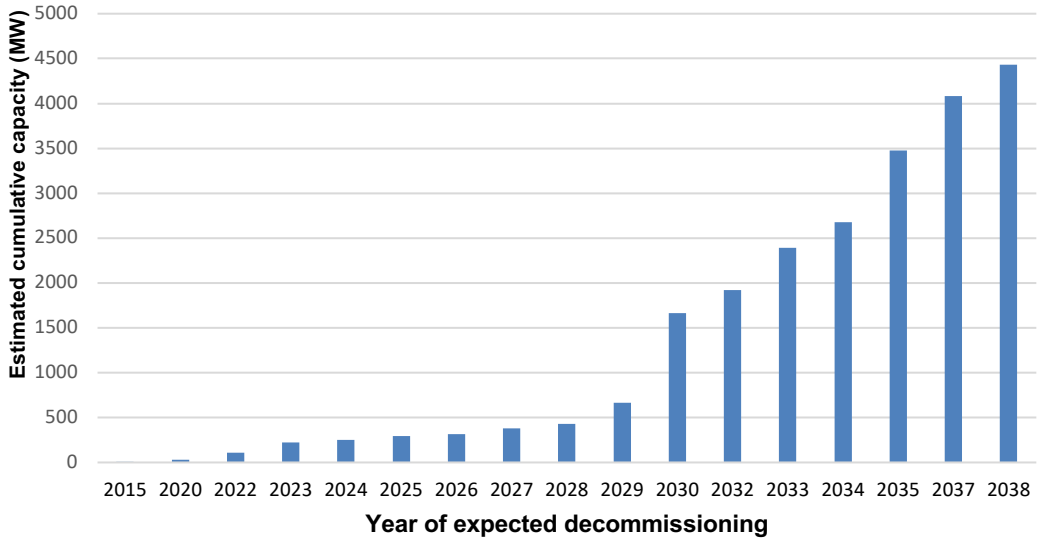

Figure 5-1 Projected cumulative offshore wind farm decommissioning (Interreg North Sea Region Decom Tools, 2019)

Decommissioning involves some level of risk that has been scarcely addressed in the literature. Risk management involves the identification, assessment, evaluation, risk treatment (mitigation/control) and revision (Shafiee, 2015). The risk assessment conducted for each phase is distinct as there are different distinct hazards and consequences that can be encountered in each phase/activity of the asset lifecycle. Although this study focuses mainly on technical risks associated with decommissioning, there are financial risks also involved.

5.1.2 Study objectives

There are several unknowns in OWF decommissioning and due to the limited research into decommissioning safety, this study adopts BNs as an advanced tool for OWF decommissioning risk assessment to gain the benefits of its capability. BNs are used in this study to model uncertainty in complex systems/operations, identify critical risk factors *conditional* on other factors, conduct both forward and backward analysis (bottom-up or top-down risk assessments), update when new data/information becomes available (permitting re-assessment of risks), and to include utility nodes in order to observe the effect of risk on costs and contingency planning. For BN applications in decommissioning risk assessment, care must be taken when including subjective parameters (e.g., organisational factors) in the model, as they may be limited in providing actual information for the purpose of improved decision-making. BNs inform decision makers like decommissioning construction asset managers, operators and regulators on safety critical factors. Identifying the potential decommissioning risks early on may also inform wind turbine and wind farm design. This is the first study that applies BNs in risk assessment of the OWF decommissioning phase of the asset lifecycle. The significance of this study is that it is the first study to present safety-critical factors in OWF decommissioning and the potential benefits in improving safety engineering practices if OWF asset operators adopt BNs.

The remainder of the paper is structured as follows. Section 5.2 presents an overview of Bayesian modelling for OWF asset lifecycle risk assessments. Section 5.3 proposes the BN methodology for application in OWF

decommissioning safety assessment. Section 5.4 presents and discusses the results, and finally the conclusion and further work are given in Section 5.5.

5.2 Research background

5.2.1 Risk analysis research in offshore wind energy

There are a number of methodologies that have been applied to risk assessment research in the offshore wind energy industry. These risk assessment methodologies include conventional methods like hazard identification (HAZID), hazard and operability (HAZOP), fault tree analysis (FTA), event tree analysis (ETA), bow-tie diagrams, failure mode and effects analysis (FMEA), failure mode, effect and criticality analysis (FMECA), etc. There are also several probabilistic risk assessment (PRA) techniques including fuzzy sets, Bayesian networks (BN), fuzzy-FMEA, manoeuvring-based dynamic risk assessment (MB_DRA), etc. (Mehdi *et al.*, 2019). According to Aven and Renn (2009), risk management is best expressed in terms of uncertainty and outcomes, with the challenge of converting subjective knowledge to probability values. According to Aven and Zio (2014), modelling uncertainty is important in risk assessment and there may be limitations in capturing *unknown unknowns* in probability estimations in risk assessment. We propose that this need offers an opportunity to adopt a method like Bayesian network (BN) in risk assessment. We apply BNs because of their capability to assess uncertain deviations/potential hazards and to *update* information/data characterising these deviations/hazards when new information becomes available.

Very few studies have focused on BN applications in offshore wind risk assessments (Leimeister and Kolios, 2018; Adedipe *et al.*, 2020). BNs have been used more recently in risk assessment studies because of their near-real-time assessment capability based on updates from operations or inspections. BNs have the capability to include different parameters including environmental, human and organisational factors during risk assessments, ability to quantify conditional probabilities based on the relationship between different parameters in the BN (Ashrafi *et al.*, 2015). In Friis-Hansen (2000), risk assessment with BNs was argued to be more efficient and flexible compared to FTA and ETA. BNs can

also be combined with other tools to improve result accuracy. For example, derivatives of BN like hierarchical Bayesian networks (HBN) can be used to model dynamic states of the different parameters/variables represented by nodes (Adedipe *et al.*, 2020). Mehdi *et al.* (2019) proposed the use of dynamic risk assessment approaches for real-time assessment updating. However, they note that dynamic risk assessment still needs to be used in conjunction with static risk assessment methods. Teflandis *et al.* (2013) proposed an automated risk assessment tool to model the dynamic behaviour of offshore wind turbines incorporating uncertainty. As presented by other scholars, BNs significantly offer a solution for adequate knowledge and information management, which is often a concern for energy asset projects like decommissioning (Locatelli *et al.*, 2020). Because of its capability to update with better or new information and the robustness with the use of both subjective and objective *prior* data, BNs show a good promise for use if rigorously adopted by the offshore wind energy industry. Additionally, in relation to risk, this further allows for more accurate modelling of technical, personnel, financial and environmental factors that can pose risks to an OWF decommissioning project (Adedipe *et al.*, 2020).

5.2.2 OWF asset lifecycle safety assessment

Safety is important throughout the OWF asset lifecycle. OWF decommissioning involves four distinct phases: planning and consenting, lifting and loading, logistics and waste management, and post-decommissioning (Adedipe and Shafiee, 2021). As seen in Figure 5-2, lifting operations have been identified to be the highest incident-prone activity in OWF operations (G+ Global Offshore Wind Health and Safety Organisation, 2020). Because decommissioning is a lifting-intensive phase, improving safety in lifting operations can improve decommissioning operation safety and the entire OWF asset lifecycle. Conventional deterministic risk assessment tools for quantitative risk analysis (QRA) are limited, therefore probabilistic risk assessment (PRA) techniques were developed to improve risk assessment. BNs can also show the relationships between different parameters connected within a network because of its conditional probability estimation capacity.

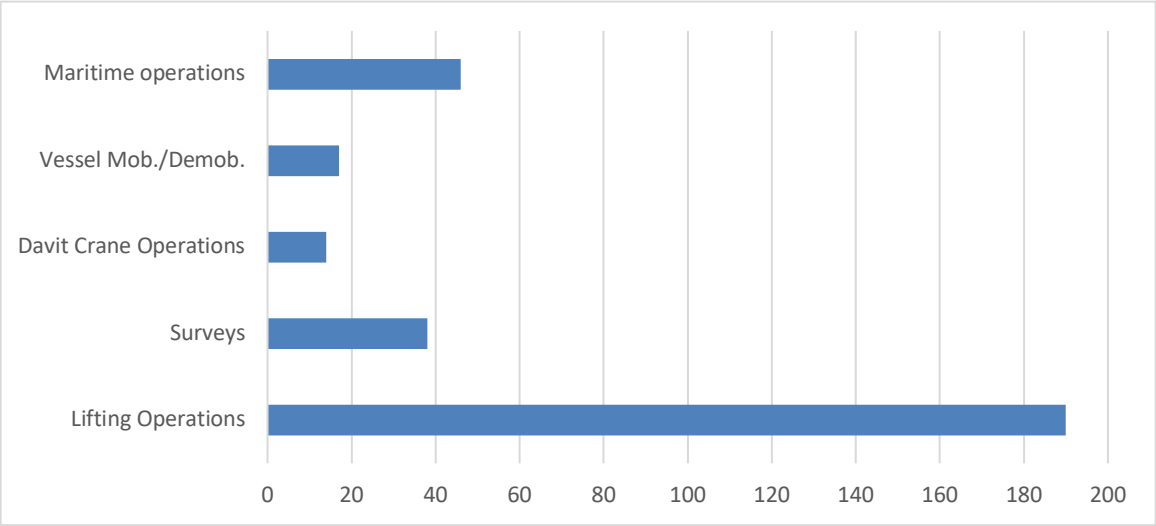

Figure 5-2 Offshore incidents (G+ Global Offshore Wind Health and Safety Organisation, 2020)

5.2.3 BN literature for OWF lifecycle risk assessment

Advanced models like BNs have been applied in different phases of the OWF asset lifecycle including design, installation, operation and maintenance (O&M) but not in the decommissioning phase. Scheu *et al.* (2016) presented the challenges involved in OWF risk assessments including the trade-off between level of detail and accuracy, incorporating uncertainty especially in novel applications, ease of understanding and communication of results at all levels within the asset management team, results highly dependent on the quality of input available for risk assessment. All of these concerns have been seen in other OWF applications as addressable using Bayesian networks, either as a stand-alone tool or in conjunction with other well-established risk assessment tools. Adedipe *et al.* (2020) presented a review of risk assessment studies that applied Bayesian networks (BN) in the offshore wind energy industry. The authors proposed BNs as an applicable tool to overcome the limitations including environmental, organisational and human related factors in risk assessment. The authors conclude that the O&M phase has received the highest number of research applications of BNs. Therefore, this study explores BN application in the decommissioning phase.

For the design phase Mendoza and Kohler (2019) proposed BNs in risk-based design, focusing on rotor and blade-response resonance hazards. They proposed the use of BNs because of its capacity to show the relationship between design parameters and the ability to add decision and utility nodes (influence diagrams). In the installation phase, Leontaris *et al.* (2018) proposed BNs with the use of Uninet software as a probabilistic decision-support tool to assess installation and logistics risks in offshore wind turbine construction supply risk management. They showed that BNs can be used to model the activity interdependence during installation operations, generating more realistic and trustworthy estimates of installation durations. This may also be explored for the decommissioning phase. Mehdi et al. (2019) researched into navigational risks around offshore wind turbines. The authors used BNs to estimate the probability of drifting accidents caused by uncertain parameters, proposing the use of dynamic risk assessment methods, rather than static methods.

Cheng *et al.* (2019) developed a fuzzy BN and Monte Carlo simulation (MCS) model to calculate OWF installation schedule risks as well as total project duration to reduce uncertainty with limited data. The authors presented the use of BNs to identify critical risk factor(s) influencing duration as well as understand the uncertainties posed by activity risks. The authors presented a case mostly for environmental factors and materials and focused very little on the safety hazards compared to the schedule risks presented. In the O&M phase, studies conducted by Li *et al.* (2020) conducted a reliability analysis on floating offshore wind turbines (FOWT) using BNs, mapped from FTA. The authors proposed the use of BNs to improve the reliability of FOWT system during OWF operations. Another study conducted by Asgarpour and Sørensen (2018) applied a BN-based risk model as a decision-support tool to estimate the remaining useful life (RUL) of assets based on updated inspection results. Dinwoodie *et al.* (2013) determined the risk profile of O&M costs using BN as a decision support tool, showing its application in cost modelling. For additional applications, readers can also refer to Dai *et al.* (2013).

Kim *et al.* (2020) used dynamic probabilistic methods (BN and clustering analysis) to quantify the risks in order to improve dynamic system safety of offshore wind turbines. For emergency response systems, Norazahar *et al.* (2017) recommended BNs for modelling human and organisational parameters affecting safety alarm systems and leading to risks on offshore installations. The authors proposed that BNs produce more realistic results compared to the use of expert judgement in criticality estimates on offshore installations. Studies in adjacent industries (such as oil and gas) have also explored the use of BNs to the asset decommissioning phase. BNs have been proposed in those fields due to the uncertainties posed by lack of experience in offshore decommissioning operations. Babaleye and Kurt (2019) proposed a framework for the application of hierarchical Bayesian analysis (HBA) for data collection and BNs to conduct probabilistic risk assessment of offshore oil and gas installation decommissioning. For logistics risk assessment, Rahman *et al.* (2020) proposed the application of advanced BNs to logistics operations of supply vessel emergency response in offshore marine locations because of the limited knowledge about the hazards and risks involved. This may be applied to consequence analysis in risk assessment. Friis-Hansen and Simonsen (2002) proposed a method for improved ship safety using BNs to obtain causal event(s) occurrence probability in a ship-ship collision accident. This method is a good reference if more than one lifting vessel is used for OWF decommissioning operations to model vessel collision risks on site. Ruud and Mikkelsen (2008) presented the steps involved in a generic offshore marine lifting operation using cranes, and then determined the factors influencing associated risk levels and identified some mitigation measures. For further reading about the applications of BNs in maritime safety, readers can refer to Hanninen (2014).

Within the offshore wind energy industry, BN applications began as early as 2002 (Adedipe *et al.*, 2020). However, a few key papers applied BNs to risk analysis. Ashrafi *et al.* (2015) presented BN applications for making inferences to assess and improve wind energy system reliability. This showed the capacity of BNs in risk level monitoring in continuous time. In Kougioumtzoglou and Lazakis (2015), BNs were applied to criticality ranking of wind energy system components

using their failure probability. A comparative analysis was done to compare the BN modelling with FMECA results for which the authors recommended the use of BNs for hazard identification. Luque and Straub (2019) presented risk-based inspection strategies based on BNs. Kim *et al.* (2020) conducted a study on collision risk assessment of offshore wind turbine installation vessels during installation operations. The authors studied passing, drifting and attendant vessel collisions and the factors that can influence them. BNs were applied to risk assessment in two ways: firstly, they were used to understand the impact of different failure causes on incidents. Secondly, they were applied in determining the risk profile of operations based on incident locations (area on a wind farm) and the anticipated consequences.

The current paper studies the application of BNs in risk assessment of OWF decommissioning lifting operations. A risk management plan is developed based on high-priority incidents to be mitigated, the related repair or contingency cost allocation, as well as the hazards that need to be deescalated. In order to manage these hazards and avoid schedule delays, or worse still, fatalities, there is a need to apply a method like BN because of its higher robustness and flexibility. As the multiple lifting operations in OWF decommissioning increases so will the number of operational uncertainties increase and BNs can incorporate such high degree of uncertainty compared with conventional techniques. Thus, a tool like BNs are ideal for risk assessment in highly uncertain operations or scenarios as the probability of occurrence of the potential causal incidents can be updated during lifting and loading operations.

5.3 The proposed model

5.3.1 Introduction to BNs

BNs are probabilistic modelling tools, which are directed acyclic graphs (DAGs) that represent problem space variables as nodes and their relationships to one another using arcs (links). They are otherwise known as belief networks as they are fundamentally based on Bayes' theorem, which states that the belief about an entity is based on existing evidence but can be changed when new evidence becomes available (Jensen and Nielsen, 2009; Pearl J., 2014; Adedipe *et al.*,

2020). BNs are gaining a reputation for being representative of real scenarios and their causations, very robust and reliable (Conrady and Jouffe, 2015). It can be expressed mathematically by:

$$P(H|D) = P(H) \cdot \frac{P(D|H)}{P(D)} \qquad \textbf{5-1}$$

Where: H is the hypothesis/incident; D is the observed data, P(H|D) is the posterior probability (probability of H given observed data, D), P(H) is the prior probability distribution or belief of a hypothesis/incident H, P(D|H) is the likelihood function of the observed data, D, and P(D) is the normalisation constant. Prior probability distributions are based on data collected that can represent the uncertain system/operation variables to be observed.

As seen in Figure 5-3, the development steps for developing and applying the Bayesian network model involve: (i) identification and classification of the variables (ii) obtaining *prior* data for each variable (iii) determining the relationships between each variable (iv) building the BN model (in the Netica software) presenting each variable as a node, the *prior* data distribution as the input for each node, using links/arcs to show the relationship between each arc (v) run the simulations (compile) with *prior* data to obtain *posterior* probability (vi) conduct analysis for mitigation/control (vii) collect updated information/data distribution based after mitigation/control and use as *prior* data (viii) inputting updated *prior* data into the model to obtain more accurate *posterior* probability results that can support decision making in areas like risk management. Bayesian networks are applied in this study for OWF risk assessment in four ways. Firstly, they were used to establish the impact that different failure causes have on the overall unwanted incident, suspended decommissioning operations, by conditional relationship modelling. Secondly, they were applied for determining the effect of reducing/treating grouped incidents related to human-error, mechanical/electrical faults or procedural events to as low as reasonably practicable (ALARP) - mitigated/controlled. Thirdly, they showed how new evidence can be incorporated from updated incident reports. Lastly, they showed

how decision and utility nodes may be introduced into the BN to develop an influence diagram.

Usually, the failure rates (deterministic or probabilistic) that are incorporated into risk assessment tools are not updated when there is new information. BNs bridge this gap in order to ensure that risk knowledge about operations is updated regularly based on recent evidence. Bayesian networks show the connection and interdependencies among the different nodes in a network and can be mapped from other models like fault tress, event trees, bow-tie diagrams, etc. (Bobbio *et al.*, 2001; Khakzad *et al.*, 2013). Compared to methods like FTA, the BNs are beneficial because of their flexibility and more realistic outputs (Rahman *et al.*, 2020). The probability values of the root nodes are the *prior* probabilities, which may be deterministic or probabilistic within the network depending on the *prior* data source. The conditional probability table (CPT) is developed for each node when developing the BN in order to model variable dependencies and interactions, incorporating the uncertainty inherent in nodal relationships. The CPT was set to represent chance nodes. BNs allow for explicit expression of different factors that can influence an unwanted outcome/incident. The nodes may have binary states (success or failure) or multiple states. A full description of BNs can be seen in Adedipe *et al.* (2020).

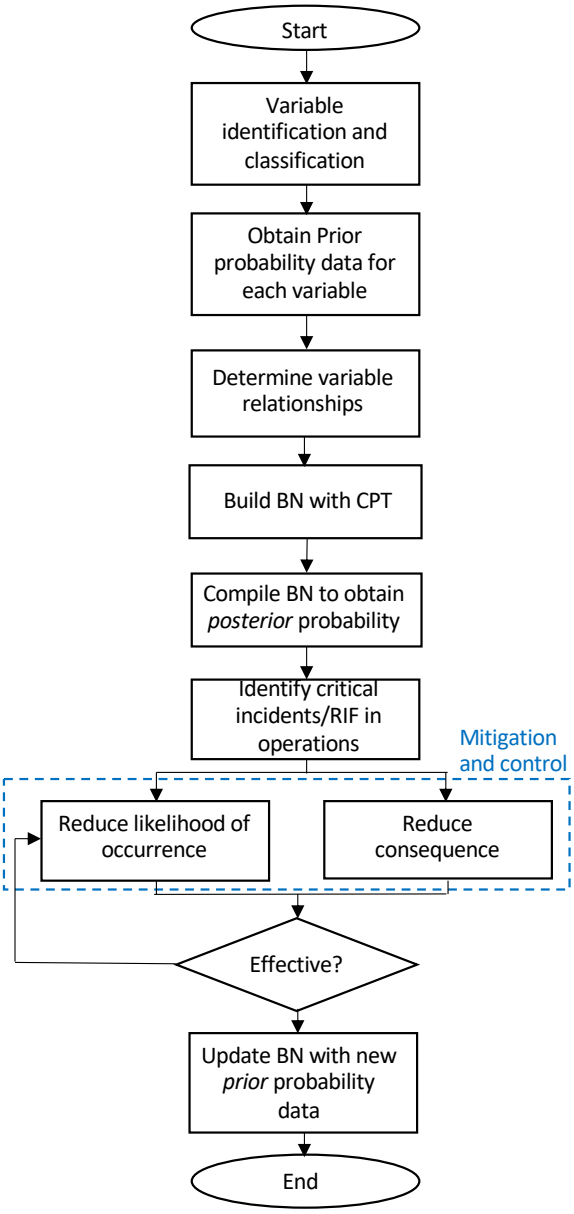

Figure 5-3 Methodology flowchart

5.3.2 Bayesian network software

There are a number of BN software available for use in different wind energy applications. Some commercially available software include Netica, Microsoft MSBN, BayesiaLab, Hugin, WinBUGS, OpenBayes, AgenaRisk and Bayesfusion (Li and Shi, 2010; Su and Fu, 2014; Ashrafi *et al.*, 2015; Li *et al.*, 2015; Ciobanu *et al.*, 2017. Adedipe *et al.*, 2020) presented a review of each software and the wind energy applications that they have been used for. The Netica software was used in the current study.

5.3.3 BN model development methodology

To develop the BN used in this study the following steps were taken: (i) the potential incidents that can lead to suspended decommissioning operations were identified and grouped by type. (ii) the relationship between each incident and potential cause was determined; this logic was used for linking the nodes in the BN (iii) *prior* failure probability data was obtained for each incident as seen in Table D-1 of the Appendix section (iv) the BN model (in the Netica software) was built by presenting each variable as a node, the *prior* data distribution as the input for each node, using links/arcs to input the relationship between each node (v) the nodal (incident) dependencies were defined by the conditional probability table (CPT) for each incident using leaky noisy-OR logic (similar to the Boolean OR operator used in other computational applications).The CPT was encoded in the BN based on the binary function of incident/no incident occurrence (incident occurrence = 1 and no incident occurrence = 0) showing the nodal relationships among the linked child and parent nodes. Table 5-1, Table 5-2, Table 5-3 and Table 5-4 show the CPT for collision, vessel damage, crane failure and suspended decommissioning, respectively (vi) after the prior data was inputted into the child nodes and CPT table developed, the model was compiled to obtain the *posterior* probability.

Table 5-1 CPT for collision incident occurrence

Manoeuvre failure	Navigation failure	Detection failure	P (Collision = 1)
1	1	1	1
1	1	0	1
1	0	1	1
1	0	0	1
0	1	1	1
0	1	0	1
0	0	1	1
0	0	0	0

Table 5-2 CPT for vessel damage incident occurrence

Stuck monopile	Loss of stability	P (Vessel damage = 1)
1	1	1
1	0	1
0	1	1
0	0	0

Table 5-3 CPT for crane failure incident occurrence

Operational fault	Hook failure	P (Crane failure = 1)
1	1	1
1	0	1
0	1	1
0	0	0

Table 5-4 CPT for suspended decommissioning occurrence

Collision	Vessel damage	Crane failure	P (Suspended decommissioning = 1)
1	1	1	1
1	1	0	1
1	0	1	1
1	0	0	1
0	1	1	1
0	1	0	1
0	0	1	1
0	0	0	0

5.3.4 BN: Overall unwanted outcome

The overall unwanted outcome in this study is suspended /halted decommissioning operations (SDO). The likelihood of occurrence of the SDO was determined after the first compilation of the model using the initial *prior* probability data. Because BNs can be used to understand the impact of more than one incident occurring at the same time during operations, the influence of each causal event can be observed. The effect of each causal event on the outcome

was determined from diagnostic, prognostic, updating and influence diagram (cost/utility) modelling.

5.3.4.1 Diagnosis and prognosis

There are three intermediate incidents for which data was obtained. The nodes each have their associated safety factors/ risk-influencing factors (RIF) proposed in this study. All nodes are interdependent, meaning a change in one node will cause a change in the other nodes. For this analysis, we input discrete variables in each node and use binary nodal states. The *prior* distribution of the failure probabilities is the first set of data used for the first set of computations. The *prior* data are based on expert knowledge and literature sources in other marine operations, because of the limited available data to date regarding decommissioning operations. Table D-1 of the Appendix section gives discrete *prior* probability dataset, showing the failure probabilities of each safety/risk influencing factor (RIF). Because of the different sources (Ugurlu *et al.*, 2015; Babaleye *et al.*, 2018; Rahman *et al.*, 2020) from which these datasets were collated, the accuracy varies; hence, the need for updating using a technique like Bayesian updating. Therefore, the incident nodes were updated with OWF data from G+ Global Offshore Wind Health and Safety Organisation (2020) OWF data collected between 2015 and 2019 as presented in Table D-2 of the Appendix section. The *posterior* probability is the conditional probability output generated after the BN is compiled. For decommissioning operations, we propose that the BN should be updated for every set of lifts, based on the occurrence/non-occurrence of incidents; on the premise that after every specified set of lifts, the operator/contractor conducts necessary inspections on cranes and other equipment.

Lifting and loading operations are the set of activities involving the lifting and loading and repositioning for another round of lifts. Lifts will be carried out for multiple wind turbines on a wind farm, so our hypothesis is that risk assessment results may not be conclusive for OWF operations until updates are carried out after each set of lifts. During lifting operations, failure may be caused by operational or equipment failures or faults. Suspended decommissioning

operations may be caused by a vessel colliding with other vessels on site like a tugboat or support vessel during repositioning after every lift/set of lifts. Similar to collision incidents, vessel allision may also be caused by a vessel colliding with a wind turbine during lifting operations. Vessel damage during lifting and loading operations can be caused by incidents involving poor cutting operations, a serious collision/allision with another asset or by swinging loads that can lead to dropped objects on the vessel. Each intermediate node is explained below with the potential incident causes.

5.3.4.2 Collision between vessel and wind turbine

Collision incidents are identified to be caused by different potential incidents between the lifting vessel and other assets (wind turbines, transportation or support vessels). The probability of occurrence of collision was estimated based on the following causal incidents: navigation, manoeuvring and detection failure. Figure D-1 shows the BN developed for a collision incident between the lifting and loading vessel(s) and a wind turbine in this case. The probability of a collision incident is conditional on the probability values of all sixteen child nodes and their corresponding RIFs. Manoeuvre failures have a higher likelihood of occurrence than the other potential incidents based on the *prior* data inputted.

5.3.4.3 Vessel damage

Vessel damage can be caused by other incidents besides collision during decommissioning operations. The events illustrated in Figure 5-4 show the causal events/incidents related to decommissioning of monopile-mounted wind turbines. From the initial *prior* data, it is found out that incidents associated with stuck monopile have a higher likelihood of occurrence compared to loss of stability. Thus, incidents associated with stuck monopile can be investigated further, without ignoring the other incidents.

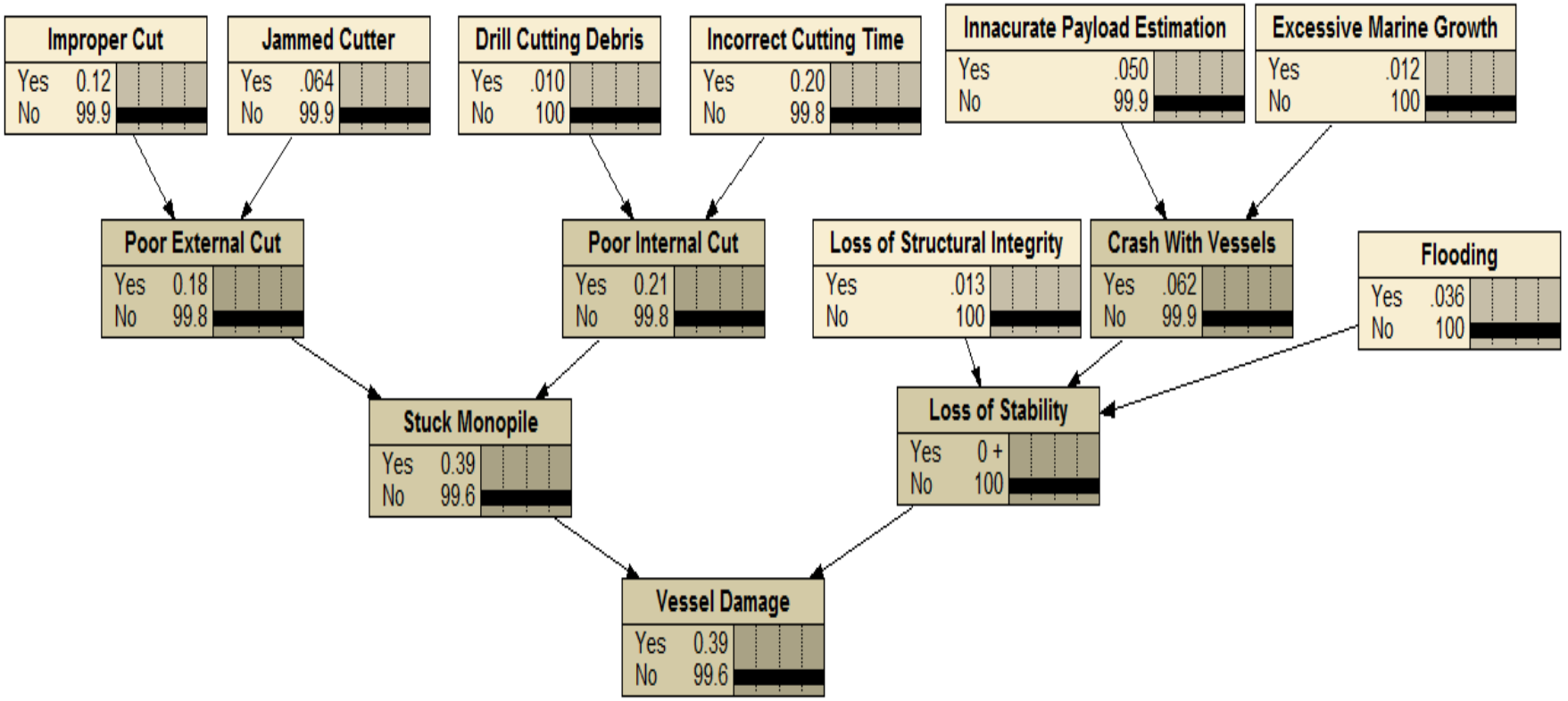

Figure 5-4 Bayesian network of vessel damage

5.3.4.4 Crane failure

Cranes are central to the lifting operations during decommissioning as their failures can hamper the success of the decommissioning project. All crane vessels and equipment must obtain an inspection certificate indicating that they are fit for use in the offshore environment and under the anticipated conditions. The crane can fail for numerous reasons and Figure D-2 (of the Appendix section) presents the causes related to hook failure and opeational faults.

5.3.5 Decommissioning risk driving factors

Risk-driving factors are identified for different incidents based on surveys from experts, sample risk registers, and the risk causes reported in literature. The risk-driving factors are different for all operations in the asset lifecycle; the risk-driving factors for installation will be different from those of operation and maintenance (O&M). We identified the risk driving factors using a BN for updating the *belief* for improved risk analysis. This study identifies several risk factors related to the critical incidents identified for lifting and loading operations during decommissioning.

5.3.6 Bayesian updating

In order to re-assess the decommissioning operation outcome (updated posterior probability with new belief), operational data were incorporated into the model. The Bayesian updating was conducted for jack-up/barge vessel, tug and crew transfer vessel incident data from G+ Global Offshore Wind Health and Safety Organisation (2020) between 2015 to 2019 summarised in Table D-2 of the Appendix section. Data for 2017 was not recorded from the source. The updates may be conducted for two main reasons during decommissioning operations – when new data becomes available and when operational safety is improved. The incident frequency was converted to probability data using **Equation 5-2** (Ugurlu, 2015). The probability estimates were calculated on an annual basis, independent of past years.

$$PO = \frac{Incident\ Frequency}{Total\ Number\ of\ incidents\ \times\ Number\ of\ years\ (annual)} \quad \textbf{5-2}$$

5.3.7 Influence diagrams

Influence diagrams are the extension of the BNs, which include decision nodes and utility nodes like the cost of intervention when risk levels reach a certain stage (Luque and Straub, 2019). The influence that interventions (repair, replacement, additional inspections, etc.) have on the operational outcomes were assessed by including a decision and utility node within the network. A binary state (repair or no-repair) was used in the decision nodes to assess the impact that interventions have on intermediate nodes in the network (collision, vessel damage and crane failure) as given in Figure D-3 of the Appendix section. The ratio of repair costs to cost of no repair (when no intervention is conducted) was assumed to be 100:1000 (1:10) (Yang and Frangopol, 2017).

5.4 Results and discussion

5.4.1 Bayesian network: Overall unwanted outcome

Figure 5-5 presents the estimates of the unwanted events (top and intermediate), with the “Yes” values showing the probability of the events occuring, expressed in percentages. Using the prior probability data in the first run of the Bayesian network, the posterior probability of suspended decommissioning operation (likelihood of occurrence) was estimated to be 0.0688. This did not account for environmental factors. Sixteen critical factors showed the highest impact on the outcome and crane failure contributed the highest to suspended lifting and loading operations, followed by collision and vessel damage, respectively. However, the three highest critical factors for each incident are presented below, where a breakdown of the unwanted outcome probability of failure is given.

5.4.1.1 Intermediate incident: collision

The initial likelihood of collision incident occurrence was 0.00085 as seen in Figure 5-5. This showed the least chance of occurrence and contribution to suspended operations. The incidents that contributed the highest to collision were

observed to be inefficient use of navigation equipment (E3), faulty manoeuvre master (E5) and error of watchkeeping officer (E6).

5.4.1.2 Intermediate incident: Vessel damage

The likelihood of vessel damage occurrence was estimated to be 0.0039 as seen in Figure 5-5. This incident showed the second largest contribution to suspended operations. The incidents that contributed the highest to vessel damage were jammed cutter (E18), inaccurate payload estimation (E22) and vessel flooding (E24). Due to the multi-lift nature of decommissioning operation, it is anticipated that there will be an increased likelihood for damage.

5.4.1.3 Intermediate incident: crane failure

The probability of crane failure occurrence was estimated to be 0.0643 as seen in Figure 5-5. This estimate is significantly higher than probability of both the collision and vessel damage incidents. For crane failure, the three highest risk influencing factors are structural failure (E25), control system fault (E26) and obstructed vision (E32). These findings are because compared to the other factors, cranes are more susceptible to degradation during operations in harsh environments like the offshore environment. The control system fault may be caused by human error when operating the control system interface. Line of sight of an operator may also be interfered with during operations. Regular inspections and other interventions, however, can reduce the likelihood of occurrence of crane failure.

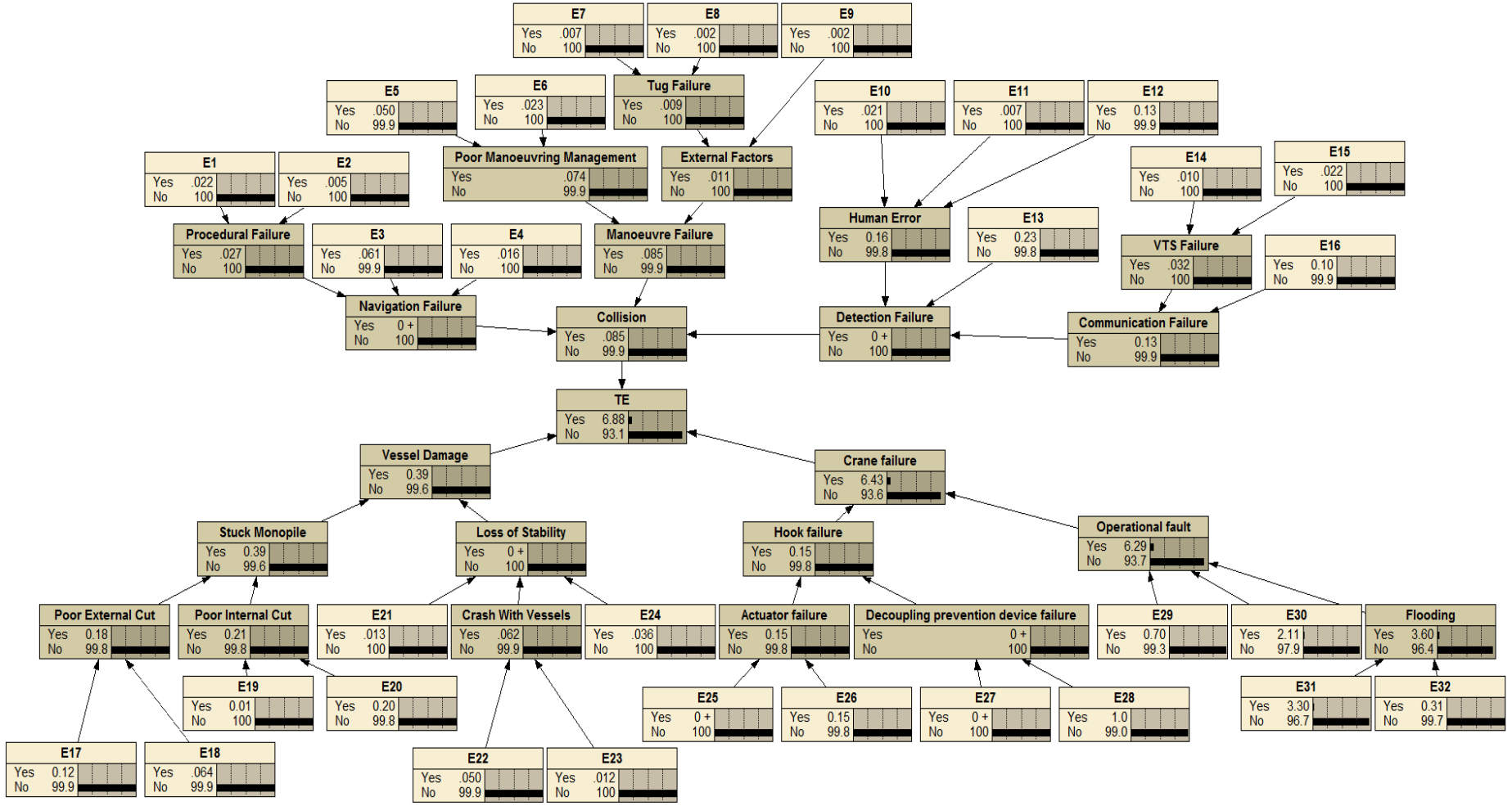

Figure 5-5 Bayesian network showing the conditional probability of suspended decommissioning operations (TE)

5.4.1.4 Diagnosis of each child node incident

An advantage of the BN application beyond the capacity of other techniques is its capacity for both forward and backward analyses (diagnosis and prognosis). Thus, in order to determine the impact that each causal incident will have on the operation success/suspension, additional forward analysis (diagnosis) was conducted. The BN was used to conduct a diagnosis of the incidents affecting lifting operations and what impacts they will have on successful/unsuccessful operations. The impact was observed by setting the “yes” state of each node in the BN model to zero, one at a time, whilst the other nodes maintaining their states. This meant a certainty that no incident occurred for the observed node. Figure 5-6 shows that the highest impact on the posterior probability outcome was observed in nodes E31, E30, E29, E32, E20, E26 and E17, respectively. The values of the other nodes were negligible and not presented.

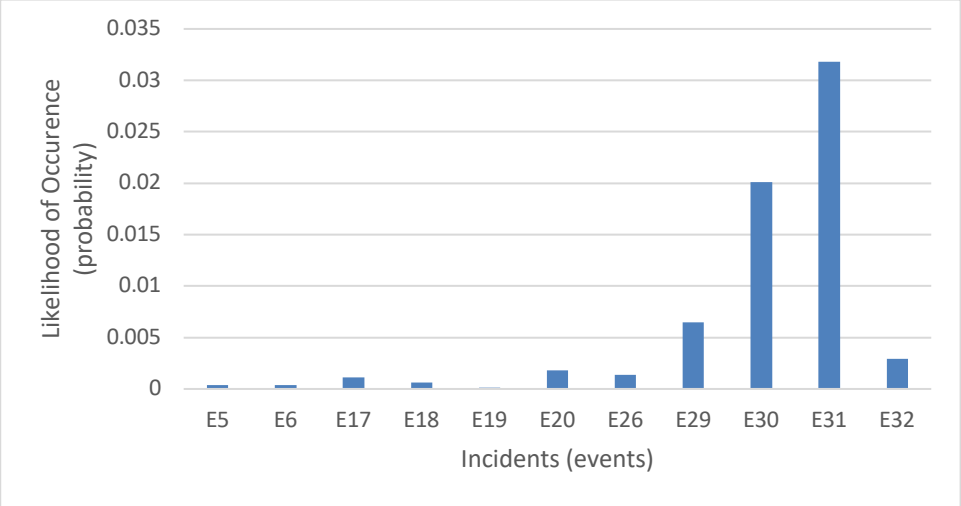

Figure 5-6 Diagnosis of each child node incident

5.4.1.5 Risk influencing factors (RIF)

The critical risk influencing factors were determined by identifying potential causes of the incidents that have the highest impact on lifting operation safety. The nodes each have their associated safety factors/ risk-influencing factors (RIF) and are proposed in this study. The high posterior probabilities are considered to be associated with the highest critical incident and thus, the safety/risk-influencing factors (RIFs). The descriptors of each critical incident

were determined and are given in Table 5-5. The relationships are presented in terms of direct or inverse proportionality. Reducing any of the RIFs will have positive implications on the safety of operations. The most critical RIFs were identified to be: visibility (V), crew fatigue (F_{crew}), number of personnel per operation (N_{crew}), proper procedures (P), crane integrity (C_I), number of WTs on the WF (N_{WT}), number of lifts (N_L), inspection frequency ($I_{freq.}$) and good equipment design ($D_{Eqt.}$).

Table 5-5 Incident descriptors

Code	Incident	Descriptors (Risk-Influencing Factors – RIFS)	Mathematical Relationship
E31	Inaccurate signal (S)	Visibility (V), Fatigue (F_{crew}), No of personnel per operation (N_{crew})	$S \propto \frac{V, F_{crew}}{N_{crew}}$
E30	Improper hooking (H)	Proper procedure (P), Crane integrity (C_I)	$H \propto \frac{1}{P, C_I}$
E29	Vibrational impact (V_I)	Number of WTs on the WF (N_{WT}), Number of lifts (N_L), good equipment design ($D_{Eqt.}$), Inspection frequency ($I_{freq.}$)	$V_I \propto \frac{N_{WT}, N_L}{D_{Eqt.}, I_{freq}}$
E32	Obstructed vision (V_O)	Visibility (V), Good Weather (W_G)	$V_O \propto \frac{V}{W_G}$
E20	Incorrect cutting time (Cut_T)	Thickness of WT (WT_{thick}),	$Cut_T \propto WT_{thick}$
E26	Control system failure (CS_F)	Certification (Cert), Inspection frequency (I_{freq})	$CS_F \propto \frac{Cert}{I_{freq}}$

E17	Jammed cutter (J)	Inspection frequency (I_{freq}), Mechanical failure (M_F)	$J \propto \frac{M_F}{I_{freq}}$

5.4.1.6 Diagnosis of grouped class of causal events

Another key benefit of using the BN tool during risk assessments is that the diagnosis of causal event groups is also possible. These grouped potential incidents can be collectively assessed to inform safety improvement actions for asset managers, operators and regulators. In this way, if a classified group of events have higher occurrences and impacts, tailored approaches to improve that incident group can be developed. This capability can provide better understanding of the impacts that certain categories of failures/faults can have on operations. For the decommissioning operations, the sixteen critical incident child nodes were grouped into three categories: human error-related incidents (H), mechanical/electrical incidents (M) and procedural incidents (P) and used for the multiple-event diagnosis. Human error-related incidents can be addressed on a case-by-case basis by training/re-training, improved research into human-mechanical systems, etc.

As shown in Figure 5-7, Figure D-4 and Figure D-5 (of the Appendix section) child nodes (incidents) can be eliminated in order to observe the effect of a grouped class of incident probabilities relevant to specific analyses. In the example presented, it is assumed that if human error-related incidents (E6, E7, E8, E31 and E32) are mitigated/controlled to ALARP, the probability of occurrence of the suspended operations decreases to 0.0337. Secondly, assuming that critical mechanical/electrical related events (E5, E18, E19, E25, E26, E27 and E29) were mitigated/controlled to ALARP, the probability of occurrence of the suspended operations was observed to decrease to 0.0597. Thirdly, assuming that critical procedural variables (E9, E17, E20 and E30) were reduced to ALARP, the probability of occurrence of suspended operations was observed to decrease to 0.0457.

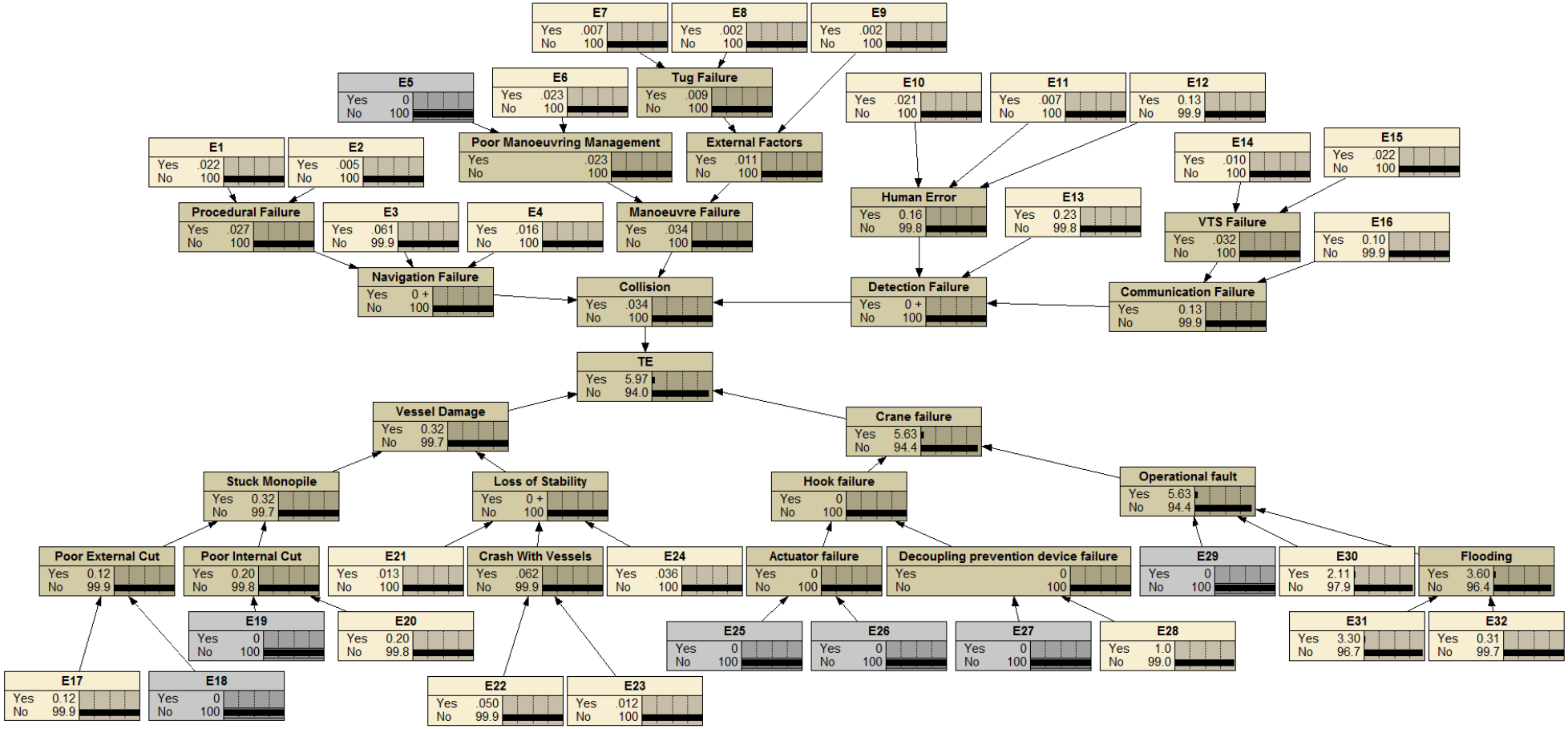

Figure 5-7 Top event (suspended decommissioning) when mechanical/electrical-related incidents are mitigated/controlled

Table 5-6 shows the grouping of the critical incidents identified. Assuming one group/class of incidents was treated (mitigated/controlled), the nodes representing the variables (incidents) within each group was set to “no” state in order to model the posterior probability obtainable after treatment. Mechanical/electrical incidents can be prevented by evaluating and improving the system reliability. Procedural incidents can be reduced by understanding the factors related to each group in operational procedures. After modelling the risk treatment of the different groups, it was seen the human error ranked the highest, followed by procedural and mechanical/electrical, respectively. This shows that if human errors are eliminated, the highest safety improvement can be achieved.

Table 5-6 Incident groups and posterior probability of suspended decommissioning when controlled

Incident groups	Variables isolated	Updated Posterior probability	Rank
Mechanical/electrical	E5, E18, E19, E25, E26, E27, E29	0.0597	3rd
Human error-related	E6, E7, E8, E31, E32	0.0337	1st
Procedural	E9, E17, E20, E31	0.0457	2nd

As Figure 5-8 shows, relative to vessel damage and collision, the crane failure likelihood reduced the most when human error-related incidents were reduced to ALARP. Relative to collision and crane failure, vessel damage likelihood of occurrence reduced the most when procedural incidents were reduced to ALARP. Lastly, relative to vessel damage and crane failure, collision likelihood of occurrence reduced the most when mechanical/electrical incidents were reduced to ALARP. Overall, based on the ranking, human errors contributed the most to each incident type which shows where the efforts of the asset management team are better to be directed. Human errors can be reduced to ALARP, even though difficult to eliminate all together, because they are dependent on subjective

judgement of the personnel. The main mitigation approach for this is to improve automation in decommissioning equipment and system.

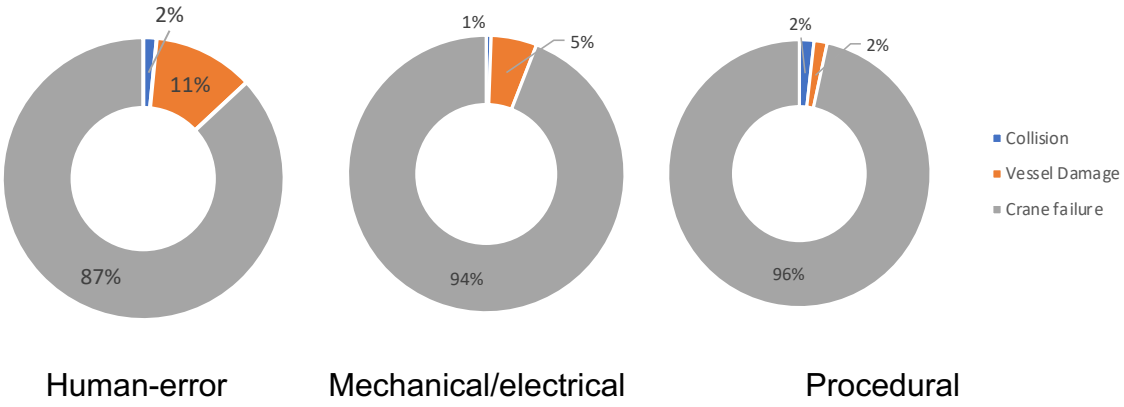

Figure 5-8 Impact of elimination of incident groups OWF decommissioning operation safety

5.4.1.7 Prognosis of suspended decommissioning operations causes

Prognosis can support safety planning when not all factors are known/well understood for a specific site. BNs can be used to estimate the possible future conditional probability of suspended operations occurring and the effect on the connected nodes, especially if not all incident probabilities are known. Nodes can be eliminated or included during prognosis, particularly if they do not apply to the operation/site being assessed. This is another method in which critical incidents can be observed if all potential mitigation/control efforts have been applied. In Figure 5-9, a prognosis of the overall outcome (suspended decommissioning operations) and the effects on the RIFs were observed. The value of the suspended decommissioning operation (TE) node was updated to show a 0.25 chance of occurrence. The influence of the updated unwanted event probability on the RIFs is presented below.

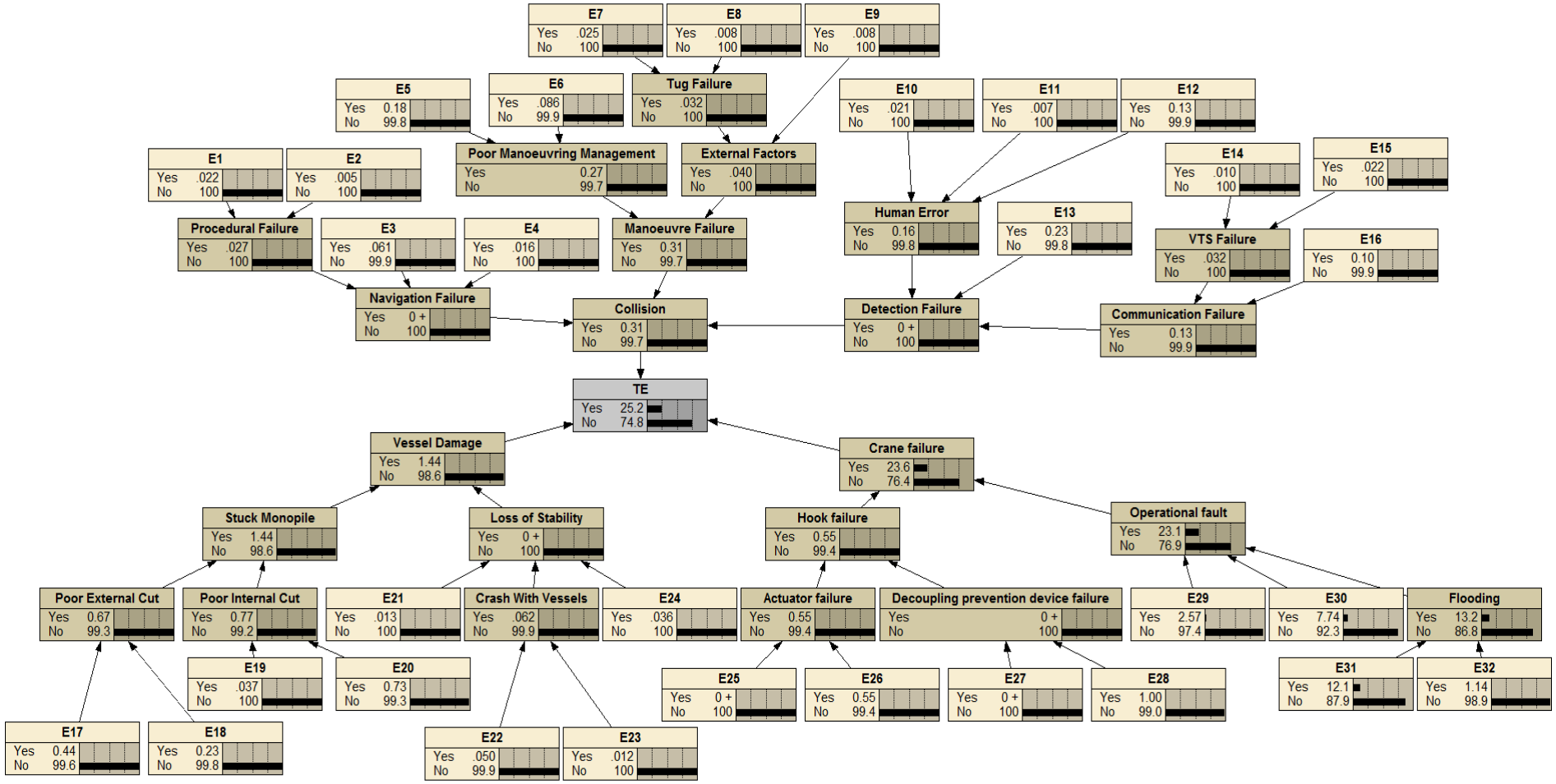

Figure 5-9 Observing the effect of increasing expected probability of occurrence the top event (suspended decommissioning)

The model was rerun, and the outcome seen in Figure 5-10, which shows the incident impacts when the posterior probability of the occurrence of suspension of decommissioning operations is increased to 0.2520. The BNs showed the same trend of increase for every quartile increase (0.252, 0.5 and 0.75) except when input parameters are updated. This was because except each node was impacted further by an external event/factor, then the prognosis will have a similar trend in theory. This will be different in practical terms as new prognostic information (data) will be obtained after every lifting and loading operation on a wind farm in order to use the updating feature of BNs for safety assessment improvement.

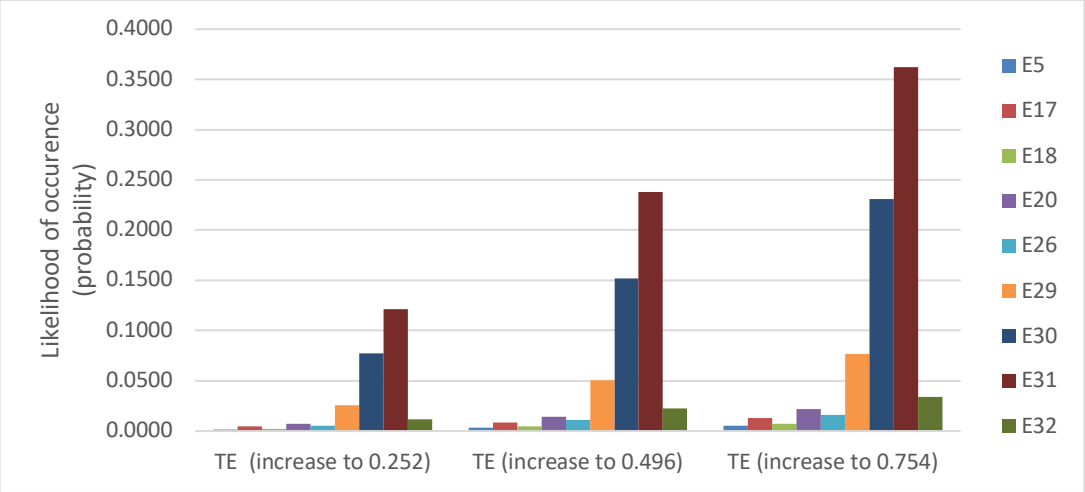

Figure 5-10 Prognosis of suspended decommissioning operations

5.4.1.8 Sensitivity analysis

The responsiveness of the BN model is seen in Figure 5-11, which shows the difference between the *prior* likelihood of occurrence and the *observed* likelihood of occurrence probabilities for each critical incident when the posterior probability is increased to 0.0252. With this capability, BNs can be used to observe the impact of potential critical events by assessing the impact one critical event has over the others. This prognostic capability of BNs can be maximised when there is more operational data available.

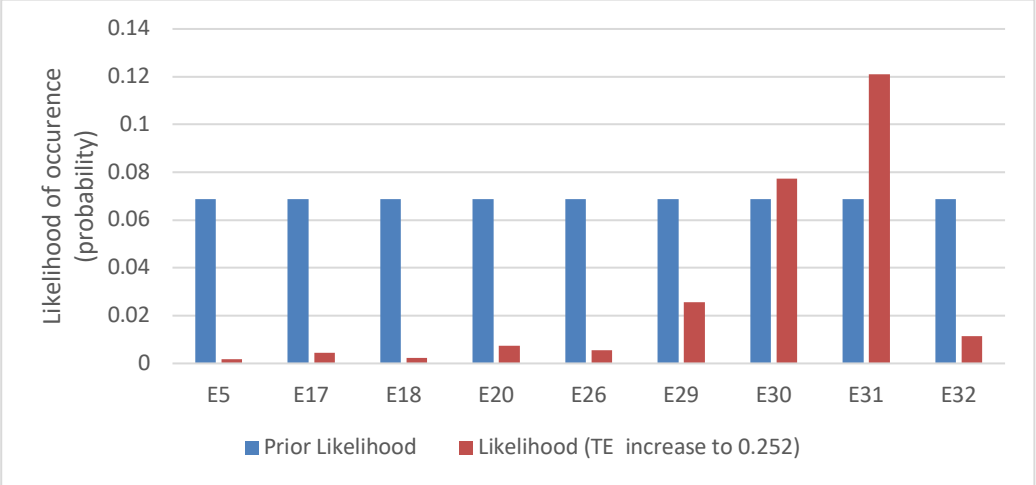

Figure 5-11 Effect of increasing likelihood of occurrence of failed operations (0.252) on decommissioning operations

5.4.1.9 Updating BNs

The first round of simulations yielded similar results to what obtained using fault tree analysis (FTA). New data for each potential incident may be obtained from operators, regulators or independent database centres regarding operations. We present a case for updating the BN using operational incident data and inputting them into the BN. In order to compare BN model results to a conventional risk assessment technique, fault tree analysis (FTA) tool was used. The first set of simulations yielded similar results for the FTA and BN. After tug failure, human error and navigation failure nodes alone were updated with new data from G+ Global Offshore Wind Health and Safety Organisation (2020). These data reported only incidents for installation to operation and maintenance (O&M), which were the closest to OWF decommissioning operations, as seen in Figure 5-12, Figure D-5, Figure D-6, Figure D-7 and Figure D-8 of the Appendix section.

From Figure 5-13, it was observed that BNs can be used to model and compare the annual likelihoods of suspended decommissioning operations with a potential to observe trends over time. Based on the recorded navigation, tug and human error-related incident data (G+ Global Offshore Wind Health and Safety Organisation, 2020) inputted in the BN model, it was found out that probability of suspended operations decreased in year 2 (update 2), increased with update 3 and marginally decreased in the following year.

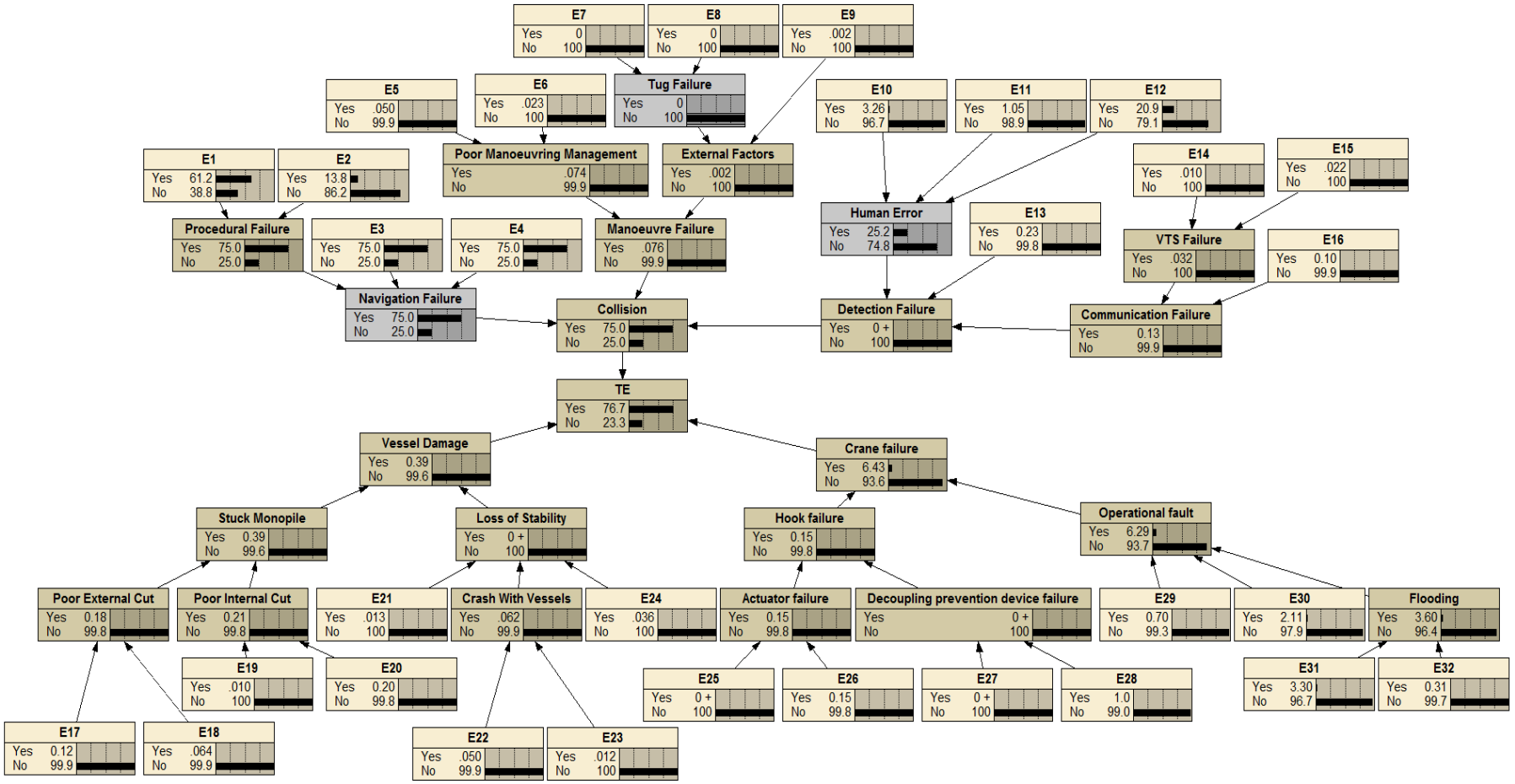

Figure 5-12 Update with 2015 data (G+ Global Offshore Wind Health and Safety Organisation, 2020)

G+ Global Offshore reported no tug, navigational failures or human-error related incidents for 2017. This increase was commensurate with increased OWF operations as reported. Thus, the likely events leading to higher risks during decommissioning can be deduced using BNs. Unless targeted safety efforts become paramount, an increase in the number of decommissioning projects can imply higher safety concerns (incidents).

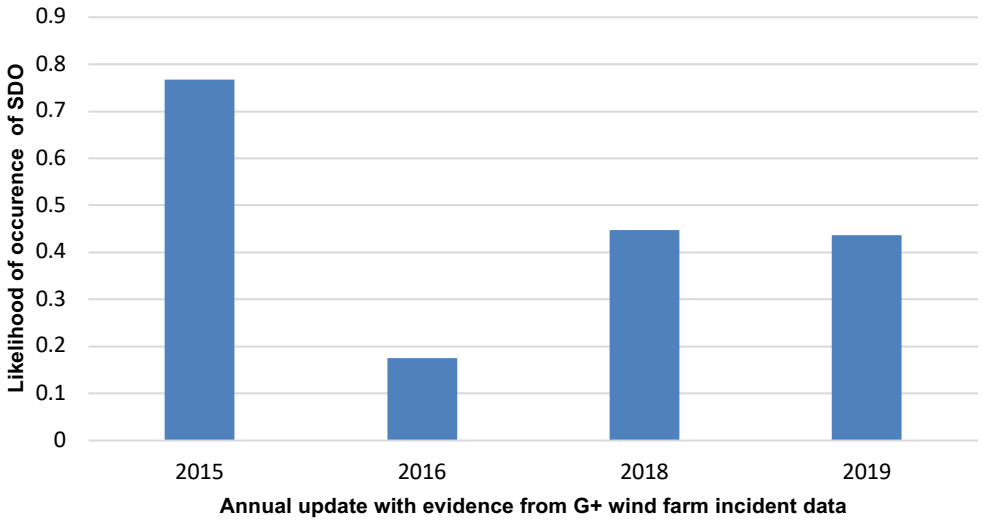

Figure 5-13 Annual probability of occurrence trend of suspended operations using OWF data

5.4.1.10 Extension to an influence diagram (decision and utility nodes)

Project risks have associated costs; thus, BN was used to assess the utility of reducing the likelihood of occurrence of the incident, i.e., how beneficial it will be to address intermediate incidents. Influence diagrams were developed with the addition of decision nodes in the BN as seen in Figure 5-14 below, Figure D-9 and Figure D-10 of the Appendix section. The utility of addressing collision, vessel damage and crane failure were each investigated.

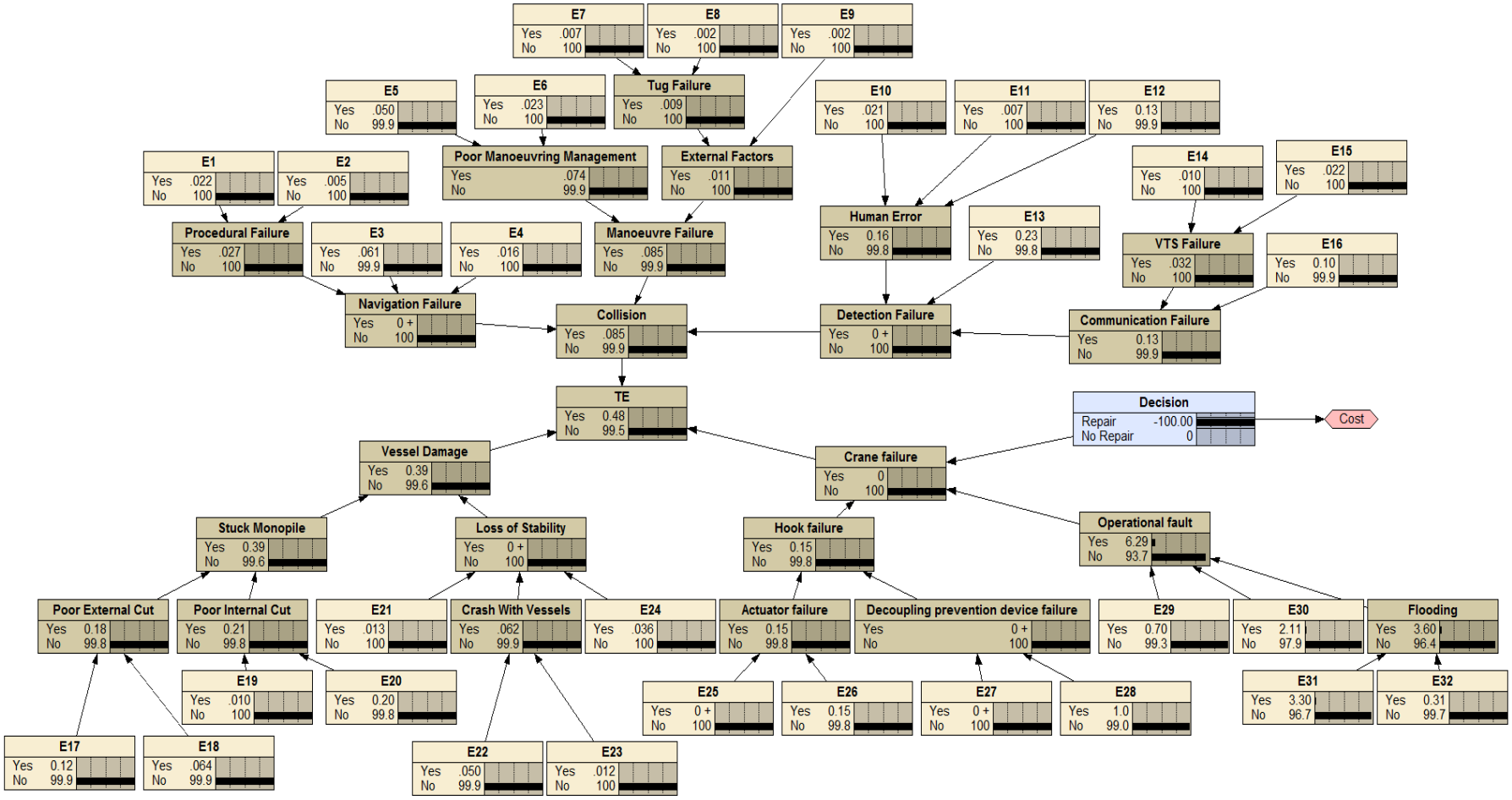

Figure 5-14 Influence diagram

As seen in Figure 5-15, crane failure improved the likelihood of occurrence of suspended decommissioning operations the most when repair (on the crane) was conducted, or failure causes were eliminated. From the chart, the likelihood of occurrence of suspended decommissioning operations decreased the most from 0.0643 to 0.005. The collision failure and vessel damage failure did not show a similar response because after the faults were treated (mitigated/controlled), shown by the utility nodes, mostly mechanical failures were treated and there is only a degree to which repairs can be made for a system to be brought back to its original operating condition after degradation. This conclusion is still limited because depending on the severity of each related incident, the consequence will inform the risk treatment approach. Thus, we propose that estimating the utility of interventions is important; however, a full risk picture with consequence assessment will produce more robust results.

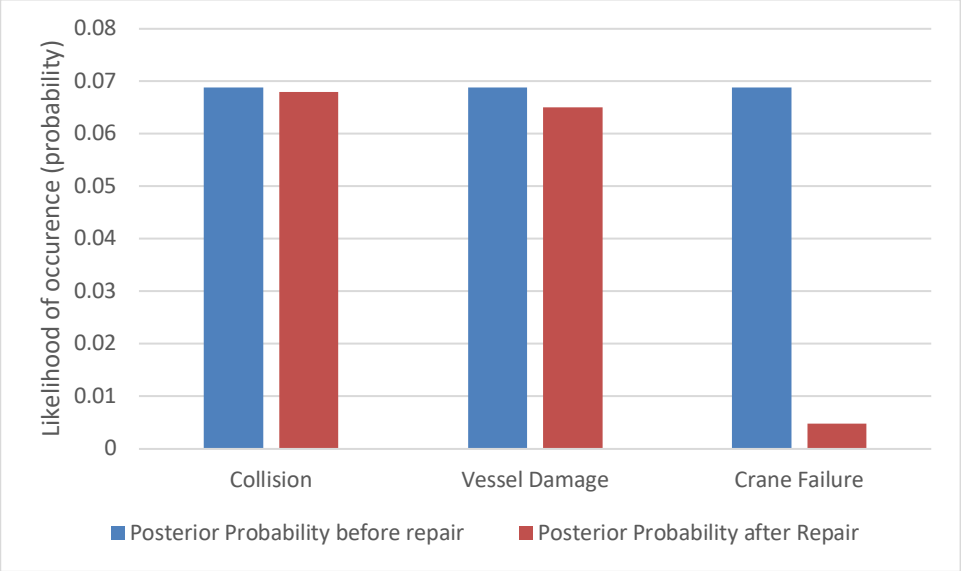

Figure 5-15 Influence of repair after risk treatment

5.4.1.11 Introducing additional variables in the BN

Additional variables (nodes) may also be included in a BN analysis that was not included in the network initially when new data is collected. The conditional posterior probability of occurrence of suspended operations can be re-estimated based on the additional nodes. Also, if other operations in addition to lifting and loading operations are to be assessed, the BN may be expanded to

accommodate the additional nodes and model the relationship among all interdependent variables.

5.4.2 Risk management strategy

In order to treat risk, the risk-critical factors to be addressed may fall under one of the two categories: likelihood-of-occurrence criticality and consequence criticality. This study focused on reducing the likelihood-of-occurrence of critical factors (incidents) that can lead to suspended decommissioning operations. These estimates will vary on a case-by-case basis because of the uncertainty involved in predicting the likelihood of occurrence of suspended operations. More so, the consequence of each incident will need to be considered on a case-by-case basis.

5.5 Conclusion and future works

Due to the small number of risk research that has been conducted on the offshore wind farm decommissioning phase, there is no doubt a gap to better understand the associated risk factors. To address this gap, we presented a Bayesian network (BN) model to identify the risks of the potential critical incidents and the corresponding safety factors associated with OWF decommissioning. BN modelling was applied to the lifting and loading phase of the decommissioning project. The study presented the identification of critical incidents, the relationship between them and critical risk-influencing factors in decommissioning. The method was also used to determine where the potential critical risks may occur and the impact of mitigation/control on the overall probability of occurrence of suspended operations, using decision and utility nodes (influence diagrams). These additional assessments that can be conducted with BNs beyond conventional techniques showed that BNs are more robust than as they have the capacity to perform both prognostic and diagnostic assessments, update with new data, and to include decision and utility nodes. With the BNs, the model becomes “smarter” as new data is used to update the network system. The *prior* probabilities of each node are inputted into the conditional probability table (CPT) and updated when new information becomes available with experience. Thus, improved risk assessment results can be generated over time.

Overall, the study applied BNs in determining what can go wrong, how likely they are to occur, what the critical incidents are and the most-critical risk-influencing factors (RIFs) related to decommissioning lifting and loading operations. The highest critical safety incidents were found to be inaccurate signal, improper hooking, and vibrational impact and the corresponding critical risk-influencing factors were found to be visibility (V), crew fatigue (F_{crew}), number of personnel per operation (N_{crew}), proper procedures (P), crane integrity (C_I), number of WTs on the WF (N_{WT}), number of lifts (N_L) and equipment design ($D_{Eqt.}$). This proposes how asset managers and asset owners can benefit from adopting a more adaptive BN-based risk assessment method in safety assessments. Beyond this, future works can explore the risks associated with other technical, environmental and regulatory aspects of OWF decommissioning. Additionally, BNs may be used to assess the reliability of safety barriers in decommissioning operations.

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6 Expert elicitation and research synthesis

6.1 Introduction

This research began on the premise that the decommissioning phase may be as cost and risk important as the installation phase. It set out to offer evidence to support the importance of understanding the cost and risk drivers. Decommissioning is generally not an income-generating phase of the overall project. Thus, this study proposes that when associated risks are clearly understood, mitigations are in place and safety is improved, the contingency costs related to execution can be reduced to a minimum. Inexperience/ incomplete knowledge in decommissioning can expose (de)construction personnel to safety threats. Technical hazards (like lifting and loading vessel incidents), personnel hazards (like falls from height or harm from dropped/swinging loads) and environmental hazards can pose very significant problems during decommissioning. This study makes a case to better understand safety management better before large scale decommissioning operations begin.

This study recommends that information for risk assessment of decommissioning operations be organized based on the risk breakdown structure (RBS) framework developed and presented in Figure 6-1. The four phases in OWF decommissioning are presented in the top row, with each segment presenting the technical, management, cost/commercial, external and personnel safety aspects involved in each phase. The responses showed that technical risks within the execution phase of the OWF decommissioning project are the most critical. A major limitation in this study was the sparsity of data from prior operations, which was to be expected due to the limited number of offshore wind farms that have been decommissioned to date. Thus, in order to identify the needs in industry this study employed a mixed-method approach. Industry expert knowledge was collected and used to categorise and evaluate findings from the theoretical study. Data from the OWF operations and related offshore fields were used as a foundation data set, and a survey was used to collect practitioner opinions on decommissioning safety practices and cost related to lifting and loading.

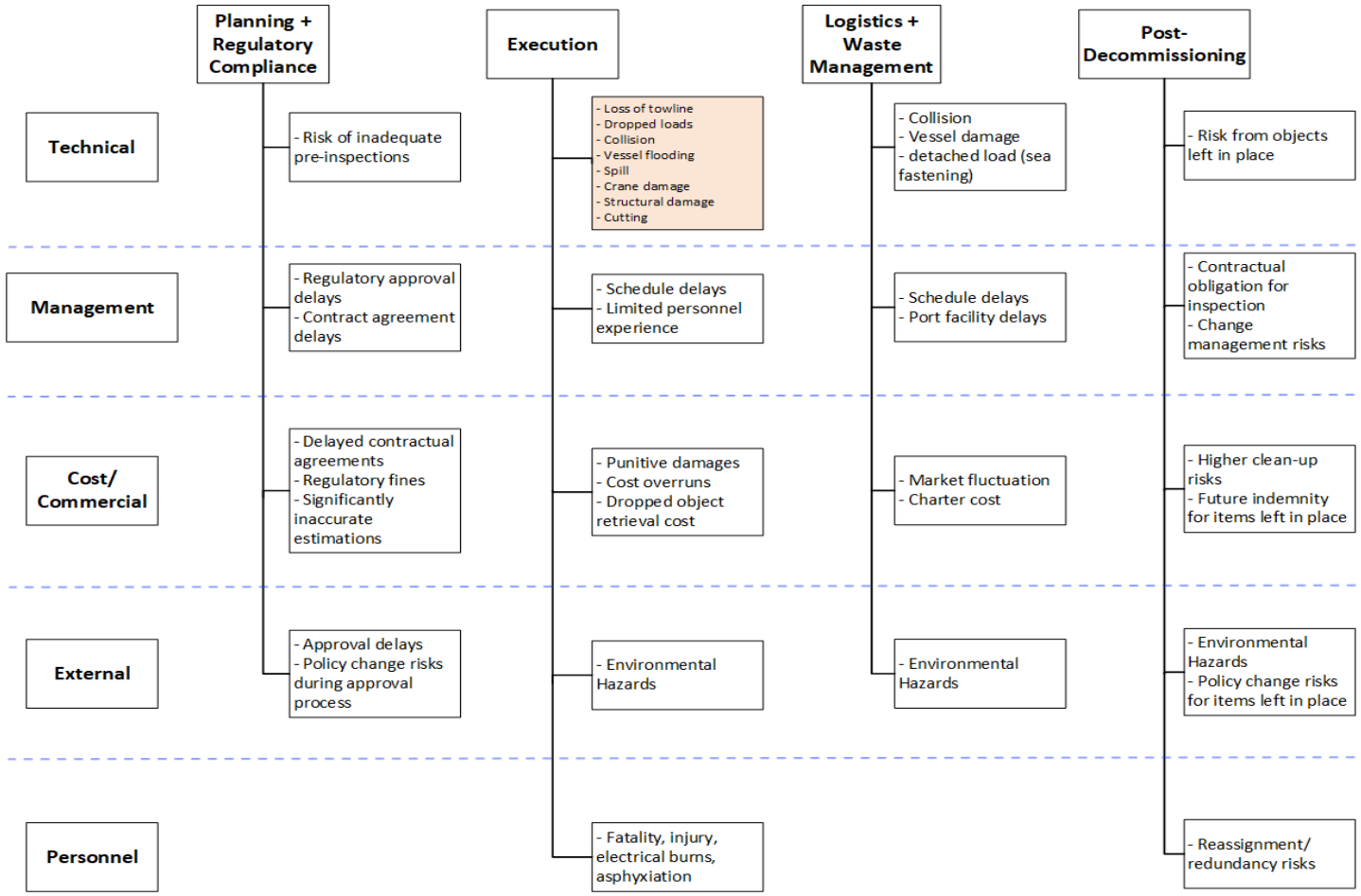


Figure 6-1 Risk Breakdown Structure (RBS)

6.2 Risk mitigation approaches and value engineering practices

Mitigation of the critical risk categories is important to consider for the decommissioning phase of the OWF asset lifecycle. These factors can be reduced by controlling, reducing, or eliminating them in relation to the different categories of risk associated with the four distinct decommissioning phases. Using the RBS as a basis, the risk mitigation approaches are presented in Table 6-1 below. In addition to risk mitigation practices in decommissioning project management, other practices like value engineering can also be adopted.

6.3 Methodology: expert elicitation

A survey was conducted to obtain opinions from industry experts to clarify the risk and potential cost in lifting and loading decommissioning operations. The responses were compared with the theoretical cost and risk assessment research findings. The data was collected through the use of a 30-question anonymous survey (presented in Appendix E), using the Cranfield University Qualtrics tool to gather two rounds of responses from participants from the 03/08/2020 to 31/08/2020. Participants filled out the survey titled “Offshore Wind Farm Decommissioning Risk Assessment Research”. The target population was composed of experts in different offshore wind energy (OWE) industry roles including project planning and developments, construction/decommissioning, operation and maintenance (O&M) and logistics and transportation. Respondents were contacted via email, LinkedIn and word of mouth from academic colleagues at different universities. The survey included a variety of questions designed to obtain a picture of the risk profile of current OWF decommissioning activities.

Among the responses, eight respondents met the criteria of active involvement in OWF decommissioning. The responses were collected and analysed from the reports generated in MS Excel format. Surveys were good for succinctly capturing the understanding of a problem from a concerned group. However, two limitations were firstly, that respondents only captured answers based on the questions asked and options provided. Secondly, the findings reported are limited and need to be further validated in future studies because of the limited responses (eight).

Table 6-1 Mitigation and control measures for the risk categories in the decommissioning phases

	Decommissioning Phases for risk mitigation / reduction / control			
Risk categories	**Planning & Regulatory compliance**	**Execution**	**Logistics & Waste management**	**Post-decommissioning**
Technical risk	Inspections of the OWF facilities must be adequately conducted to prevent any hazards during lifting operations.	Failed parts should be promptly replaced, and equipment use discontinued until repair / replacement is satisfactory. Inspection records can be digitised and stored in an inspection databank for access and improved learning in OWF decommissioning.	Endure loads are adequately fastened and checked. Appropriate vessel and accidental limit states to be determined to lower / eliminate vessel damage related incidents / hazards.	Objects left in place must be monitored and adequately marked on site for other users of the sea. Adequate arrangements must be made to inspect these items in perpetuity.
Management risk	To reduce potential schedule risks posed by approval delays, the right documentation must be collated based on available standards and updated. Contract management among the decommissioning	Adequate documentation of incidents / hazards and ease of access to them. Investigation reports made easily accessible.	Port facility delays can be reduced as more decommissioning ports come into operation. Robust management methods will be developed specific to OWF decommissioning. OWF	Contractual obligation risks can be minimised by beginning negotiations as early as is practically possible. Change management risks must also be well managed

	contractors and subcontractors can also cause management and schedule risks/delays. Care must be taken to ensure that liabilities or other terms and conditions (T&Cs) are understood and agreed by all parties involved.	Training of personnel and supervisors for decommissioning-specific projects.	asset managers must keep abreast of policy changes / improvements.	for personnel working on the project long-term.
Cost / Commercial risk	Contractual agreement delays can also pose threats to OWF decommissioning projects and delays can lead to increased costs or insurance pay-out in the event of incidents. An OWF asset manager must ensure that the commercial interest of the organisation is protected. If the decommissioning contractors encounter some incidents, there can be likely regulatory fines. OWF decommissioning-specific contract types can be developed in the future.	Adequate contingency / management financial reserves. Determining the number of emergency evacuation vessels needed per site based on OWF size / layout. Costs of punitive damages, cost overruns or cost of retrieval of dropped objects should be adequately covered in contract and contingency costs provided.	Market fluctuation risks can be hedged by using the most appropriate financial instruments. As decommissioning is not an income-generating project, optimal financial instruments should be determined. Charter costs can be reduced if planning is done and contracts lock-in the vessel-charter costs. As OWF end-of life management planning improves, ideal vessels may be developed that will be optimal for decommissioning at reduced charter costs.	Adequate arrangements must be made to keep these items on the books of an organisation in perpetuity. Future indemnity must be assured for assets / items left in place.

External risk	Risks posed by policy changes mid-way through planning / the approval process can impact on decommissioning operations. A way around this is to keep abreast of regulatory climate and plan in the direction of the changes as much as reasonably practicable.	Determination of accurate safety zones in the event of environmental hazards.	Transportation hazards caused by bad weather should be minimised / eliminated by ensuring that voyages to / from site is done in good enough weather conditions.	Environmental hazards must be well accounted for in relation to the items left in place. Adequate monitoring should also be in place to ensure that no items are dislodged from their original place or the right intervention procedures are put in place. Likely policy changes must be well managed for items left in place.
Personnel risk	-	Use of adequate PPE, improved training and planned prompt response to move personnel to safe zone on site. Minimise duration of working in enclosed spaces. Ensure appropriate harness is used by personnel.	-	Re-assignment / redundancy risks must be managed with good change management practices related to decommissioning.

The average ranking of the response results analysed from the survey are presented below. The data collected was used to understand the operational concerns in OWF decommissioning in order to craft a rounded strategy pathway for proposing improvements and further research. The data was analysed based on the average ranking of different risks and cost factors in the current decommissioning practices.

6.3.1 Suspension of decommissioning operations

Operators may suspend decommissioning operations for a number of reasons. Based on the responses in Figure 6-2, the three factors with the highest average rated causes were fatality, compromised safety of personnel and potential environmental hazards, respectively. This was in good agreement with one of the most critical risk factors identified from the theoretical findings. Personnel related safety delays can have a significant impact on the project duration and thus can lead to increased execution costs. To reduce decommissioning costs, it is recommended that safety improvements in operational procedures be made in the areas previously identified, as investments in planning time to optimize safety procedures are likely able to reduce overall risks of cost overruns. The least important reasons for suspension of operations include extended project schedule, project cost overrun and insufficient research, respectively. This may be in part because decommissioning projects, once begun, are very costly to stop or suspend. In addition, at some point in time due to regulatory requirements decommissioning must be completed regardless of the cost reduction efforts.

Thus, non-critical but commercially challenging factors may not warrant suspension unless they become extreme. An interesting finding was that “insufficient decommissioning technology research” was rated the least because decommissioning operations will commence with existing technology, even without improvements. In addition, existing technology may be sufficient for the level of activity for now; however, automation may be required as operations increase. It is unknown yet if decommissioning technology is sufficient for decommissioning. What is unknown is the extent to which lifting vessel technology improvements can improve operational efficiencies. This is important

to note because unless critical costs and risks are understood, operations will continue as usual and little progress or improvement will be made in OWF decommissioning.

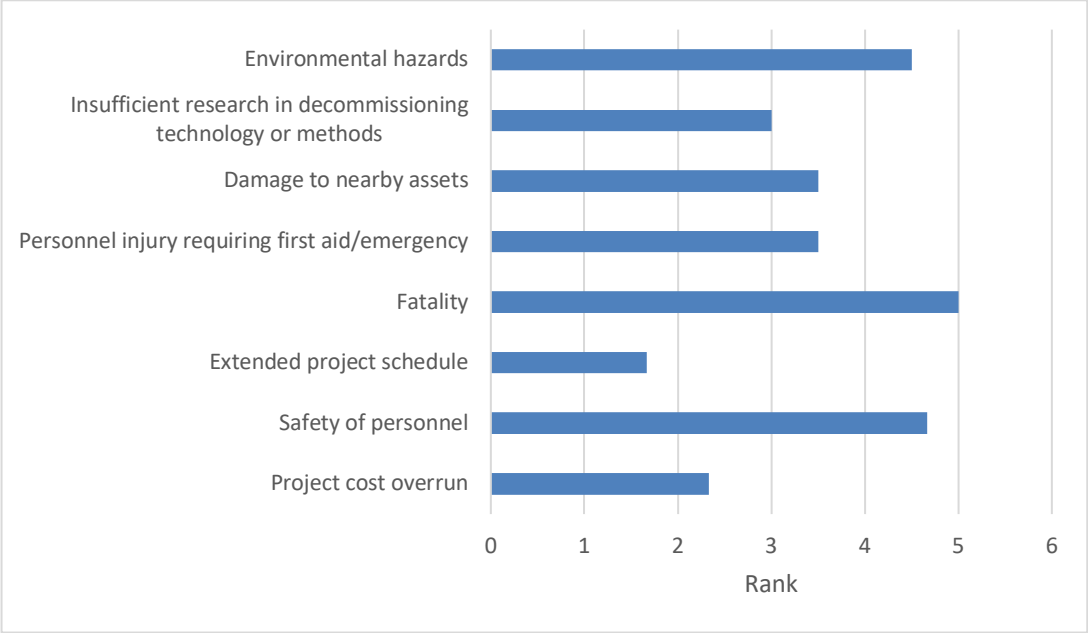


Figure 6-2 Critical factors for suspending decommissioning operations

6.3.2 Barriers to decommissioning safety

Ten decommissioning safety barriers were listed for respondents to rank in order of priority, as seen in Figure 6-3. “Lack of experience” was the highest ranked by respondents. There are limited ways to address this barrier, and although training may be able to reduce the impacts somewhat, it can most significantly be improved with practical experience gained during real decommissioning activities in the future being collected and acted on using rigorous lessons learned procedures. The second highest rated barrier to safety was “insufficient information about potential hazards”, which was consistent with the premise of this study that safety management can only be maximised when potential safety threats are known and well understood. Of equal ranking were “insufficient research in decommissioning technology or methods”, “low return on investments”, “regulations and guidelines not robust enough for OWF decommissioning activities”, “regulatory inhibitions in approving safety devices or technologies”, “technology readiness level (TRL) of new safety devices”,

“contractor competence” and “insufficient research in decommissioning technology or methods”.

The average ranking scores reinforce the fact that safety may be hindered by “lack of experience in OWF decommissioning”. Two strategies proposed to address the lack of experience is to ensure that new knowledge is adequately shared cross-industry and that decommissioning operations research is facilitated. “Costly technology adoption and safety device approval” was ranked next. “Logistical constraints” were the least ranked in relation to safety although theoretical findings concluded that in decommissioning cost assessments logistics is a significant factor. Logistics are not likely to be a limitation for decommissioning safety because asset managers (based on the responses) may be confident that logistics operations are sufficiently safe to date. However, with the increasing body of research on maintenance vessel safety on OWF sites, care should be taken not to ignore decommissioning logistics safety. In terms of cost, if logistics safety is compromised, the decommissioning project will be more costly because of the compounding day rate charges associated with schedule extensions. These findings suggest that cost-critical factors are not necessarily the same as risk-critical factors.

6.3.3 Decommissioning activity improvements

The respondents rated areas of priority for improvement based on current practices as seen in Figure 6-4. Based on the highest average ranking, results showed that “tool/technique development” is the most important factor, followed by “safety improvements”, “logistics/vessel technology improvements”, “improved safety regulations” and “process automation”, respectively. It can be inferred that a better understanding of the requirements of decommissioning processes and related safety aspects will enable the development of tools/techniques to deliver more efficient and safe operations. Also, it can be inferred from the responses that practitioners would like to see improvements in safety and safety regulations. The existing decommissioning regulations and guidelines need to be evaluated in the context of OWF safety requirements.

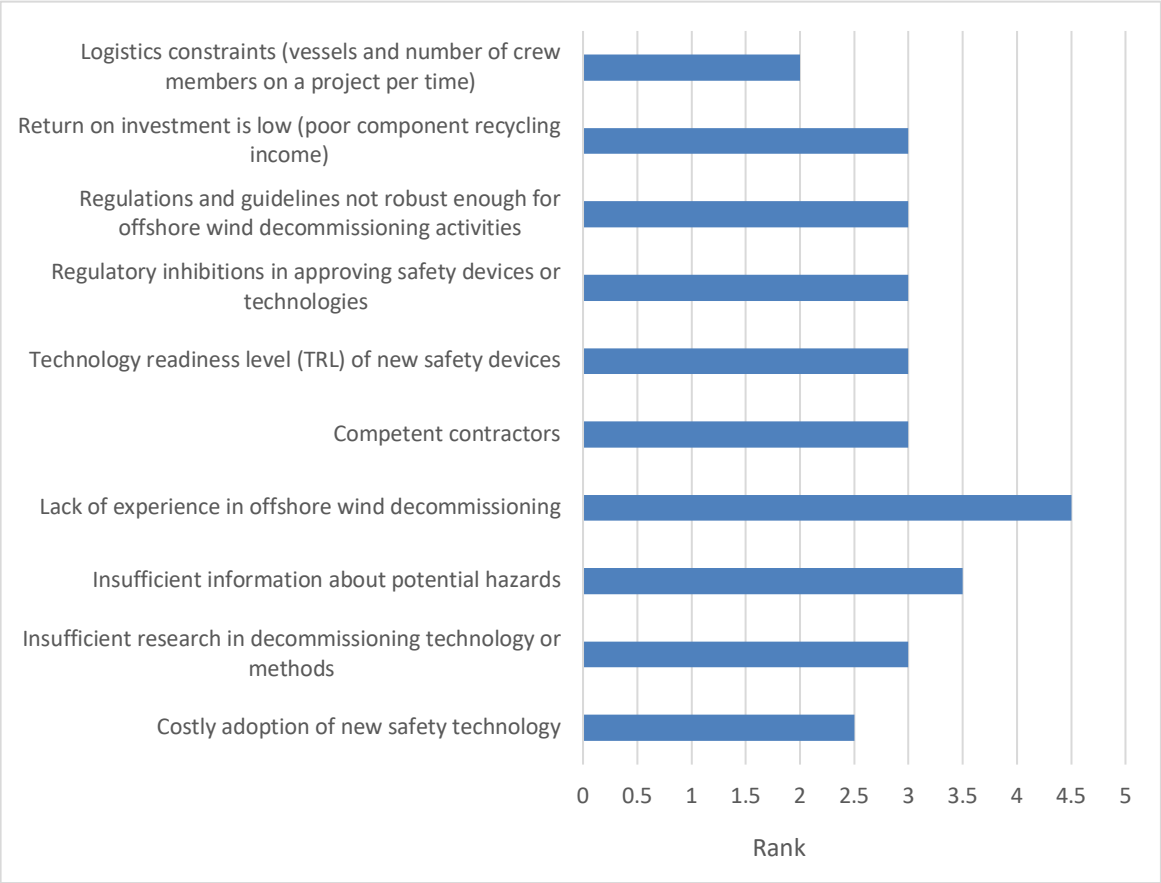


Figure 6-3 Barriers to decommissioning safety

Another picture that emerged from the responses was that “tool/technique development” is central to decommissioning improvements. This is perhaps to be expected, as improved tool/technique development can deliver more efficient and safer practices. “Process automation” scored the least in the survey responses for this aspect. It can be argued that automation is not of paramount importance relative to the other factors presented, especially in contrast with tool/technique development. This is in part because it is difficult to automate a process that has not been well practiced to date and until the OWF decommissioning area becomes more mature (with more lessons learned and challenges better understood), automation will be of low priority for asset managers. When OWF decommissioning operations become more standardised, research into automation may then be explored. The areas where it is suggested that process automation can be of benefit in the short term will be in the use of granular data collection of incident and near-miss records to direct improvement needs.

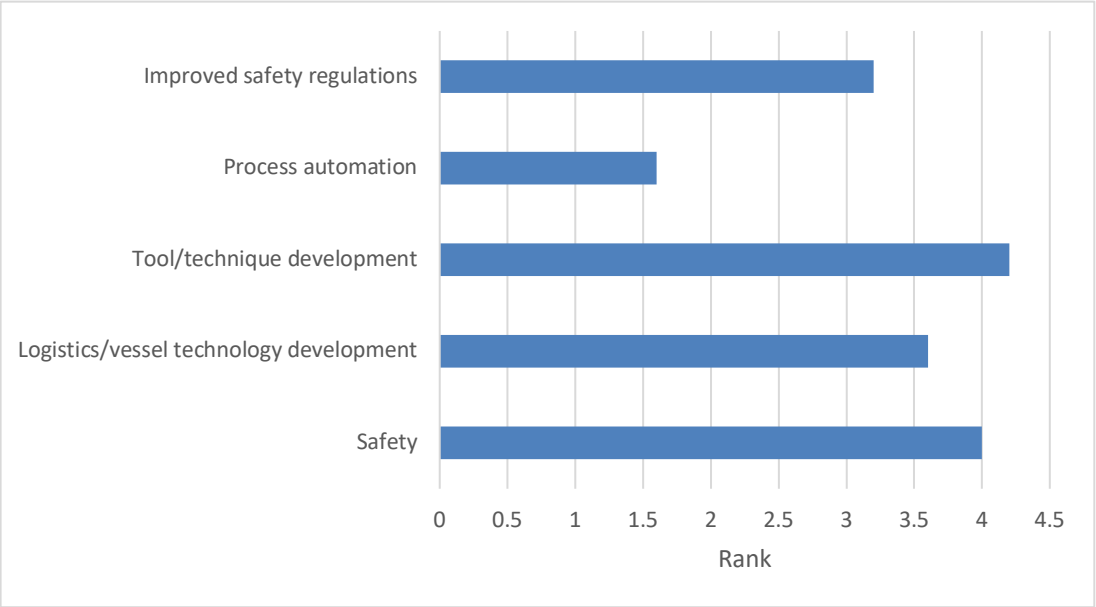


Figure 6-4 Decommissioning activity improvements

6.3.4 Risk profile of decommissioning operations

The risk profile of decommissioning activities was ranked as seen in Figure 6-5. On average, respondents rated “lifting and loading operations” as the highest activity on the risk profile. This is consistent with findings from data for prior OWF activities, and with the theoretical risk assessment study results obtained. Of slightly lesser rank were “cutting”, “post-decommissioning” and “logistics and transportation”. The first set of responses were in good agreement with literature findings and theoretical estimates. Ranking lowest were “waste management”, “site surveys/clearance” and “facility preparation”. On one hand, as suggested by the responses, site waste management may not be considered to have a grave impact on the risk profile of offshore decommissioning at this time; however, as OWF decommissioning is better understood and more rigorous environmental regulations roll out, the site waste management risk profile may change. On the other hand, segments of waste management, like onshore site waste processing, will be critical to consider in the overall risk management profile. The safety in repurposing, reuse or recycling of components is important in safety management, especially with the increase in practices for the circular economy. Therefore, waste management risk profiles can be further investigated.

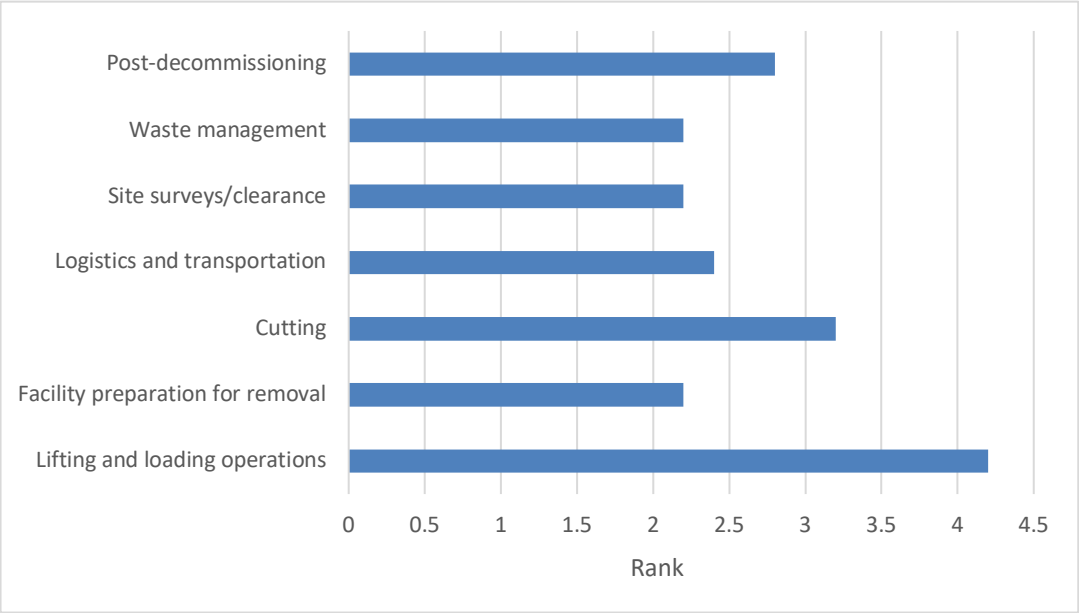


Figure 6-5 Risk profile of decommissioning operations

6.3.5 Lifting Configuration

Respondents ranked different lifting configurations based on their related resource intensity (man hours and equipment) and cost (£). Based on the responses in Figure 6-6 the full lift, full-rotor lift, and bunny-ear lift configuration were the costliest methods. These lifting configurations require heavy lift vessels, which are very expensive to charter. Sometimes different vessels will be used to lift the WTGs and the foundations, depending on the number of units to be lifted, the crane capacity and design or the cutting strategy. Manipulation of the WTGs removed is also more time consuming when loading larger sections onto the vessel. Conclusions are difficult to make about the duration for each type of lift. Therefore, a multi-criteria decision analysis can be conducted to determine the optimal set of lifting operations and which configuration should be avoided for each site. The safety levels associated with each lifting configuration can also be determined by conducting a comparative assessment of the quantitative risks associated with each configuration. However, because of the limited number of decommissioning operations that have been conducted to date, that is difficult to determine. In addition to cost, there are many other factors that need to be considered for the lifting configuration selection.

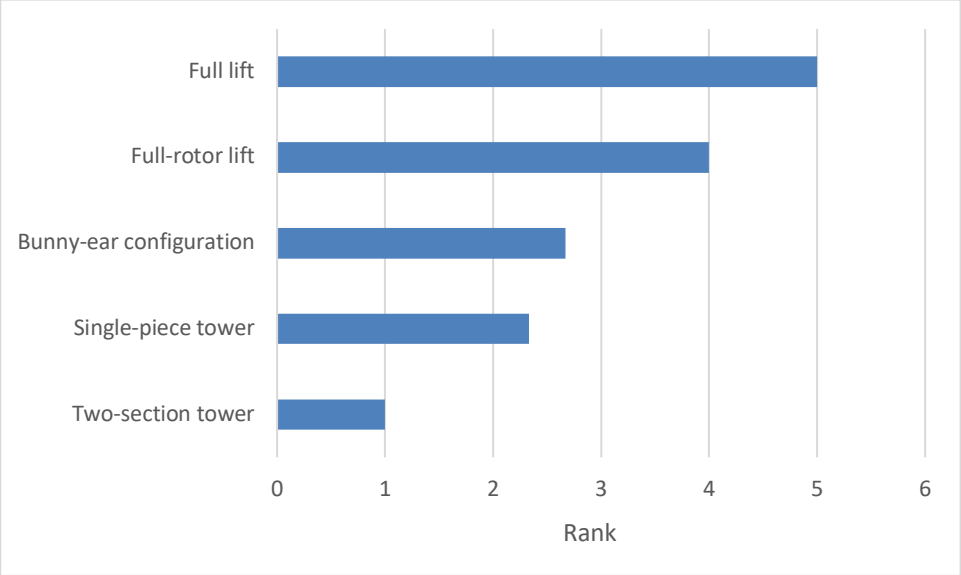


Figure 6-6 Lifting configuration ranking by resource intensity and cost

6.4 Overall cost and risk-driving factors

This research contributed significantly to identifying opportunities for improvement in OWF decommissioning operation cost and safety assessment. A cost breakdown structure (CBS) model was proposed to make decommissioning activities more cost-efficient, technical. Potential safety hazards were also determined for each decommissioning phase activity and the critical safety factors identified for lifting and loading operations. The use of BNs for risk assessment was proposed for near-time updates with new information during decommissioning operations. The results of the theoretical assessments were compared with industry practitioner perspectives on the cost and risk profiles of OWF decommissioning. Table 6-2 summarises the highest cost and risk critical factors, in no order of criticality, on the basis of categories: technical, personnel and operations management. Some management-related risk drivers overlapped with the technical risk drivers and as such were not repeated.

Table 6-2 Cost and risk-driving factors

Category	Cost-driving factors	Risk-driver
Technical	• Number of wind turbines (N_{WT}) • Number of lifts (N_L)	• Number of wind turbines (N_{WT}) • Number of lifts (N_L)

	• Weight of wind turbines (W_{WT}) • Water depth (WD) • Distance to shore (D_{shore})	• Weight of wind turbines (W_{WT}) • Good equipment design (D_{eqt}) • Visibility • Crane integrity • Inspection frequency (I_{freq})
Personnel	• Number of crew (N_{crew})	• Fatigue (F_{crew}) • Number of crew (N_{crew}) • Personnel safety
Operations management	• Duration of activities (D)	-

After performing a HAZID study for all the operations, only lifting and loading operations were investigated further with the most safety-critical factors identified. Both the cost *and* risk-drivers were identified as seen in Figure 6-7, highlighted in the blue and green sections, respectively. The critical factors common to both the cost and risk (shown in the overlapping section) were: ***Number of wind turbines (N_{WT}), Number of crew (N_{crew})***, **Number of lifts (N_L) and Weight of wind turbines (W_{WT})**, in no order of importance. There is no one-size-fits-all approach to risk assessments, especially in a relatively new field like OWF decommissioning. Therefore, a focus on managing the decommissioning operations based in the overlapping critical factors as a priority will be a good strategy for asset managers and regulators

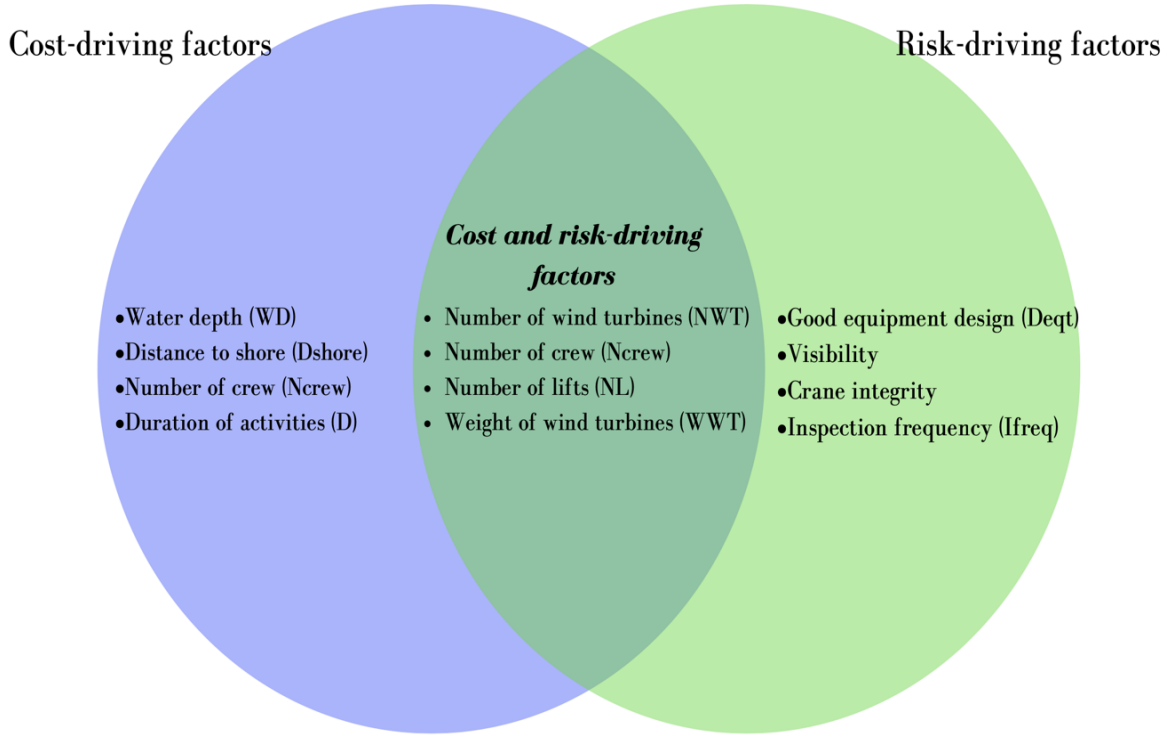


Figure 6-7 Highest cost and risk-critical factors

6.5 Research synthesis

This research adopts cost and risk management approaches for OWF decommissioning. In this section, the synthesis of results of all approaches, findings and significances are presented. Table 6-3 summarises the novelty, argument, scientific soundness, and contributions within each objective. This integrates the results from each chapter, demonstrating how they have come together to fulfil the overall research aim: ***"to evaluate decommissioning activity cost and risks to identify primary decommissioning cost and risk-drivers for new offshore energy systems (e.g., wind energy). The cost and risk-drivers identified will be used to propose cost and risk reduction methods, which will improve efficiency and safety in the critical activities involved."*** The table presents the categories and ranks of each cost-driver and risk-driver and identifies where there are any overlaps. The study significance/contributions are also discussed. The first objective was achieved by conducting an extensive systematic literature review to determine the existing decommissioning practices in OWF and offshore oil & gas industries, cost

management research, risk management research, existing decommissioning cost and risk reports, and Bayesian network applications in offshore wind energy. The findings from the first objective identified gaps and areas for further investigation, and served as a foundation for the articles written into the chapters that followed.

Chapter 2 achieved the fourth objective, which systematically identified, evaluated and assessed BN applications in the OWE industry. It made a case for the applicability of BNs in the entire OWF asset lifecycle. A key finding from that study showed that BNs had been used in risk assessment, however, there was no past application in the OWF decommissioning phase. The second objective was achieved in Chapter 3 by conducting a decommissioning cost estimation study. The CBS model developed can help asset owners, managers, regulators understand the cost-critical factors. This model can be applied on a case-by-case basis for each potential decommissioning project. A comparative study was conducted with past research findings and used to verify the model. Chapter 4 achieved the first half of the third objective and presented results from a risk analysis study for decommissioning operations using both quantitative and qualitative methods. The HAZID study was conducted for each phase of the decommissioning project and an FTA was conducted to identify the factors that can influence the likelihood of occurrence of failures during lifting and loading operations. Scenario analysis was conducted using the ETA and a risk matrix. The crane fault/failure-related incidents were identified to have the highest risk likelihood and impact. The risk numbers generated were not absolute as they only present a guide for researchers and practitioners in safety studies and development, and conducting different scenario analyses will yield different results.

Following from Chapters 2 and 4, Chapter 5 applied BNs to risk assessment of lifting and loading operations during decommissioning. This BN protocol was applied to a case study, presenting an update with recent OWF incident data based on current practices. The argument of that article/study centred around

showing how BNs can be used in diagnosis and prognosis of potential OWF decommissioning risk influencing factors (RIFs).

Chapter 6 addresses the second part of the third objective and the fifth objective. A risk breakdown structure (RBS) framework was developed from literature study and results obtained from survey conducted with decommissioning experts used to validate results from models proposed. The findings highlighted the impactful areas that ought to be key safety focuses going forward, and for which risk management practice improvement should be developed for the offshore wind energy industry. Some of the key findings were that personnel-related risks were the most important in terms of safety, which was consistent with the results obtained using the theoretical approaches. It was argued that improving safety is also a means to reduce decommissioning costs and project risks. This presented a strategic pathway for cost and risk management practices. The outcomes will be beneficial to different stakeholders in the OWE industry for decommissioning asset management.

Table 6-3 Synthesis summary

Objective	Novelty	Argument	Scientific soundness (Methods/Validation)	Significance/contribution
1. To conduct a systematic literature review of the current offshore wind energy sector applications of semi-automated tools and techniques (Bayesian networks) in the different phases of the asset lifecycle.	Chapter 2 presents a systematic review of existing advanced assessment method (BNs) and its applications in the wind energy industry. Chapters 3, 4 and 5 include the literature reviews of OWF decommissioning operations and the current state-of-the-art of cost and risk assessment in offshore wind.	This study presented evidence of BN applications in different phases of the OWF asset lifecycle and its potential for application in other areas also. There is limited research in OWF decommissioning compared with OWF installation, as many assets have just begun to be retired from 2017. There was a need to investigate potential areas of	It involved a systematic review of BN application literature, cost estimation and risk assessment. Relevant databases were used to source for past research including journal publications, conference proceedings, PhD dissertations, industry reports, best practice documents and software user guides.	The results and findings provide an understanding of knowledge gaps, state-of-the-art methods used and areas of development in BN model applications in the OWE industry, cost, and risk management in the OWE industry.

		development in OWF decommissioning.		
2. To identify, evaluate and assess innovative solutions to reduce/mitigate the cost/risks associated with decommissioning of offshore wind assets.	Chapters 2 and 5 presented BNs as a potential innovative solution for use in the OWE industry. This study is the first to present BN application to OWF decommissioning risk assessment.	The BN was shown as an applicable tool for risk assessment, also incorporating decision and utility nodes.	BNs results were presented for the application to OWF decommissioning operations (lifting and loading phase). In place of FTA application for likelihood estimation, the study showed the BN ability to improve estimates using operational or future data for updates.	Grouping of incidents was proposed when assessing impacts on decommissioning operations for more targeted safety improvements. Operators and regulators can use this approach to determine areas of safety improvements on a case-by-case basis.
3. To develop an integrated framework to identify, evaluate and estimate cost-critical activities in decommissioning of offshore wind energy.	Chapter 3 was the first article to present a Cost Breakdown Structure (CBS) framework/model for OWF decommissioning and apply it to identify the cost-critical factors in OWF decommissioning.	A CBS model can be used to reduce costs based on the decommissioning phases/modules. It can also support the identification of the highest cost-critical factors in OWF decommissioning.	A mathematical CBS model was developed for OWF decommissioning and validated using past studies, comparing results and offering recommendations for reducing cost-critical factors identified.	The LCCA estimates for the decommissioning phase can be improved and cost-critical factors better understood by asset managers and regulators.

4. To develop a systematic risk analysis framework to identify, evaluate and mitigate risk-critical activities in decommissioning of offshore wind assets.	Chapter 4 is the first study to present a risk assessment of OWF decommissioning operations. Chapter 6 shows the risk breakdown structure (RBS) for decommissioning based on different risk groups anticipated in decommissioning operation.	The highest incident rate in OWF was found to be lifting and loading. This study presented scenario analysis for determining the risk-critical factors in OWF decommissioning lifting and loading operations using established methods. Crane related-incidents were the most risk-critical. Therefore, avenues should be taken to ensure safety during crane operations during decommissioning.	HAZID study was conducted, FTA, ETA and risk matrix analysis was conducted as a baseline case for decommissioning risk assessment of lifting and loading activities. Scenario analysis (using the ETA) was used to present and validate risk-critical event.	Using time-tested methods used in industry, OWF decommissioning risk assessment is presented to help asset managers and regulators understand the areas for safety improvement in OWF decommissioning operations. It was proposed that crane related incidents had the highest risk impact on the suspension of decommissioning operations.
5. To collect and analyse existing offshore wind farm decommissioning	Chapter 5 presented a case study of the risk assessment applying the BN and	An argument was made for BN applications in OWF	The qualitative methodology supported the quantitative methodologies	This presents an OWF decommissioning strategy pathway particularly for safety and cost

protocols, cost and risk factors, in view of the theoretical assessment findings, and provide recommendations for improved industry practices.	its updating capacity with existing OWF incident data. Chapter 6 presents the survey results from expert elicitation on the different areas in decommissioning where improvements are required/anticipated.	decommissioning risk assessments and cost related decision-making using decision nodes (influence diagram). The survey findings in Chapter 6 underpin the overall strategy pathway presented by the methods proposed in this study. Although there are many risk and cost-drivers, the use of the CBS model and innovative modes of risk assessment for decommissioning should focus on the most cost and risk-critical factors.	presented in the other parts of the research. The responses from OWF decommissioning practitioners show an overlap in the factors highlighted from this study and the experiences/anticipations from the practitioner perspective.	management. It will support asset managers/owners, regulatory bodies and researchers in understanding and identifying the areas of future development.

7 Conclusion and future works

Ultimately, cost and risk estimates in OWF decommissioning are laden with uncertainty. The central argument presented was that the cost and risk factors in OWF decommissioning need to be better understood and a framework developed which can be used for identifying them. Thus, research was conducted to better understand the costs and risk drivers, identifying those that warrant further research, could benefit from economic efficiencies and provide opportunity for safety improvements. The strategies described throughout this study contribute by offering potential pathways to reduce cost and risks for OWE businesses in the management of assets at their end-of-life. With the critical factors identified, stakeholders can focus on further areas of development. Asset management strategies can be optimized by adaptive cost and risk assessment strategies. Therefore, the study also applied Bayesian networks in the assessment to show its capabilities in OWF decommissioning applications. The dependencies of decommissioning operation success on the cost and risk-critical factors were also mapped to determine the extent of their influence on overall decommissioning success.

7.1 Key contributions to knowledge

The research focused on three central themes: firstly, cost-critical factor identification and reduction using a cost breakdown structure. Secondly, risk - critical factor identification and reduction using HAZID, FTA, ETA and a multi-level risk matrix. Lastly, application of BNs for improved risk assessment and cost decision-making. In addition, to understand the existing concerns from the perspective of industry practitioners, a survey was conducted which identified areas of concern for the OWE decommissioning sector, and an OWF decommissioning RBS framework was developed.

1. Systematic literature study of the application of advanced uncertainty modelling in offshore wind using BNs (Chapter 2).
2. Development of a CBS model as a framework for estimating and assessing the impacts of the most critical cost-drivers in OWF

decommissioning. When stakeholders apply this model, cost reduction and schedule optimisation can be accomplished, particularly for the safety-critical tasks (Chapter 3).

3. Process flowcharts of the different activities in OWF decommissioning where presented for the first time in this study. They can be used as a tool for additional studies in cost and risk assessment (Chapter 3).
4. Robust analytical models for cost estimation for OWF decommissioning activities (Chapter 3).
5. Determination of the highest risk-critical factors (risk influencing factors, RIFs) and proposing analytical descriptors of the critical RIFs in OWF decommissioning (Chapter 4).
6. Proposal of a pathway using advanced Bayesian methods to identify, mitigate or control the risk drivers in OWF decommissioning. Overall, the most critical cost *and* risk-drivers determined include: Number of wind turbines (N_{WT}), Number of crew (N_{crew}), Number of lifts (N_L) and Weight of wind turbines (W_{WT}) (Chapter 5).
7. Risk breakdown structure (RBS) of OWF decommissioning operations and mitigation methods for the risk-critical factors (Chapter 6).
8. The overall cost and risk driving factors and the overlaps between both (Chapter 6).

This study is significant due to the increasing number of future OWF decommissioning operation estimates, the identification of OWF decommissioning cost and risk-critical factors will enable asset managers, owners and regulators to choose the most appropriate strategic areas of focus. Thus, managers and regulators can better shape policy, safety guidelines, technological improvement and operational improvement targets. Stakeholders will be able to devise strategies to minimize whole-life project costs, and reduce detrimental impacts caused by inadequate understanding of the operational inefficiencies and safety threats in decommissioning. Each part of the study is important for different stakeholders in the efforts towards decommissioning cost and risk reduction, including asset managers/owners, regulators, offshore wind construction project managers and researchers.

7.2 Research limitations

There were a few limitations to the research including:

1. A major limitation in this study was the sparsity of data from prior operations, which was to be expected due to the limited number of offshore wind farms that have been decommissioned to date.
2. The risk assessment outcome of different operations were subject to both the likelihood and consequence of occurrence of hazardous events, which in application will be site dependent.
3. The cost and risk- critical factors were based on lifting and removal (loading) operations as the costliest and safety sensitive activity. Not much exploration was conducted for other tasks in as much depth, which may introduce some level of bias.
4. The cost model was seen to scale because of the ability to quantify cost based on the model proposed. The risk models, however, were scaled using the BN, which incorporates uncertainty based on limited data. Until more decommissioning operations have been conducted, the BN model accuracy will need to be updated with new data for it to offer the highest levels of accuracy.
5. The number of participants used in the validation part of the study. Due to the limited number of offshore decommissioning projects that have taken place, there was a smaller pool of study participants reached that had the requisite background / experience required for the insight required.

7.3 Future outlooks

The proposed future outlooks and research include:

(i) Identification of necessary safety barrier improvements for decommissioning operations. Scenario analysis may be conducted to reduce the consequence of occurrence of different incident scenarios.

(ii) Collection of decommissioning operation incident data to monitor real activities and learn from experience, and to generate Bayesian network input distributions for improved predictions/estimates of probability of

hazards and risk potential of operations in all decommissioning phases.

(iii) Research into risk-based methods for selecting optimal lifting configurations and identification of their associated costs and risks, with the aim to reduce operational risks during lifting and loading operations.

(iv) This study recommends a further investigation into methods for selecting the optimal lifting configuration considering both cost and risk profiles, as opposed to selecting a default configuration for use or using the same as was used for installation.

(v) Waste management methods need to be improved for a circular economy and policies need to be developed to ensure that the waste streams of decommissioning are well managed.

(vi) Financial and transmission asset (cables) risk assessment and risk management of items left in place can be researched further.

(vii) Methods for selecting the optimal lifting configuration for OWF decommissioning since different configurations have their associated costs and risks.

APPENDICES

Appendix A

Table A-1 A detailed analysis of the reviewed studies about BN application in wind energy

Reference	Year	Mathematical Problem	Input	Output	Specifications	Challenges of solution	Advantages	Limitations
Cheng *et al.*	2002	Estimation of uncertainties in displacement of WT blades	Sample data of extreme flap moment from 50 simulations	100-year estimate of blade response using different distribution functions	Bayesian Averaging (BA) method is used	Simulation results still have to be analysed statistically	Compared to Maximum deflection theory, BN produced more accurate results	Data was obtained from simulations and not real measurements
Garbatov and Soares	2002	Bayesian updates of model parameters for floating structure fatigue reliability assessment	Material constants, initial crack size, geometry parameter	Posterior probability function of time to crack initiation, and reliability of structure	Uncertainties are associated with time to crack initiation, inspection quality and material properties	There is a need to improve reliability analysis techniques by considering anticipated degradation and accounting for estimation uncertainties	Bayesian updating improves O&M decision-making based on system reliability	Accuracy of BN updating method depends on the posterior function used for the estimation
Rangel-Ramírez and Sørensen	2009	Integration of CM with BN inference	Model uncertainty from wind load effects, posterior density function, design parameters	Accumulated reliability index, lifecycle reliability, RBI information	Fatigue prone hot-spots on WT support structures are analysed. Reliability is assessed by the S-N approach	Offshore WFs require improved maintenance planning methods due to the extreme conditions	Inspection plans are updated with better informed reliability data	N.A

Sørensen	2009	CBM using pre-posterior Bayesian decision theory	Updated damage accumulation model, Design parameters	Probability of failure at a particular time, overall O&M cost	Lifetime probability of failure for WT gearbox was simulated using FORM software	It is complicated to calculate costs, failure rates, and damage models for WT gearbox	Risk-based Bayesian method can be used to make decisions under uncertain conditions	N.A.
Li and Shi	2010	Wind speed modelling with taking into account parameter and model uncertainties	2-year wind speed records at 10m height, prior distributions for each parameter	Posterior mean and variance of BMA predictions given the observed data	WinBUGS is used to obtain the parameter samples for the prior distribution. BMA and MCMC are used for wind speed distributions	Conventional statistical models are not applicable as they only focus on parameter uncertainty but not model uncertainty	The uncertainty can be better accounted for by using an averaged model. BMA produced more robust long-term wind speed distributions for all sites	Candidate models still need to be selected to perform BMA. It is difficult to visually analyse plots from BMA
Nielsen and Sørensen	2010a	Damage size and failure probability updating with new information for RBI planning using BN	Wind load, prior distribution of number of cycles, material parameters, load measurements	Failure probabilities, posterior distribution of damage size	It generates 30,000 samples to calculate posterior distribution. Damage sizes are entered annually in the model	Damage models are used to describe damage development. The uncertain parameters are described using stochastic models	Incorporating inspection results and load monitoring produces more reliable damage models and failure estimates	N.A.
Nielsen and Sørensen	2010b	Probabilistic modelling to update damage size / failure probability with CM / inspection data	SCADA data, wind loads	Updated failure probability, damage size estimates, expected annual cost of repair	Only fatigue cracking failure mechanism is considered. Crack propagation follows Paris' law	Damage models have many uncertainties which have to be quantified for more reliable and accurate damage size estimation	Incorporating CM and inspection results improves the accuracy of reliability estimations	N.A.
Sloughter *et al.*	2010	Explicit wind speed modelling of full predictive PDF using BMA	Wind speed dataset of observation stations	Verification rank for a raw ensemble forecast histogram and probability	Data is available for 340 days from 35,230 station observations. Discretised wind speed data is	When sparse data is available, fitting of predictive PDF is challenging	BMA produces bias-corrected forecasts. It can produce 48-hour ahead wind speed forecasts by	BMA may not perform well if there is substantial topography at sub-grid scales

				integral transform (PIT) histogram	rounded to the nearest whole knot		improving predictive PDF sharpness	
Sørensen and Toft	2010	Use of probabilistic models and reliability estimates to improve design based on new test information	Design variables (rotor height, tower diameter and thickness, foundation radius, etc.), stochastic variables (maximum wind pressure, turbulence intensity)	WT design is optimised based on reliability levels. The damage at failure is estimated during amplitude testing	An integrated uncertainty modelling is proposed for optimum WT design based on optimal reliability estimates. Application case study was a model for local buckling failure of support structures	Uncertainties must be incorporated into WT design	Test results and uncertainty can be included in the design process. Both physical and statistical uncertainty and expert judgement can be incorporated into the design	N.A.
Ye *et al.*	2010	Improved fault detection using three tests to detect the system states	SCADA data, power output, rotor speed, blade pitch angle	WT performance features	Tests from the Multi-dimensional Scaling (MDS) method are used as inputs to BN for improved decision-making	N.A.	This method produces better fault detection results because different matrices are used in the fault detection	N.A.
Blonbou	2011	Short term (15-minute ahead) wind power prediction using adaptive Bayesian learning	Wind speed data, wind power production data	Future values of electrical power generated	Wind speed and power production are measured at sampling rate of 1Hz. Neural networks are trained with Bayesian procedure	N.A.	Bayesian framework helps to forecast the interval within which generated power should be observed. It allows for control of the network complexity	N.A.
Carta *et al.*	2011	Estimation of long-term wind speed frequency	10-year mean hourly wind speed and	Cumulative relative frequency histogram of wind speed, mean	Two commercial WTs of 330 and 800kW were chosen. Model evaluation	Insufficient data makes it difficult to predict wind behaviours at WF sites.	Allows for the use of wind speed data from different reference stations. Less error	N.A.

		distribution for a WF site with limited measurements	direction data from 4 weather stations	wind power density, mean annual energy output	technique uses 10-fold (cross-validation) method to evaluate the errors		between real and estimated energy outputs is obtained	
Chen and Hao	2011	Gearbox fault diagnosis	Sample data, types of fault (e.g. tooth profile error, broken gear tooth, shaft imbalance, etc.), fault feature	Marginal probability density of a fault node	Sample data is described by a *n*-dimensional vector. Fault features, e.g. RMS, kurtosis, mean are selected and BN is used to calculate the conditional probability	There are six forms of fault in WT gearbox and it is difficult to correctly recognise and diagnose these faults using traditional methods	Less computation time, good convergence and strong real-time property. State identification and fault diagnosis under uncertainty can be made with BN	N.A.
Nielsen and Sørensen	2011	Optimal O&M planning based on Bayesian pre-posterior decision theory	Weather data, failure rate data	Framework for reliability modelling of WT blades	A decision is made on when and how to maintain and repair WT components. Damage models are associated with uncertainties	Corrective maintenance in O&M is flawed because it may lead to failures occurring at times of limited accessibility to the assets	Information from NDI techniques can be used to update reliability model using Bayesian methods	N.A.
Toft *et al.*	2011	Updating reliability assessments with NDI data from WT blades using BN	Data from blade NDI	Updated reliability or probability of failure	Defect positions are generated randomly within the model. Defects are repaired when detected	NDI techniques are still prone to many uncertainties	Reliability can be improved by updating with NDI information	The reliability is dependent on POD of the NDI technique used for inspection
Toft and Sørensen	2011	Probabilistic design and reliability updating of WT blades with test data using BN and ML methods	Material strength coefficient of variation, number of tests	Reliability index in a year given number of tests	Bayesian method was used to estimate ULS function. Only one failure mode was considered in the reliability estimation	Design uncertainties are inherent in WT blades. Full-scale tests contain uncertainties	Estimation of uncertainty of material strength is possible even with little test data. Data from past full-scale tests may be used for prior data used in the analysis	The Bayesian method is dependent on the number and quality of prior test data

Chen *et al.*	2013	Detection and location of faults	SCADA data, outputs from a Venn diagram analysis	Fault probability, root causes depending on the input data	The BN modelled the relationships between the condition of pitch system and sensor readings. SCADA data was used to train the BN	There is a gap for automatic use of SCADA data in failure diagnosis	BNs can make inference about the probabilities of all connected events. The sensor readings are collected online and used to update the BN in fault diagnosis	BN can become too complex. The accuracy of the BN model depends on the quantity of input data
Plumley *et al.*	2012	Degradation modelling of WT systems to determine optimal O&M	N.A.	Probability density functions and updates	The BN was tested by running different failure mode scenarios using changes in temperature and metal particles within the lubricant. LabVIEW was used to show how BNs can be used.	Although condition monitoring systems are effective, false positives increase O&M cost. Thus, a method is required to improve the accuracy and robustness of the results	BN allows evidence to be propagated in the model in order to update the posterior probability of the model	N.A.
Fernández-Cantí *et al.*	2013	Non-linear set membership model estimation and fault detection	N.A.	Feasible dataset and verification that model matches dataset	The faults of pitch system were detected using 50000 sample data generated by a Simulink model	There are some challenges for executing Bayesian estimations	The Bayesian set-membership approach requires less run-time than statistical methods	N.A.
Lee *et al.*	2013	Wind turbine extreme load estimation	N.A.	N.A.	Bayesian spline method is used to extrapolate extreme loading response of WTs. The results are compared with the binning method of load estimation	The binning method cannot accurately estimate the uncertainty of extreme loads. When the binning method is used, there is an overestimate of the extreme loading on WT	The Bayesian spline method produces less parameters than the binning method for extreme response estimation. It is also more flexible in data handling	N.A.

Mardfekri and Gardoni	2013	Fragility estimation for a WT support structure using probabilistic models	Deformation capacity, shear capacity (yield stress and ultimate stress), wind speed, wave height	Fragility estimates (in relation to serviceability, yield and ultimate limits) based on wind speed	Fragility estimates were developed for three failure modes: drift, shear and bending failure, based on the wave heights at different wind speeds	Deterministic methods do not account for uncertainties and have inherent biases	Bayesian methods can update the model based on newer information from FEA of the structure	N.A.
Van Buren *et al.*	2013	Reduction of model uncertainty in WT blade dynamics modelling	FE model parameters (trailing edge, spar cap and Z spring)	Posterior predictions of the blade model	The posterior probabilities of five parameters were obtained	N.A.	Parameter uncertainty can be included in the model using Bayesian inference	N.A.
Wang *et al.*	2013	Identification of uncertain and fuzzy vibrational generator fault signals	Data about generator state	Failure rate of generator, mechanical drive system	Feature recognition and Bayesian methods are used to detect faults. The BN structure is created with the fault symptoms and fault layer.	Conventional methods cannot accurately identify fault types and their location in generator	BN has the capacity to estimate system reliability under uncertainty	Bayesian inference quality is dependent on an accurate selection of fault signal events
García *et al.*	2014	Wind power forecasting using DBN for more than 5 hours ahead	2-year wind farm data, including: wind speed and direction, temperature, humidity, pressure	Wind power forecasts from the BN are compared with time-series method	10-minute input data is used for training and testing the model	Classical techniques of wind power forecasting do not account for many variables. Thus, their precision is limited	Methodology for DBN can be used for different forecasting problems. The average error is more acceptable than with other techniques	Daily variable data are not considered

Nielsen and Sørensen	2014	O&M decision updating	N.A.	Optimal O&M decision	Probability of failure and accuracy of monitoring results are calculated	The decisions about repair affect the associated costs of O&M. A method for O&M updating is required	Pre-posterior decision analysis using Bayesian methods can be used to determine the best O&M planning option	Approximation techniques still need to be used in Bayesian analysis
Su and Fu	2014	Reliability model using BN to incorporate uncertain wind speed effects	10-year failure data records	Reliability of WT with varying speed	BN is mapped from a WT submodule fault tree. AgenaRisk tool was used for model reliability	Conventional reliability estimation methods do not account for component interrelationships and dynamic wind speed	The BN method includes the advantages of fault tree, uncertainty and environmental factor impact	N.A.
Bracale and De Falco	2015	Improved accuracy in wind power forecasting with a Bayesian method	Shape and scale parameters for the wind speed distribution	More accurate time series model	A mixture Weibull distribution (MWD) was used to model the wind speed	Uncertainties associated with the wind power resource availability were modelled by probabilistic methods	Probabilistic wind power forecasting is improved with Bayesian inference with incorporating changing environmental conditions	The model used the deterministic power curve provided by the WT OEM
Fernández-Cantí *et al.*	2015	Fault detection and isolation using Bayesian set-membership approach	Residuals, fault indicator vector and associated indexes	Distributions for the residuals, posterior probabilities of different fault scenarios given the alpha-coefficients	The errors in the model are bounded by the Bayesian Set-membership framework	Other models use very large detection thresholds, which increase the likelihood of false detections	The method combined the advantages of reduction in model error and false positive. False alarms were reduced. There was an improved detection time	N.A.
Kougioumtzoglou and Lazakis	2015	Risk and cost assessments for improved decision	Probability of failure (from OREDA Handbook)	FMECA and HAZID matrix, total probability of	The most critical components of WTs were identified. BN was used	In order to incorporate all risk factors and model uncertainty,	BNs can be used for HAZID analysis and include the	N.A.

		making in WT installation and O&M		failure, total cost of failure	for the risk assessment and cost analysis for WT O&M strategy	a more robust tool has to be developed	utility (cost) associated for most critical events	
Li *et al.*	2015	Reliability assessment of WTs	Initial conditional probabilities of WT states	Predicted WT state and absolute error	BN was used to validate the proposed Goal Tree, Success Tree and Master Logic Diagram (GTST-MLD). BN was modelled in MSBNx	Conventional reliability models do not account for logical and functional relationship between WT components	N.A.	N.A.
Mardfekri and Gardoni	2015	WT structural performance assessment in the event of multiple hazards	Virtual experiment data (obtained from FEM in extreme wind and seismic loads), spectral acceleration, wind speed	Estimation of fragility (as a function of spectral acceleration and mean wind speed), annual probabilities of structural damage	MCS is used to estimate the fragility of WT support structures. All potential hazards are taken into account. Probabilistic seismic demand models are updated.	There are few works taking foundation stiffness into account in WT structural response. The conventional models are computationally expensive and may produce inaccurate structural responses	This assessment can help decision makers optimally design WTs. Uncertainties can be incorporated to reduce result bias. Faster processing time with improved accuracy	N.A.
Pan *et al.*	2015	Presentation of errors in probabilistic wind power forecasting	Wind speed, wind direction, temperature, air pressure and humidity	Predicted wind power curve	Sparse Bayesian Learning (SBL) is used to develop a probabilistic forecasting method for wind power. Parameters of the kernel functions are optimised in order to improve SBL model by using the modified-Gaussian kernel	Probabilistic models focused on non-parametric methods, which need more data and are computational-intensive. Previous methods cannot provide full probability density functions. In order to forecast by minutes, the Gaussian distribution cannot	With SBL, there is no need to estimate some parameters and thus there is less computation time. The model has better performance than others	The method performs poorly with large datasets. The accuracy of the model is not the best for very short-term or very long-term wind power forecasts

					function and Particle Swan Optimisation (PSO)	represent the error distributions		
Sinha and Steel	2015	Failure prediction and maintenance planning and execution	Online CM data, inspection reports, service records, component manuals, wind farm information, etc.	Key performance indicators of maintenance regimes in operation	A failure dependency model is developed based on BN taking into account relationships between failures and failure root causes	Failure prediction is difficult because of inadequate understanding of WT behaviour under stochastic conditions. There is a need for a dedicated software tool and relational database for O&M planning	The failure dependency database design is useful for O&M planning when different failures, root causes and their likelihoods of occurrence are interconnected	More failure data is required to improve the reliability of the model
de Bessa *et al.*	2016	Use of time-series and data analysis to detect and isolate faults in a WT system	Wind speed, sensor signal database, probability of fault occurrence from Gibbs sampling	Probability indication of each detected and isolated fault	A two-part fault detection and isolation (FDI) system was used. The fuzzy Bayesian module is used for classifying the detected faults	Using existing data and model-based methods, not all faults within a WT system can be identified and isolated	Fuzz Bayesian method was able to detect and isolate multiple faults occurring at the same time by extracting information through Gibbs sampling	In some instances, the fuzzy-Bayesian model confused a wind variation with a fault
Herp *et al.*	2016	Continuous monitoring and performance evaluation of WTs using multivariate statistical model	SCADA data	Prediction of bearing failure (by over-temperature)	Continuous monitoring as a maintenance strategy was used	Threshold detection has been used in the past for WT monitoring. It does not take into consideration the probabilistic events within the system. BN was used because the Hotelling's T^2 approach did not consider the likelihood of the classification	The BN method takes into account the likelihood of the classification, making supervised controls more flexible	Misclassification rates are still high with Bayesian methods, even though reduced

Park and Law	2016	Solving the wind farm control problem by maximising wind power output using the BA algorithm	Wind speed, wind direction, number of turbines, yaw set angles, induction factors	Wind farm power production	The BA method is made of two parts: learning and optimisation. The non-cooperative control solutions are used as the prior data for the BA algorithm. Simulation was performed for validation	Conventional wind farm control strategies are non-cooperative in which the wake effects cannot be accounted for to maximise a collective power output. The proposed method in this study is based on cooperative WF control	The BA algorithm can find improved output values for every input. This method requires limited amounts of data for optimum control estimations. Noisy function values can also be used.	Although BA algorithms can use noisy function values, increased noise levels in data reduces the rate of convergence, slowing down the iteration process
Pattison *et al.*	2016	WT reliability estimation taking into account environment factors, accessibility, failure modes, etc.	SCADA data, CM indications	Probability of failure of WT gearbox, impact of maintenance actions, short-term degradation forecast	DBM method was used for risk assessment and maintenance scheduling of WT gearboxes	Conventional techniques do not account for WT dynamic behaviours	Bayesian methods can help capture the dynamic degradation over time. System state can be estimated based on different maintenance scenarios	N.A.
Ciobanu *et al.*	2017	Power supply reliability assessment using BNs for WTs	Minute-by-minute meteorology parameters such as wind speed and solar radiation	Reliability estimation	Hugin software was used to process the data. The variables used were discretised	BNs are very complex and difficult to synthetically explain and the number of possible structures is exponential	It is a useful tool for monitoring and state diagnosis of the wind power supply network. It has the capacity to predict future availability conditions	More variables need to be included in the probabilistic estimation to ensure robustness
Florian and Sørensen	2017	Impact of using risk-based maintenance on optimal O&M planning of WT blades	Initial crack size, material parameters, mean turbulence intensity	Posterior distributions for mean initial crack size, material parameters, total	Reliability estimates for blade degradation were updated using BNs. Load distribution was obtained by Rainflow counting and	Current maintenance strategies cause higher WT downtimes and increase the LCOE	The degradation model can be updated with inspection results	The method has not taken into account weather prediction for O&M schedules

				risk/cost during blade lifetime	fitted to Weibull distribution. Failure time was estimated by MCS			
Galanis, G.*et al.*	2017	Improved numerical wind simulations to reduce systematic biases, error and forecast uncertainty	4-year meteorological station data from 9 stations	Time series and percentiles for real and ideal data for different meteorological stations	Tests were performed for both actual and ideal datasets (to test data in a controlled space). Weibull prior distributions were used for the Bayesian-Kalman filter model	Current solutions to wind speed modelling have limitations with errors when performing forecasts	Reduced CPU memory, elimination of systematic prediction errors, reduction of mean bias and real convergence of the modelled probability density function to the observations	Severe changes in data used leads to unexpected discontinuities. Difficulty in matching the modelled and observed data easily
Jin and Liu	2017	Reliability improvement of WT gearbox	Historical gearbox data and expert opinion	Failure probability of each element of the faulty gearbox	Two gearbox failures were considered: tooth surface contact fatigue pitting and toot root bending fatigue fracture	Minimum cut sets need to be solved when using fault trees as the method for reliability calculations	BNs are more suitable than fault trees for reliability analysis as they do not need to solve minimum cut sets for reliability estimations, avoiding the non-cross-computing process	N/A
Jing *et al.*	2017	Fault diagnosis improvement to improve wind energy output	Fault data records	Conditional probability of candidate faults and their diagnosis	First, a sensor data layer is established and then a fault list is used to create the BN. The method was tested using WF fault data	Current approaches focus on data from different components and are difficult to apply to the entire WT. It is challenging to obtain quantitative diagnostic results	Faster fault searches. Improved fault diagnosis accuracy	Limited training data and restricted conditions make diagnosis difficult
Nabdi *et al.*	2017	Decision logic to choose preliminary	Variables of state of different	Probability of failure of system	N.A.	Current modelling tools rely primarily on expert	BN can be used to incorporate numerous	The model presented did not fully account

		WT concepts using probabilistic states estimation	components, failure rate of components, unavailability of components, repair rate of components	components for two design concepts		judgement, surveys and manufacturing databases to build WT structural models	design knowledge into a model. BN has powerful analytical and modelling capacity. BN allows for system state to be determined for different operational scenarios	for more criteria for optimisation improvement.
Nielsen and Sørensen	2017	Optimal O&M planning with lifetime cost estimation using CBM	Mean wind speed, wave height	Cost of inspections, repairs and lost production over WT lifetime, power production for 1-hour intervals	Bayesian updating is used to determine posterior probability for the component state. Costs are due to inspection, repair and lost production in the event of a failure	The conventional methods do not include inspection and monitoring information in decision making. Theoretical tools become difficult to handle because of increased decision parameters	Online monitoring can be included into the model	N.A.
Pobočíková *et al*	2017	Wind speed modelling using four probability distributions	Wind speed	Parameter estimation using ML method, histogram of PDF for wind speed	Parameters were estimated with STATISTICA and wind speed was modelled in MATLAB	N/A	N/A	N/A
Tatsis *et al.*	2017	Fatigue damage estimation (response prediction) of a WT	Vibration data, mean wind speed	Estimated and actual fatigue damage	Modelled in FAST software to generate the vibrational data. Bayesian filter was used for noisy data	The conventional stress predictions do not account for uncertain behaviour and response of structures	Improved accuracy of dynamic response estimation using CM data	Using model-based techniques for global response analysis is computationally intensive

Wang *et al.*	2017	Wind power forecasting using both deterministic and probabilistic techniques	Wind power dataset	Wind power forecasts using Variation Bayesian method	A new model (ARMKR) is used to process multi-resolution wind power data. A Gaussian mixture model was used to model the error	Conventional methods like quantile regression have discontinuities in the PDF for the wind power forecasts. They ignore some information when dealing with high-resolution data	Bayesian methods produce continuous PDFs even for interval forecasts. The variational Bayesian method is used to optimise all parameters	N.A.
Yang *et al.*	2017	Prediction of wind power using Naïve Bayesian with particle swarm optimisation (PSO) and rough set (RS)	Numerical wind power (NWP), wind speed	Prediction intervals at different confidence levels, segmentation and non-segmentation optimisation prediction intervals	Data (numerical wind power and wind speed) were recorded every 15 minutes. RS theory was used to handle the datasets and Naïve Bayesian classifier was used to establish a power class	The accuracy of conventional methods depends largely on the point forecasting value. Previous methods also require large computational capacity and can be limited for real applications	Higher prediction performance, higher coverage and narrower average bandwidth for wind power forecasting intervals	N.A.
Afshari-Igder *et al.*	2018	Probabilistic wind forecasting	Historical wind power data	Optimal prediction intervals for different times	Approximation methods for prediction uncertainties like Bayesian methods are used to obtain the PI	Uncertainty in wind power forecasting cannot be solved by conventional methods	More reliable PIs of wind power improve forecasting accuracy	N.A.
Asgarpour and Sørensen	2018a	Prediction of maintenance time using a Bayesian-based prognostic model	Average failure rate, operational data like: degradation data and RUL of the	Posterior degradation model of a component based on updated	Posterior degradation model is updated based on updated shape and scale parameters from CM-based observations	Computational complexity limits the use of many prognostic approaches in practice	BN allows more than one threshold and predictive maintenance strategy to be considered. It is applicable	N.A.

			components, expert judgements	shape and scale parameters			to different components and failure modes	
Asgarpour and Sørensen	2018b	Fault detection for a WT component using a hybrid multi-agent model	Diagnostic model input/agents, SCADA data (vibration, temperature and oil particle), prognostic model input	Posterior confidence levels of diagnostic agents for main bearing, short term O&M planning framework	Both confidence matrix and diagnosis matrix were inputted in the decision model. Faults detected by the diagnosis agents are confirmed by inspections, and the initial confidence matrix is updated by BN	There is no generic diagnostic model suitable for all WTs. Conventional methods result in high O&M costs due to unplanned failures of WT components	Improved fault detection by Bayesian updating of the initial confidence matrix. It can help in short-term O&M planning with significant cost reduction	N.A.
Ding *et al.*	2018	Fatigue life prediction of WT gearbox using varying-load method	Material properties, teeth number, Young's modulus, Poisson's ratio, diametral pitch, base circle radius, outer circle, pressure angle	Fatigue life is predicted and updated with Bayesian methods	CM data and uncertain parameter distributions are used to model the degradation process. Crack is propagated based on stress analysis in FRANC2D programme	Existing methods use constant loads to approximate external load during fatigue prognosis. When using model-based methods, it is difficult to model complex components	Uncertainty is reduced and life prediction is improved by Bayesian updating given the measured crack length	N.A.
Han *et al.*	2018	Probabilistic wind speed forecasting with comparing post-processing methods	Wind speed data	Verification rank histogram of EMOS and BMA forecasts	Six post-processing methods are used for ensemble model output statistics (EMOS) and Bayesian model averaging (BMA) models	Current forecasting methods are subject to bias	Among the forecasting methods, the BMA models had the highest accuracy	Different prediction accuracies for different stations were observed

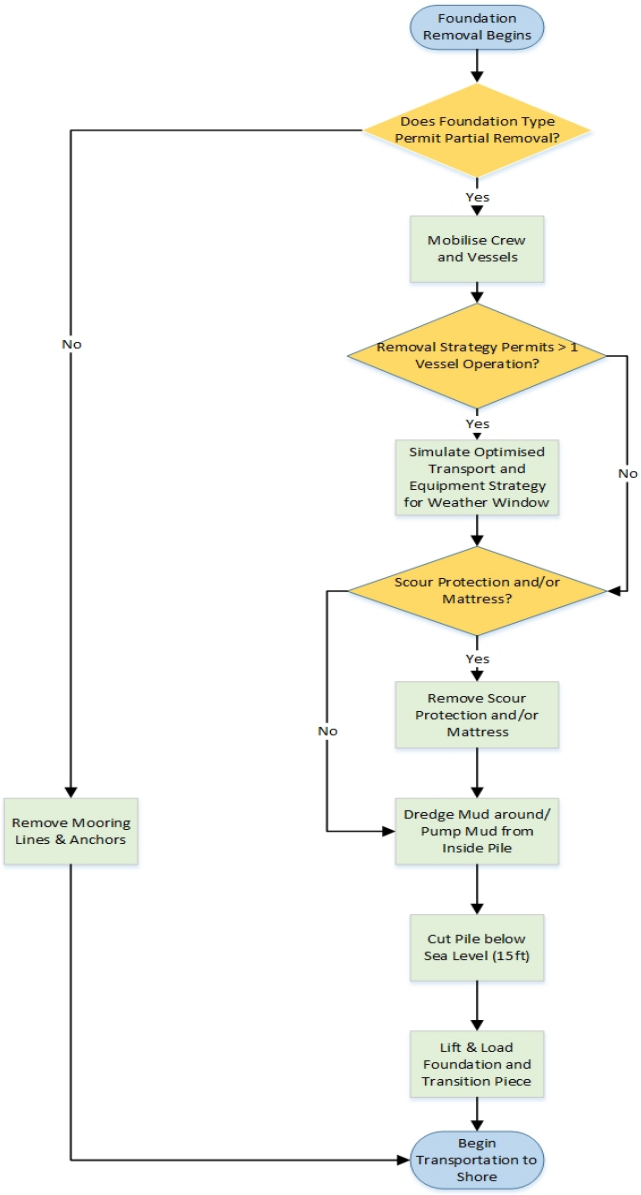
Herp *et al.*	2018	Bearing failure prediction using Bayesian methods	Temperature measurement residuals	Failure state prediction, RUL prediction given run-to-failure time series	Run-to-failure time of bearings is used to train the prior data used in the model. Hyperparameter are updated to train the model	Other methods of fault estimation do not consider improvement of the model precision	It predicts the bearing over-temperature events. The accuracy improves on a daily timescale while precision improves on a weekly timescale	Convergence is only possible with a large number of time series because of the strong-data-driven nature of the model
Joshuva and Sugumaran	2018	Fault identification in WTs	Vibration data obtained from accelerometer	Classification results and accuracy of different classifiers	Five blade failure features were identified using ML and statistical analysis. Six classifiers, including Lazy Bayesian Rules Classifier (LBRC), were applied	Conventional methods require performance improvements for considering different types of fault parameters	LBRC model requires little running time	LBRC classifier was seen not to be superior to other classifiers. It may require more memory than non-lazy algorithms
Reder and Melero	2018	Predictive failure modelling for improved O&M of WTs	Failure data for components, environmental data (wind speed, rain, temperature), WT data (hub height, diameter, etc.)	Monthly predicted failures, conditional probabilities of failure for different components	Naïve Bayesian classifier was used to incorporate uncertainty. Sensitivity of failures in WT subsystems was analysed based on accuracy and Matthews correlation coefficient	Conventional failure prediction methods assume constant failure rates. Advanced WT reliability models do not always account for the variable environmental conditions of the WTs	Improved prediction accuracy	The technique for the pitch and yaw system had poor performance
Song *et al.*	2018	WT health state monitoring using Bayesian methods	10-minute SCADA data	Distributions of normal and abnormal WT SCADA parameters, variations of	Three Bayesian methods were used (bin, multivariate normal-based, and copula). Data from two WTs were used	Higher resolution diagnosis is required for WT health state monitoring	Bayesian methods are superior to power curve-based monitoring method. The Bayesian-copula method was very effective in one-step ahead prediction	It is challenging to determine the most useful criteria for identifying the normal and abnormal

				SCADA parameter values for WTs	from 10-minute data for 2 months			conditions using SCADA data
Uzunoğlu	2018	Development of a BN model for O&M planning using subjective expert opinions	SCADA data, expert opinions	Posterior probability density function updates, fused subjective opinions, and cost assessment	BN is updated with newly available SCADA data. The model is applied to data of pitch control failures from 2009-2015	Current methods do not quantify uncertainties from software reliability, control system reliability, and weather conditions	The model is updated with new information (SCADA data and expert opinion). Method can be extended to different maintenance data	N.A.
Lazakis and Kougioumtzoglou	2019	Risk and cost analyses of different lifecycle phases of offshore WTs using BNs for installation and O&M	Failure data for each WT subcomponent, failure cause data (from OREDA Handbook)	Failure probabilities for different components, estimation of annual cost of failure	Main system was divided into 11 subsystems. BN was used to validate FMECA and HAZID results	Identifying hazards accurately is a key in decision-making	BN is a more flexible method than FTA/ETA, as it can combine both objective and subjective data. BN improves reliability and criticality analysis for improved O&M planning	N.A.
Moghaddass and Sheng	2019	Cost-sensitive anomaly detection using BN with limited data	Real-time sensor data	Percentage of anomalous sample data removed after parameter estimation	2500 sample data were used (2000 for training and 500 for modelling). MCMC was used for data training	Conventional data-driven anomaly detection methods are inefficient. A trade-of between misclassification errors and detection rates must be defined	The cost sensitive BN decision tool allows for anomaly prediction with lower cost and risk. It can be used with limited data for training and modelling	Intensive computations. During data training, not all anomalous samples can be found
Wang *et al.*	2019a	Improved accuracy in wind power	Historical wind power data, wind speed data	It estimated power curves to show	HSRM and RSRM are optimised by BN methods. 6000 WT datasets are	There are inconsistencies in available wind power data. Parametric techniques are	HSRM and RSRM are considered good methods	The methods require more training times for improved accuracy

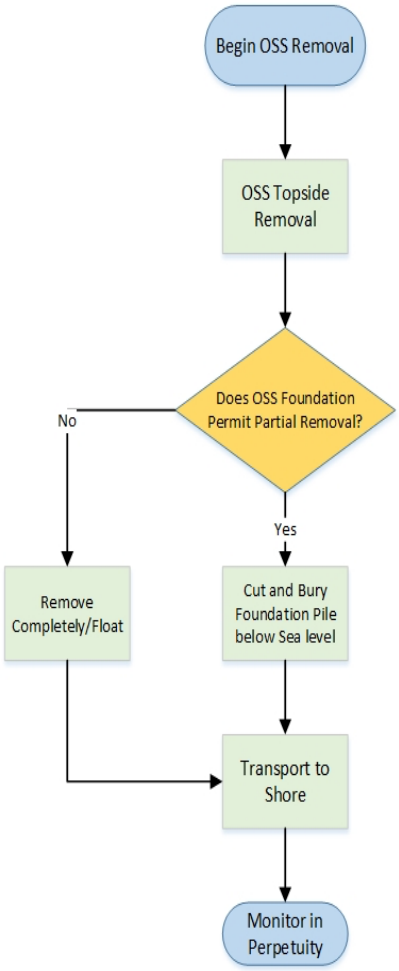
		forecasts using inconsistent datasets		normal and inconsistent datasets	collected at different seasons of the year, collected every 10 minutes	limited in modelling the dynamic characteristics of power curves	for improving the quality of wind power forecasts	
Wang *et al.*	2019b	Use of sparse Bayesian-based method to improve wind speed forecasting	Wind speed data	The performance of different models was compared using the same datasets	Sparse Bayesian-based robust functional regression model was developed to forecast 10-minute ahead wind speed	There are usually outliers in the dataset that affect accuracy of predictions. Pre-processing accuracy depends on the quality of pre-processed data	The downsides of having outliers within the datasets are reduced. The method is also more robust because of high-resolution data	N.A.
Xie *et al.*	2019	Improved short-term probabilistic wind power forecasting	Historical wind power data, wind ramp datasets	Prediction error for wind ramp datasets, posterior predictive wind power distributions, probabilistic wind power forecasts	1000 datasets of hourly wind power were used. No performance improvement is observed when historical data increases	Conventional methods underestimate uncertainty in wind power forecasts. They do not fully describe the predicted wind power distribution	Reliable for informing regarding real-time risk management	N.A.
Zhong *et al.*	2019	Real-time fault diagnosis using efficient signal processing methods	Vibration signals from online CM system of the gearbox	Identification of faults more quickly and precisely than traditional techniques	Signal data pre-processing and pattern recognition with ML techniques. WT gearbox fault features were extracted using Hilbert-Huang transforms and correlation methods	Conventional fault diagnosis techniques lead to large costs due to big and noisy datasets	Since this method is data-driven, it does not require many parameters. This is a more adaptive and accurate fault diagnosis method	The accuracy of diagnosis depends on quality of input data. It is only designed for binary classification problems (i.e. healthy or faulty)

Appendix B

Figure B-1

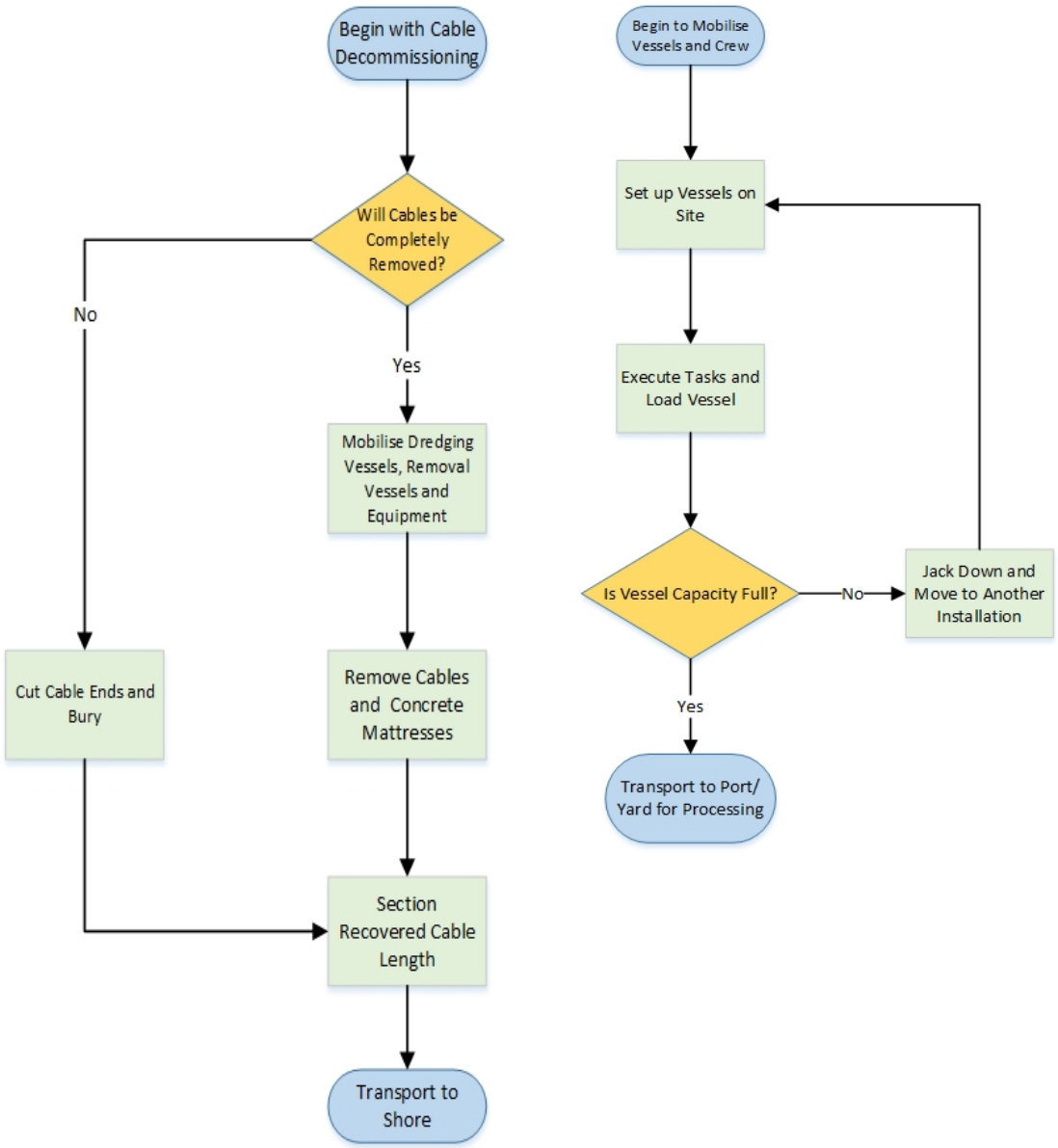


(A) Foundation removal activity flowchart



(B) OSS Removal flowchart

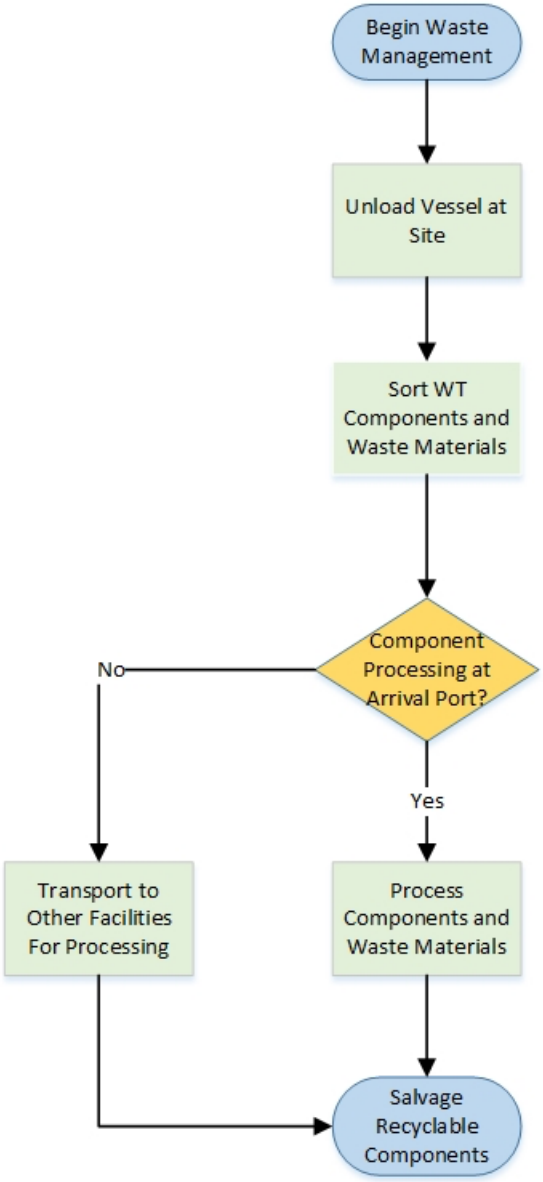
Figure B-2



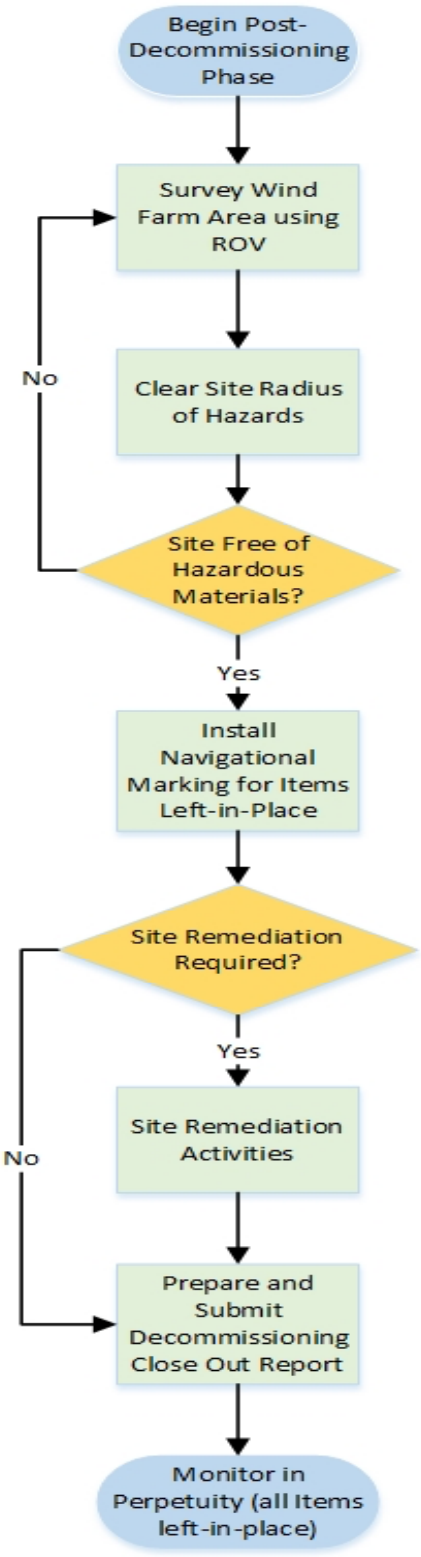
(A) Cable decommissioning flowchart

(B) Logistics flowchart

Figure B-3



(A) Waste management workflow



(B) Post decommissioning flowchart

Table B-1 ***Planning and Regulatory Approval***

Parameter	Symbol	Value	Units	Reference
Engineering planning base cost	C_{E-Plan}	862,500	£	Dataset
Project Management	C_{PM}	6% of $C_{decom-total}$	£	Statoil (2014)
Regulatory Approval*	C_{RA}	-	£/	Excluded (BEIS, 2019)
Permits	C_{Permit}	0.13% of $C_{decom-total}$	£	Shafiee *et al.* (2014)
Amendments	$C_{amend.}$	-	£	Excluded (BEIS, 2019)
Environmental Impact Assessment survey	$C_{EIA-Survey}$	8,938	£/MW	Dataset
Facilities audit and assessment	C_{Audit}	-	£	Included in C_{E-Plan}
Consultation	$C_{Consult}$	-	£	Included in C_{E-Plan}
Contractor and vendor fees	C_{fee}	-	£	Included in C_{E-Plan}
Insurance	C_{insure}	41,600	£/MW	Dataset
Contingency	$C_{Conting.}$	10-30% of Base Decom Cost	£	Estimated

*For renewable installations there is currently no charge in the UK. This may subject to change in the future.

The execution cost is modelled based on the types of vessels to be used to carry our preparation, removal and transportation activities. For the preparation

activities, the vessels used are usually OSVs, workboats or crew boats (Gjødvad and Ibsen, 2018). It is assumed that only one

Table B-2 Execution

Parameter	Symbol	Value	Units	Reference
Number of wind turbines	N_{WT}	100	-	Shafiee *et al.* (2016)
Size of the wind farm	A_{WF}	-	m^2 or km^2	-
Wind turbine weight	W_{WT}	552.5	tonnes	Dataset
Foundation weight	W_F	760	tonnes	Dataset
Array cable weight	$W_{cable-A}$	30.5	kg/m	Dataset
Met tower weight	W_{MT}	570	tonnes	Dataset
Number of lifts per turbine	$N_{lifts-WT}$	4	per vessel	Assumed
Number of lifts per offshore substation	$N_{lifts-OSS}$	1	per vessel	Assumed
Weight per lift	$W_{per\ lift}$	variable	tonnes	-
Cost of marine growth removal	$C_{removal-MG}$	Dependent on man hours	£	-
Array cable laying vessel rate	$r_{cable-A}$	-	km/day	-
Cost of fixtures per unit	$C_{fixt./unit}$	-	£/unit	-
Number of fixtures	$N_{fixt.}$	3	fixture/turbine	Assumption
Vessel capacity required	$V_{capacity}$	Variable based on vessel used	tons	-
Time for turbine and OSS preparation	t_{prep}	2-4	Days**	Assumption

Time for WT removal	$t_{L\&R-WT}$	449.75	Days	Shafiee *et al.* (2016)
Time for foundation removal	$t_{L\&R-found.}$	543.44	Days	Shafiee *et al.* (2016)
Time for power cable decommissioning	$t_{cable-decom}$	246.50	Days	Shafiee *et al.* (2016)
Time for miscellaneous removal (scour protection, concrete mattress)	$t_{L\&R-misc.}$	variable	Days	-
Time for met tower decommissioning	$t_{MT-decom}$	2.8	Days	Dataset
Time for offshore substation decommissioning	$t_{OSS-decom}$	2	Days	Assumption

** Times are estimated based on vessel days taken.

Table B-3 Logistics and Waste Management

Parameter	Symbol	Value	Units	Reference
Distance from port to landfill	D_{port}	50	km	Dataset
Number of trips to and from port	N_γ	variable	-	-
Duration of trips to and from port	t_γ	variable	days	-
Port rental cost per annum	$C_{port/annum}$	13,375,000	£/Year	Dataset
Water depth	WD	40	m	Shafiee *et al.* (2016)
Equipment cost per day (crane)	$C_{eqt/day}$	variable	£/day	Shafiee *et al.* (2016)

Offshore Personnel cost	$C_{K/day}$	300	£/day	Castro-Santos *et al.* (2018)
Onshore Personnel cost	$C_{K/day}$	150	£/day	Dataset
Number of Personnel	N_K	variable	men/activity	-
Barge rate	C_{barge}	1,035.75	£/day	Dataset
Tug rate	C_{tug}	5,918.60	£/day	Dataset
Heavy lift vessel (HLV) rate	C_{HLV}	288,900	£/day	Dataset
Jack up (JU)rate	C_{JU}	149,800	£/day	Dataset
Anchor handling tug vessel (AHTV)	C_{AHTV}	84,400	£/day	Dataset
Crane vessel rate	C_{crane}	138,000	£/day	Dataset
Array cable laying vessel rate	C_{ACLV}	85,600	£/day	Dataset
Offshore support vessel (OSV) rate	C_{OSV}	2,071.51	£/day	Assumption similar to crew boat
Self-propelled installation vessel (SPIV) rate	C_{SPIV}	187,350	£/day	Kaiser and Snyder (2012b)
Crew boat/Workboat rate	C_{WB}	2,071.51	£/day	Dataset
Accommodation	-	4,500	£/day	-
Crew boat rate	C_{CB}	2,071.51	£/day	Dataset
Number of vessels required	N_V	variable	-	-
Array cable removal vessel rate	$C_{A-removal}$	0.3	km/day	Dataset
Export cable removal vessel rate	$C_{E-removal}$	0.7	km/day	Dataset

Vessel Mob/Demob rate	$C_{mob/demob-V}$	138,000	£/day	Dataset
Heavy lift crane Mob/Demob rate	$C_{mob/demob-HLC}$	276,000	£/day	Dataset
Cost of navigation markings	$C_{Nav-mark}$	-	£	-
Unit waste processing cost	$C_{w-proc/unit}$	92.04	£/tonne	Dataset
Weight of materials (non-recyclable)	Wt_j	815.28	tonnes	Dataset
Weight of recyclable materials	W_j^R	543.52	tonnes	Dataset
Unit processing cost of wind turbine	$C_{proc.-WT}$	92.04	£/tonnes	Dataset
Unit processing cost of foundation	$C_{proc.-F}$	46.02	£/tonnes	Dataset
Unit processing cost of met tower	$C_{proc.-MT}$	46.02	£/tonnes	Dataset
Unit processing cost of array cable	$C_{proc.-AC}$	9,102	£/km	Dataset
Array cable length	L_{AC}	133.11	km	Dataset
Truck cost	$C_{truck/km}$	0.41	£/km	Dataset
Capacity of trucks	W_{truck}	24	tonnes	Dataset
Distance to processing centre	$D_{process.}$	50	Km	Dataset
Distance to landfill	$D_{landfill}$	50	km	Dataset
Landfill cost	$C_{landfil}$	19.77	£/tonnes	Dataset
Salvage value per unit weight of each material	$SV_{per\ unit\ wt.}$	205.40	£/tonnes	Dataset

Area for site clearance	A	70.14	Km^2	Dataset

Vessel costs are inclusive of fuel costs.

Time to complete each activity and the sequence is dependent on the removal concept selected in the decommissioning programme.

Table B-4 Post-decommissioning

Parameter	Symbol	Value	Units	Source
Seabed survey cost	C_{surv}	19,620	£/MW	Dataset
Site clearance radius	R	70.14	km^2	Dataset
Site clearance cost	C_{SC}	51,542.4	£/km^2	Dataset
Site monitoring	C_{Sm}	7,230	£/MW	Dataset
Site remediation	C_{rem}	7,230	£/MW	Dataset
Miscellaneous cost	C_{misc}	7,500	£	Assumed

Appendix C

Table-C-1 Prior probability input data (Ugurlu *et al.*, 2015; Babaleye *et al.*, 2018; Rahman *et al.*, 2020)

Nodes		Symbol	Probability
Navigation failure	Faulty procedure	E1	2.17×10^{-4}
	Violation of procedure	E2	4.88×10^{-5}
	Inefficient use of navigation equipment	E3	6.09×10^{-4}
	Poor route selection	E4	1.62×10^{-4}
Manoeuvring failure	Faulty manoeuvre master	E5	5.02×10^{-4}
	Error of watchkeeping officer	E6	2.34×10^{-4}

	Wrong tug manoeuvre	E7	6.71×10^{-5}
	Improper tugboat use	E8	2.09×10^{-5}
	Piloting failure	E9	2.23×10^{-5}
Detection failure	Fatigue	E10	2.07×10^{-4}
	Alcohol abuse	E11	6.7×10^{-5}
	Risk assessment error	E12	1.33×10^{-3}
	COLREG violation	E13	2.34×10^{-3}
	Ship information failure	E14	1.03×10^{-4}
	Lack of coordination	E15	2.17×10^{-4}
	Poor communication between vessels	E16	1.03×10^{-3}
Hook failure	Structural failure	E25	4.17×10^{-8}
	Rigging fault	E26	1.5×10^{-3}
	Decoupling prevention device failure	E27	2.0×10^{-6}
	Failure of manual control	E28	1.0×10^{-2}
Operational fault	Vibrational impact	E29	7.0×10^{-3}
	Improper hooking	E30	2.11×10^{-2}
	Inaccurate signal	E31	3.3×10^{-2}
	Obstructed vision	E32	3.1×10^{-3}
Stuck monopile	Improper cut	E17	1.2×10^{-3}
	Jammed cutter	E18	6.4×10^{-4}
	Drill cutting debris	E19	1.0×10^{-4}
	Incorrect cutting time	E20	2.0×10^{-3}

Loss of stability	Loss of structural/hull integrity	E21	1.33×10^{-4}
	Inaccurate payload estimation	E22	5.0×10^{-4}
	Excessive marine growth	E23	1.2×10^{-4}
	Flooding	E24	3.6×10^{-4}

Table C-2 Minimal cut set (MCS) for suspended/halted decommissioning operations (top event).

MCS	Probability	MCS	Probability
$E5$	5.02E-04	$E1.E2.E3$	6.4491E-12
$E6$	2.34E-04	$E2.E3.E4$	4.8145E-12
$E7$	6.71E-05	$E10.E13.E14$	4.9891E-11
$E8$	2.09E-05	$E10.E13.E15$	1.0511E-10
$E9$	2.23E-05	$E10.E13.16$	4.9891E-10
$E17$	1.20E-03	$E11.E13.E14$	1.6148E-11
$E18$	6.40E-04	$E11.E13.E15$	3.4021E-11
$E19$	1.00E-04	$E11.E13.E16$	1.6148E-10
$E20$	2.00E-03	$E12.E13.E14$	3.2056E-10
$E29$	7.00E-03	$E12.E13.E15$	6.7535E-10
$E30$	2.11E-02	$E12.E13.E16$	3.2056E-09
$E31$	3.30E-02	$E21.E22.E24$	2.394E-11
$E32$	3.10E-03	$E21.E23.E24$	5.7456E-12
		$E25.E27.E28$	8.34E-16
		$E26.E27.E28$	3E-11

Figure C-1 Risk Matrix with multiple consequence classes (BSI, 2002; 2019)

Severity Ranking	Consequence (C)				Probability (P)				
	Personnel	Assets	Economic	Environmental	1 Unlikely	2 Low Probability	3 Possible	4 Probable	5 Likely
0	Zero injury	Zero damage	Zero cost	Zero effect					
Low (1)	Single injury requiring first aid	Minor damage to one asset	Minimum financial los/premium/interest (£)	Minor spill within a small radius					
Medium (2)	Multiple injuries requiring first aid	Minor damage to multiple assets	Low financial loss/premium/interest (£) + cost from schedule delay	Minor spill within a wide radius					
High (3)	Single injury requiring medical attention	Local damage to one asset	Moderate financial loss/premium/interest (£) + contingency cost + schedule delay cost	Large/concentrated spill within a wide radius with minor effect					
Major (4)	Multiple injury requiring medical attention	Major damage to multiple assets	High financial loss/premium/interest (£)	Major effect					
Catastrophic (5)	Fatality	Extensive damage/loss of asset	Maximum financial loss (£)	Massive effect					

The asset consequence depends on whether the removed modules are intended for disposal or reuse. It is assumed that there is good visibility during all decommissioning operations.

Table C-3 Risk matrix for intermediate events (collision, vessel damage and crane failure)

Intermediate event	Frequency rank	Consequence safety/hazard promoting factors	Consequence rank				Risk index			
			P	A	E	EN	P	A	E	EN
Collision/contact	3	Hull damage	0	1	2	0	-	3	6	-
		Loss of stability	2	1	2	0	6	3	6	-
		Detached/dropped load	1	4	3	3	3	12	9	9
		Man overboard	4	0	4	0	12	-	12	-
		On collision course with another vessel	0	5	5	0	-	15	15	-

Vessel damage	3	Water ingress	0	2	3	0	-	6	9	-
		Flooding	0	3	3	0	-	9	9	-
		Loss of stability	2	1	2	0	6	3	6	-
		Detached/dropped load	0	2	3	3	-	6	9	9
		Sink/capsize	4	5	5	3	12	15	15	9
Crane failure	4	Loss of crane/load integrity	0	3	2	0	-	12	8	-
		Swinging/dropped load	0	4	3	2	-	16	12	8
		Within dangerous zone	4	4	0	0	16	16	-	-
		Loss of crane strength	4	3	4	0	16	12	16	-
		Ineffective remedial/corrective action	3	5	5	0	12	20	20	-

P - Personnel consequence

A - Asset consequence

E - Economic consequence

EN - Environmental consequence[1]

[1] Personnel consequence, P, refers to the crew health- related impacts such as injuries requiring first aid, medical attention or fatalities. Asset consequence, A, refers to damages to the lifting vessel and the WT if retrieved parts are intended for reuse. Economic consequence, E, refers to financial losses. Environmental consequence, EN, relate to environmental damages caused by incidents like spills, unrecovered dropped objects, etc.

Appendix D

Table D-1 Prior probability input data (Ugurlu *et al.*, 2015; Babaleye *et al.*, 2018; Rahman *et al.*, 2020)

Nodes		Symbol	Probability
Navigation failure	Faulty procedure	E1	2.17×10^{-4}
	Violation of procedure	E2	4.88×10^{-5}
	Inefficient use of navigation equipment	E3	6.09×10^{-4}
	Poor route selection	E4	1.62×10^{-4}
Manoeuvring failure	Faulty manoeuvre master	E5	5.02×10^{-4}
	Error of watchkeeping officer	E6	2.34×10^{-4}
	Wrong tug manoeuvre	E7	6.71×10^{-5}
	Improper tugboat use	E8	2.09×10^{-5}
	Piloting failure	E9	2.23×10^{-5}
Detection failure	Fatigue	E10	2.07×10^{-4}
	Alcohol abuse	E11	6.7×10^{-5}
	Risk assessment error	E12	1.33×10^{-3}
	COLREG violation	E13	2.34×10^{-3}
	Ship information failure	E14	1.03×10^{-4}
	Lack of coordination	E15	2.17×10^{-4}
	Poor communication between vessels	E16	1.03×10^{-3}
Hook failure	Structural failure	E25	4.17×10^{-8}
	Rigging fault	E26	1.5×10^{-3}

	Decoupling prevention device failure	E27	2.0×10^{-6}
	Failure of manual control	E28	1.0×10^{-2}
Operational fault	Vibrational impact	E29	7.0×10^{-3}
	Improper hooking	E30	2.11×10^{-2}
	Inaccurate signal	E31	3.3×10^{-2}
	Obstructed vision	E32	3.1×10^{-3}
Stuck monopile	Improper cut	E17	1.2×10^{-3}
	Jammed cutter	E18	6.4×10^{-4}
	Drill cutting debris	E19	1.0×10^{-4}
	Incorrect cutting time	E20	2.0×10^{-3}
Loss of stability	Loss of structural/hull integrity	E21	1.33×10^{-4}
	Inaccurate payload estimation	E22	5.0×10^{-4}
	Excessive marine growth	E23	1.2×10^{-4}
	Flooding	E24	3.6×10^{-4}

Figure D-1 Bayesian network of collision event

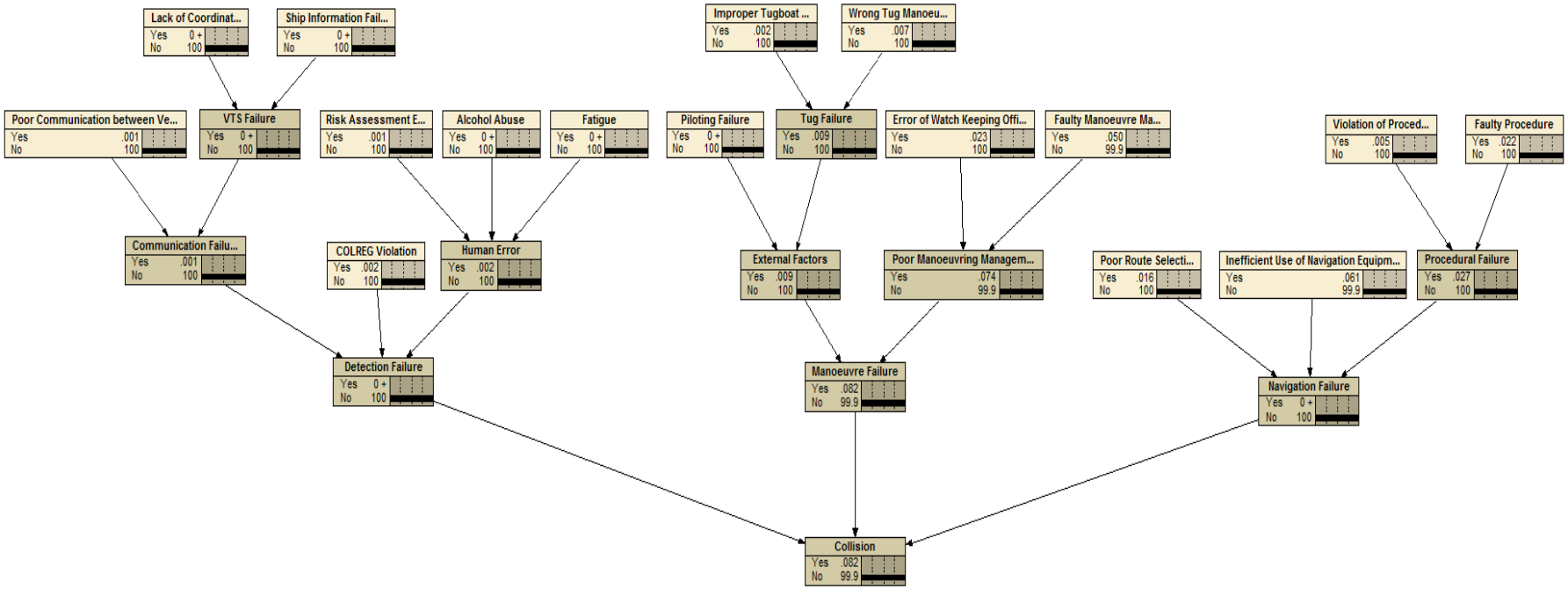


Figure D-2 Bayesian network of Crane failure

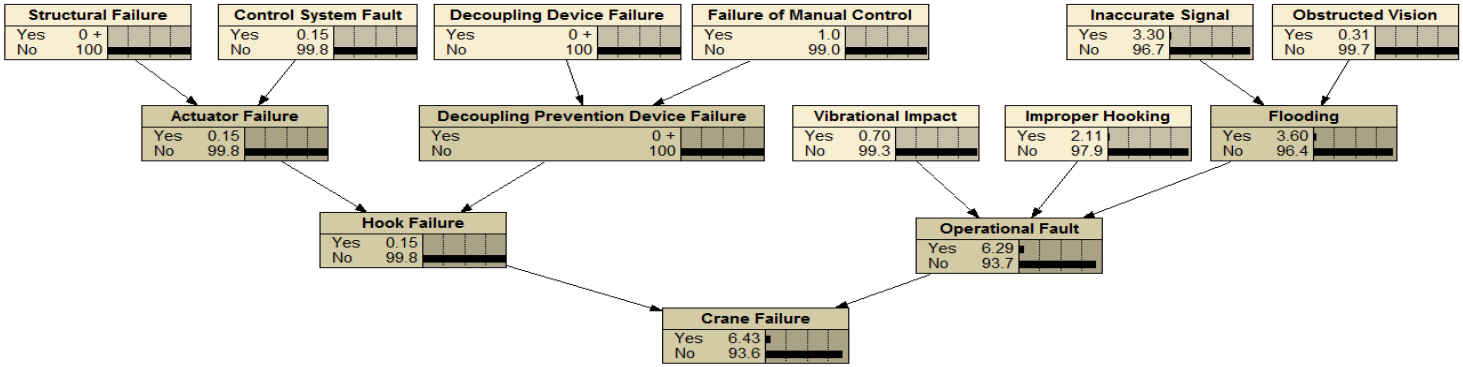


Table D-2 Update prior probability and posterior probability

	Update Input Probabilities (G+ Global Offshore Wind Health and Safety Organisation, 2020)			
Year	**2015**	**2016**	**2018**	**2019**
Tug Failure	0	0	0	0.0602
Navigation failure	0.75	0.1111	0.4	0.355
Human error	0.25	0.4444	0.2	0.3871
Posterior Probability (TE)	0.767	0.175	0.448	0.436

Figure D-3 Influence diagram for crane failure intervention

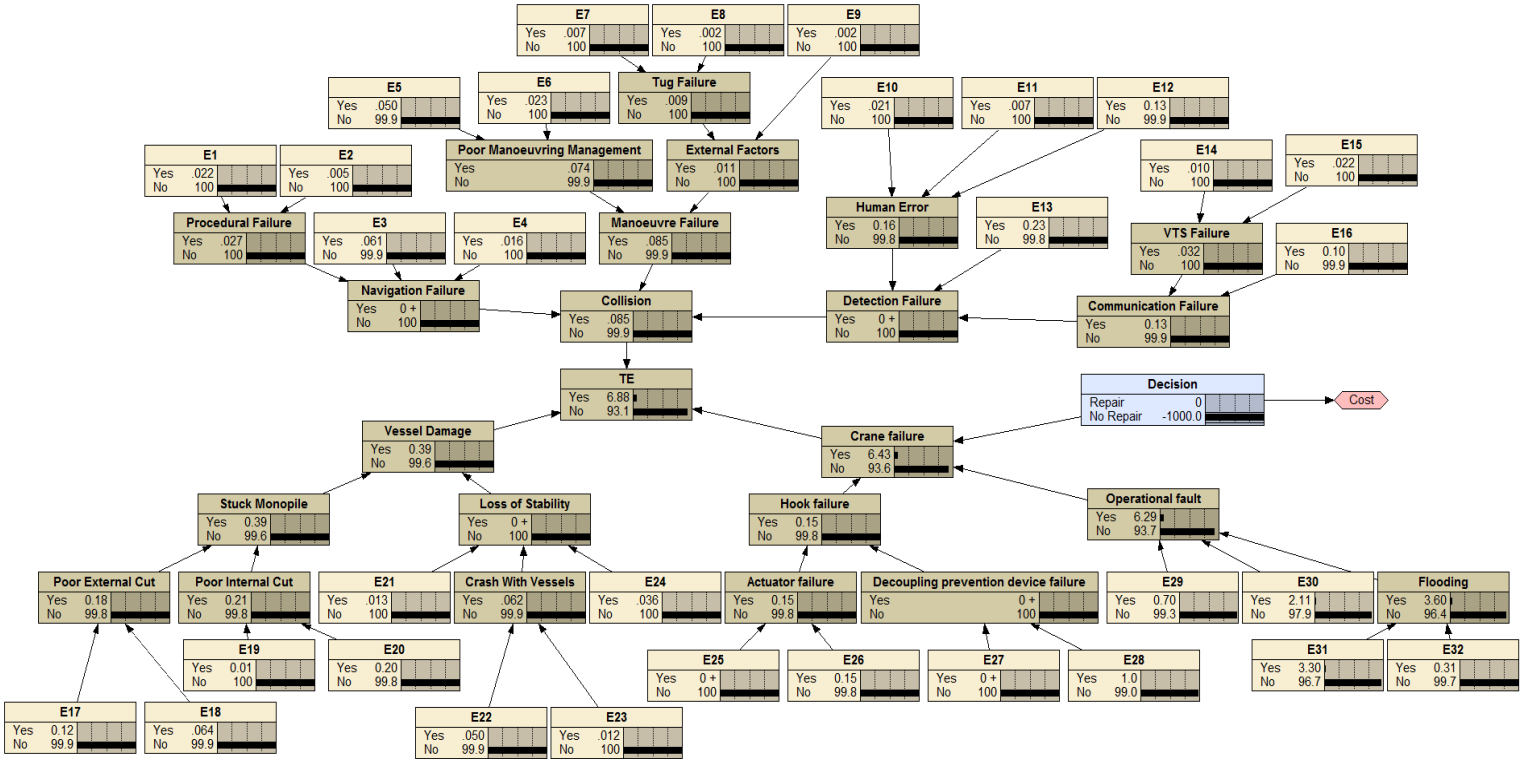


Figure D-4 Human error-related variables eliminated

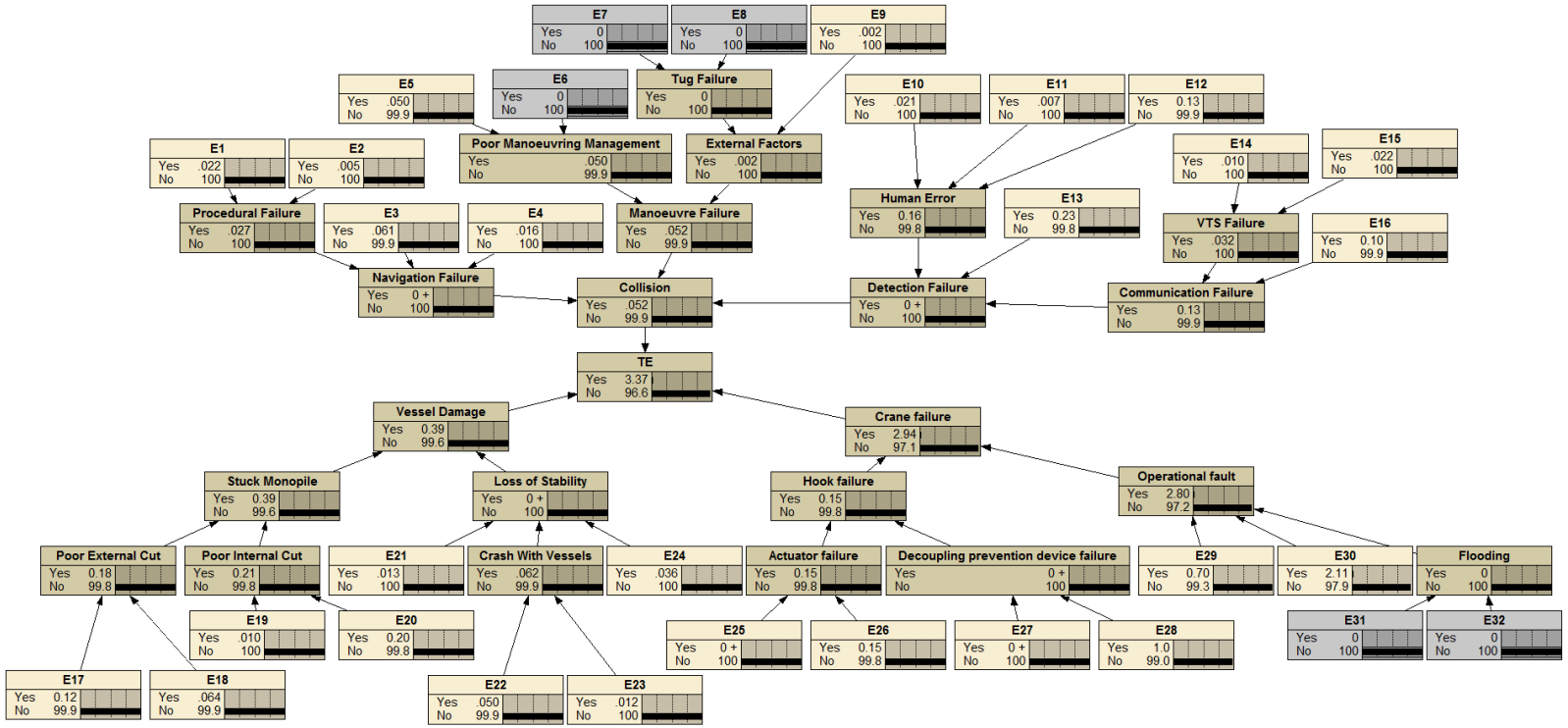


Figure D-5 Procedural-related faults eliminated

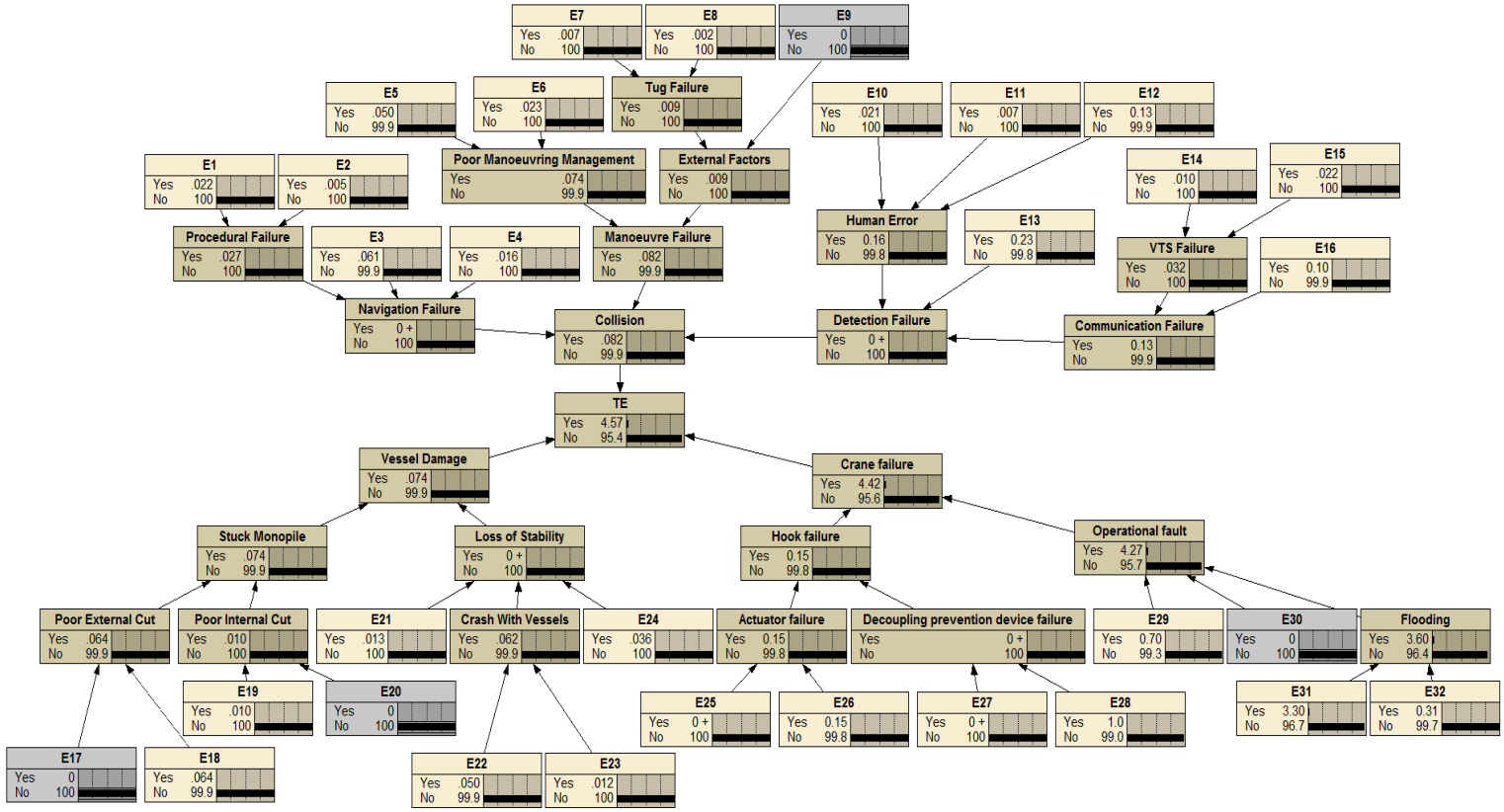


Figure D-6 Update with 2016 data (G+ Global Offshore Wind Health and Safety Organisation, 2020)

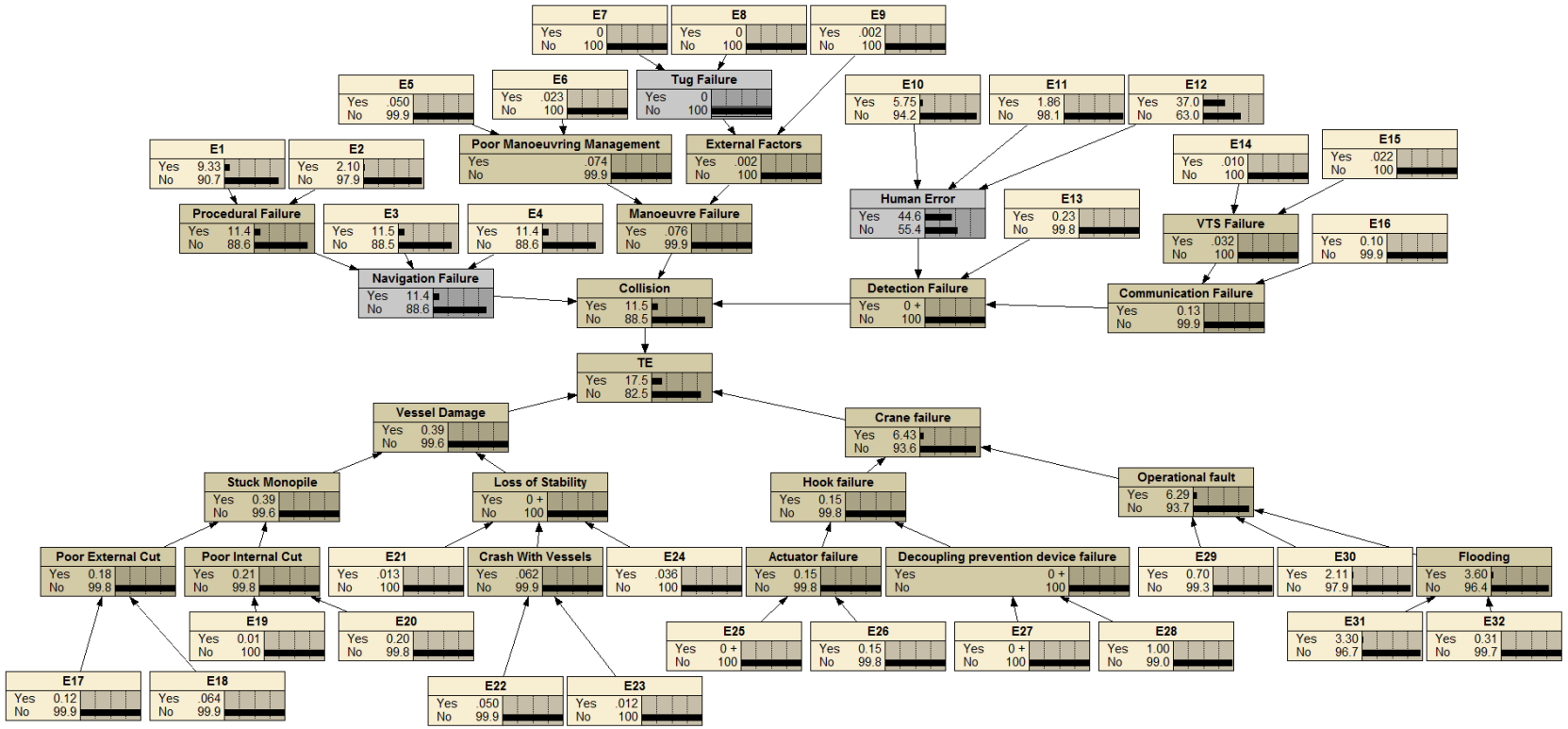


Figure D-7 Update with 2018 data (G+ Global Offshore Wind Health and Safety Organisation, 2020)

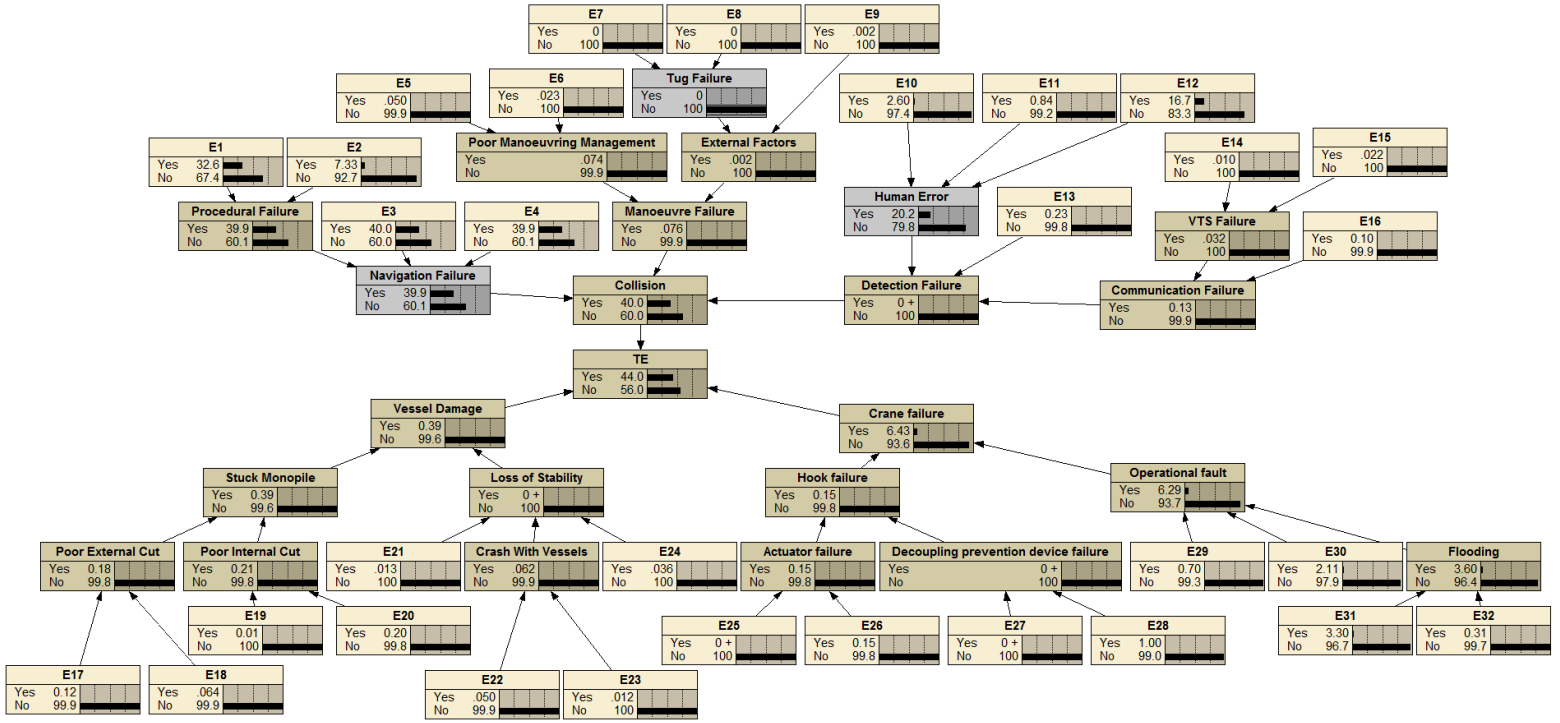


Figure D-8 Update with 2019 data (G+ Global Offshore Wind Health and Safety Organisation, 2020)

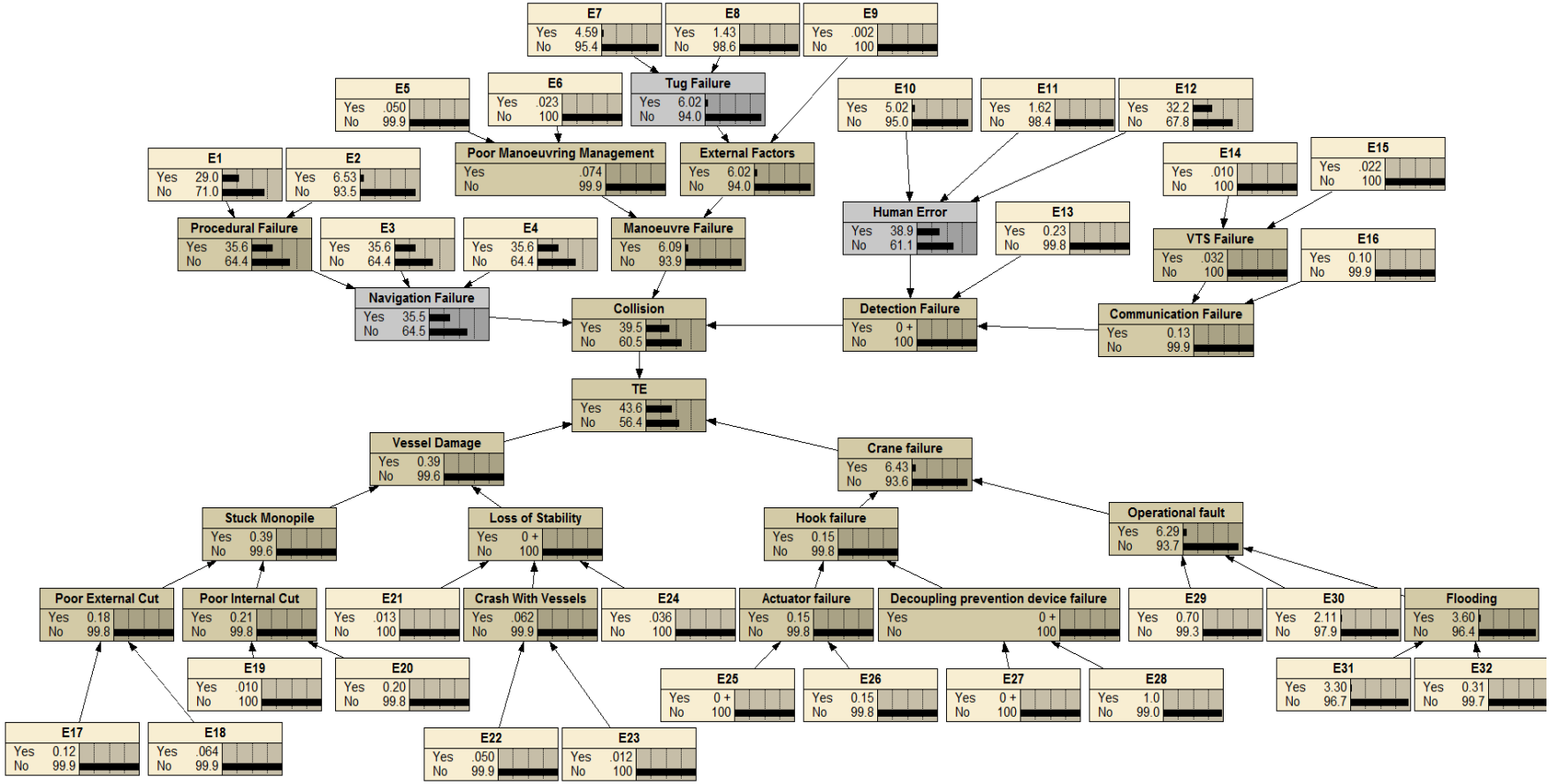


Figure D-9 Influence diagram for collision intervention

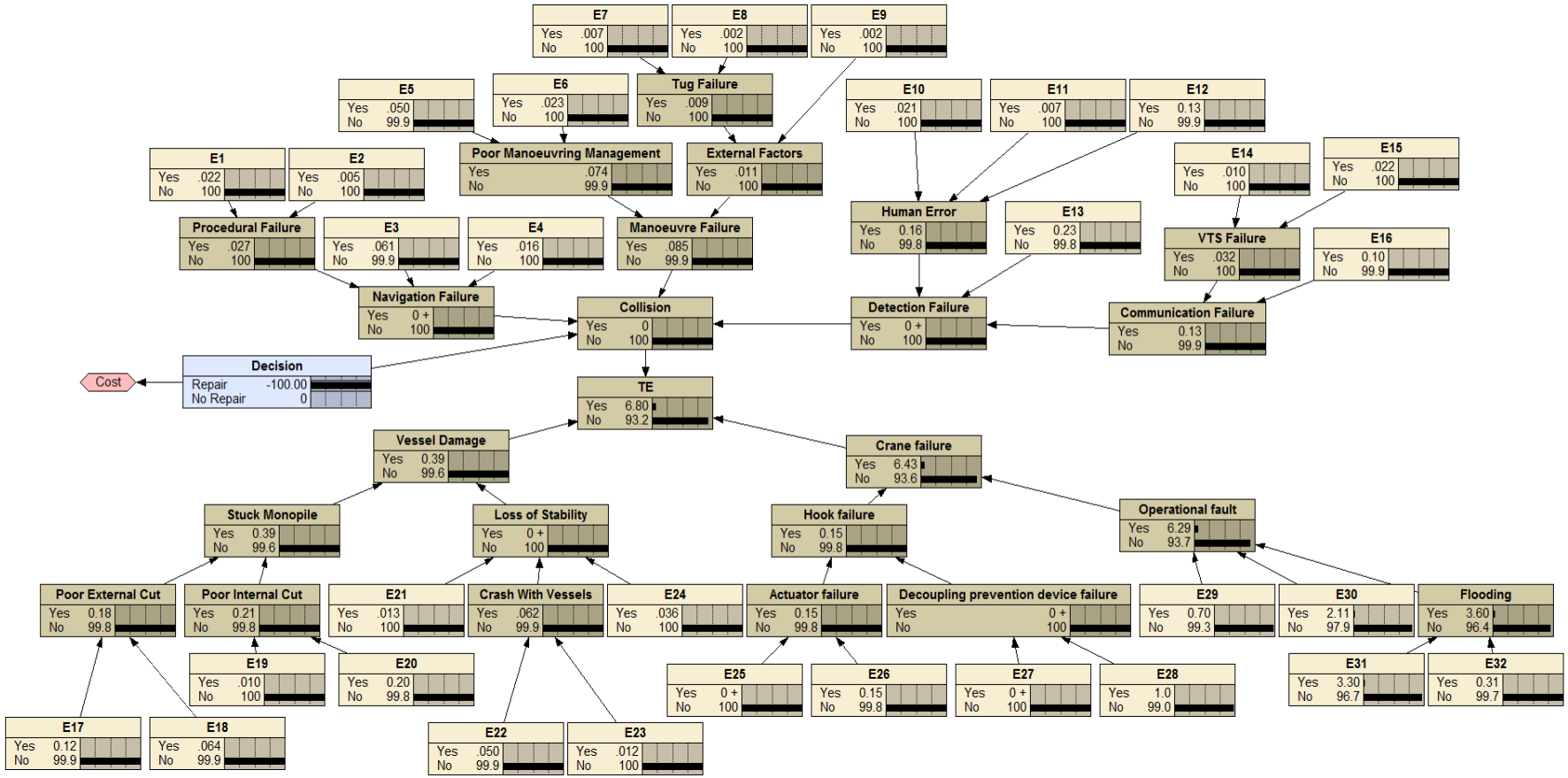
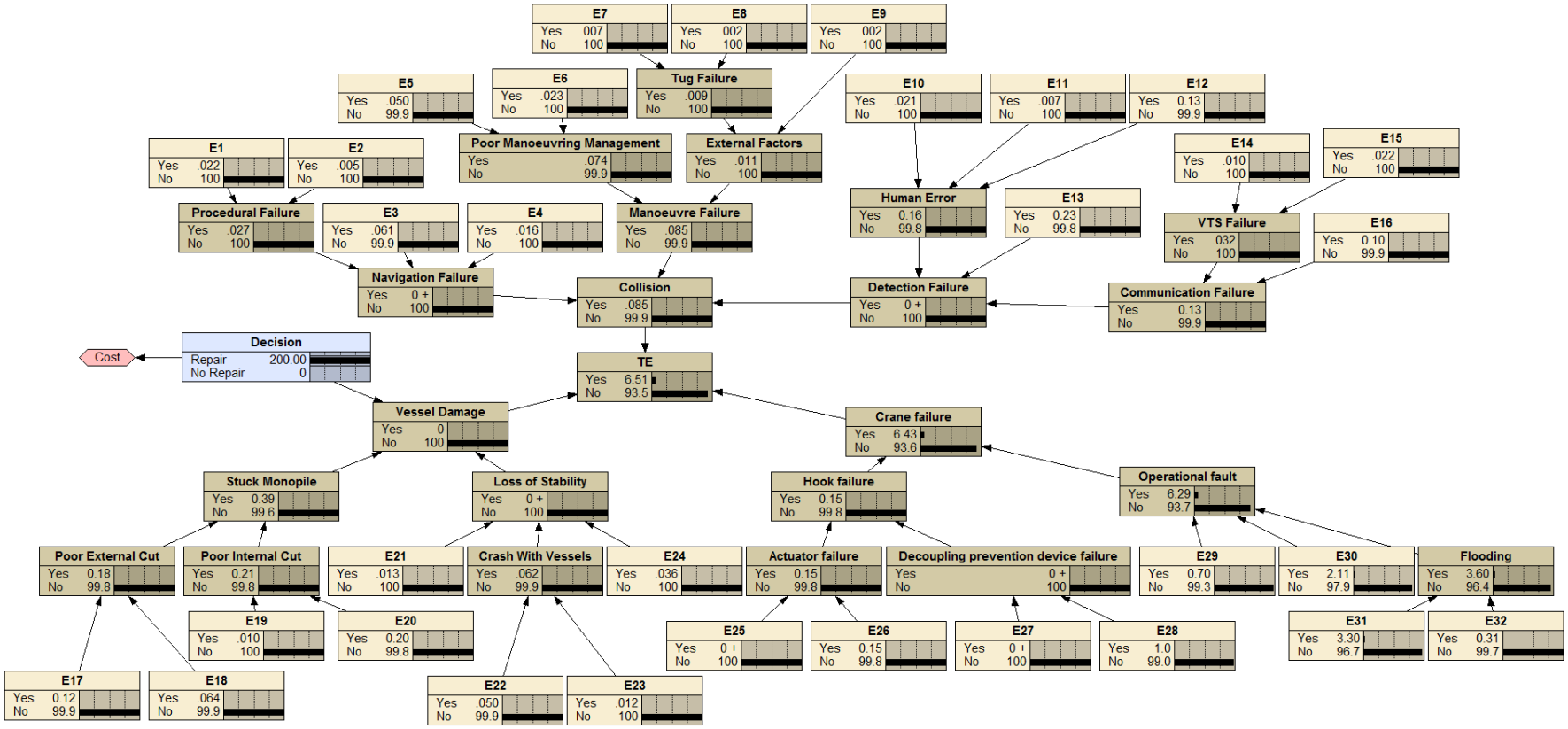


Figure D-10 Influence diagram for vessel damage intervention



Appendix E

Research Questionnaire: Identification of decommissioning risks in the offshore industry

Informed consent form

Title of the survey:	Identification of decommissioning risks in the offshore wind industry
Name of the researcher:	Tosin Adedipe
Researcher's contact details:	*tosin.adedipe@cranfield.ac.uk*
Supervisors' contact details:	*p.r.hart@cranfield.ac.uk* *m.shafiee@kent.ac.uk*
Participant number:	
Date:	23/03/2020

The following information is provided to inform you about the research project and your participation in it. Please read this form carefully and feel free to ask any questions you may have about this study and the information given below. You will be given a copy of this consent form.

Purpose of the study:
Offshore wind decommissioning has, in recent years, started to gain traction due to the ageing life of offshore wind assets. Thus, this research survey will be used to collect data to get a picture of the current risk profile of key marine activities in offshore wind decommissioning. In order to improve the safety of offshore decommissioning activities and reduce the economic risks associated, this study uses different techniques to perform risk identification, assessment and analysis.

The information you provide in this survey will help us perform a risk assessment based on the data we process. We appreciate the time and attention you give in filling in this questionnaire and acknowledge your contribution. The data collected is anonymized and will be stored in a protected data storage. In order for the data collected to be duly processed, the end date for responding to this survey is **30/08/2020**.

Part 1: consent to participate and ability to withdraw.

1. I confirm that I have been informed about this survey and I agree to take part.

2. I understand that all personal information I provide will be treated with confidence and my name will not be used in any report, publication or presentation.
3. In responding to this survey, I have been provided with a participant number. The researcher(s) will record data against my participant number instead of recording my name. The file linking my name to my participant number will be accessible only to the main researchers and will be securely destroyed after **30/08/2021**.
4. I understand that I can withdraw from this project at any stage by informing a member of the research team, for whom contact details have been provided. I also understand that I can withdraw my data for a period of up to **two years from today**, as after this time it will not be possible to identify my individual data from the aggregated results as explained in point 3.

Part 2: confirm the security of data storage.

I understand that the data I provide will be used by Cranfield University for the purpose of research. The data will be stored on the University's network that can only be accessed by authorised users, in line with UK Data Protection Act 2018. ☐

Part 3: datasets to be created and what will happen to each.

1. Survey responses will be recorded and securely stored on the Cranfield University network as a document. These documents will be securely deleted as soon as they are no longer required.
2. Survey responses are anonymised at collection. These responses may be published in full, in support of findings (e.g., in journal articles, conference papers). I understand that my response will be anonymised, and findings published.
3. Analytical software will be used to aggregate the results of the research. I understand that the aggregated data will be published in support of the research findings ☐

Yes, I confirm that I have read and understand the information provided and give my consent to taking part in this research. ☐

No, I do not give my consent to taking part in this research ☐

Purpose of the Study:

Offshore wind decommissioning has, in recent years, started to gain traction due to the ageing life of offshore wind assets. Thus, this research survey will be used to collect data to get a picture of the current risk profile of key marine activities in offshore wind decommissioning. In order to improve the safety of offshore decommissioning activities and reduce the economic risks associated, this study uses different techniques to perform risk identification, assessment and analysis.

The information you provide in this survey will help us perform risk assessment based on the data we process. We appreciate the time and attention you give in filling in this questionnaire and acknowledge your contribution. The data collected is anonymized and will be stored in a protected data storage. In order for the data collected to be duly processed, the end date for responding to this survey is **30/06/2020**.

The following questions help us to have a better idea of the demographics of our respondents. They ask about the industry, sector and role you work in. If you have overlapping roles, please select all that apply.

1. Please indicate the sector of industry you work in (Select all that apply)
   - ○ Original equipment manufacturer (OEM)
   - ○ Wind farm operator
   - ○ Independent service provider (ISP)
   - ○ Regulatory body
   - ○ Other (please specify)

     _____
   - ○ Not applicable

2. What role within the offshore wind industry do you work in? (Select all that apply)?
   - ○ Wind turbine production and manufacturing
   - ○ Project planning and development
   - ○ Financing and insurance
   - ○ Construction/decommissioning
   - ○ Testing and certification
   - ○ Asset Management
   - ○ Operation and maintenance (O&M)
   - ○ Logistics and transportation
   - ○ Waste management
   - ○ Regulatory
   - ○ Research
   - ○ Other (please specify)

     _____
   - ○ Not applicable N/A

3. Have you been involved in decommissioning activities in the past?
   - ○ Yes
   - ○ No

The next few questions are based on Hazard identification (HAZID). The scales are used in the order below.

Very Low	Low	Moderate	High	Very High
1	2	3	4	5

4. On a scale of 1 to 5, by how much will the following incidents/hazards **influence** your organisation's choice to **suspend/halt decommissioning activities**?

○ Project cost overrun	1	2	3	4	5
○ Safety of personnel	1	2	3	4	5
○ Extended project schedule	1	2	3	4	5
○ Fatality	1	2	3	4	5
○ Personnel injury requiring first aid/emergency	1	2	3	4	5
○ Damage to nearby assets	1	2	3	4	5
○ Insufficient research in decommissioning technology or methods	1	2	3	4	5
○ Environmental hazards	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

5. Before and during lifting and removal operations, which of the following risk assessment techniques are actively referred to?
   - ○ HAZID
   - ○ FMEA/FMECA
   - ○ FTA
   - ○ Other (please specify)
   - ○ N/A

6. There are different types of lifting configurations used during installation and decommissioning. Please rank the lifting configurations in terms of resource intensity (man-hours and equipment) and cost (£).

 Two-section tower	
 Single-piece tower	
 Bunny-ear configuration	
 Full-rotor lift	
 Full lift	

7. In order of importance, please drag and drop the following components in terms of resource intensity (man-hours and equipment) and ***cost (£) during lifting and removal*** activities in offshore wind farm decommissioning?

High resource intensity and cost
Moderate resource intensity and cost
Low resource intensity and cost

- ○ Blades
- ○ Hubs
- ○ Tower
- ○ Nacelle
- ○ Cables
- ○ Foundation
- ○ Masts
- ○ Offshore substation (OSS)

8. On a scale of 1 to 5, to what extent are the following **barriers to decommissioning safety**?

○ Costly adoption of new safety technology

1 2 3 4 5

○ Insufficient research in decommissioning technology or methods

1 2 3 4 5

○ Insufficient information about potential hazards

1 2 3 4 5

○ Lack of experience in offshore wind decommissioning

1 2 3 4 5

○ Competent contractors

○ Technology readiness level (TRL) of new safety devices

1 2 3 4 5

- Regulatory inhibitions in approving safety devices or technologies
  1 2 3 4 5
- Regulations and guidelines not robust enough for offshore wind decommissioning activities 1 2 3 4 5
- Return on investment is low (poor component recycling income)
  1 2 3 4 5
- Logistics constraints (vessels and number of crew members on a project per time) 1 2 3 4 5

9. In relation to offshore wind decommissioning activity improvements, what aspects do you think should be prioritized, on a scale of 1 to 5 (1 being the least important, 5 being the most important)?

- Safety 1 2 3 4 5
- Logistics/vessel technology development 1 2 3 4 5
- Tool/technique development 1 2 3 4 5
- Process automation 1 2 3 4 5
- Improved safety regulations 1 2 3 4 5

10. On a scale of 1 to 5, what is the likelihood that each one of the following contribute to hazards during decommissioning activities?
- Human factors 1 2 3 4 5
- Mechanical/electrical factors 1 2 3 4 5
- Environmental factors 1 2 3 4 5
- Regulatory factors 1 2 3 4 5

11. How likely will the following potential human factors contribute to a hazardous event/incident, on a scale of 1 to 5? (1 being the least likely, 5 being most likely).
- Poor communication 1 2 3 4 5
- Operator carelessness 1 2 3 4 5
- Personnel tiredness 1 2 3 4 5
- Limited personnel competence/training 1 2 3 4 5
- Inadequate equipment inspection 1 2 3 4 5
- Poor work supervision 1 2 3 4 5
- Obstruction 1 2 3 4 5
- Other (please specify) 1 2 3 4 5

12. On a scale of 1 to 5, how would you rate the risk profile of the following during offshore wind decommissioning operations based on your knowledge/experience?

○ Lifting and removal operations	1	2	3	4	5
○ Facility preparation for removal	1	2	3	4	5
○ Cutting	1	2	3	4	5
○ Logistics and transportation	1	2	3	4	5
○ Site surveys/clearance	1	2	3	4	5
○ Waste management	1	2	3	4	5
○ Post-decommissioning	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

The next questions relate to lifting and removal operations only.

13. Within lifting and removal operations, please rank the safety threats based on your understanding of their importance in decommissioning programme success, by dragging and rearranging each incident/hazard relative to the others.

- ○ Collision
- ○ Vessel damage/drift
- ○ Ballast system failure
- ○ Crane failure
- ○ Hoist failure
- ○ Fire/explosion
- ○ Other (please specify)

In the following sections, an occurrence matrix will be used to rank different events based on their likelihood of occurrence.

Rank	Likelihood of occurrence	Possible incident/failure rates
5	Very high	1 in 2 – 1 in 3
4	High	1 in 8 – 1 in 20
3	Moderate	1 in 80 – 1 in 400
2	Low	1 in 2000 – 1 in 15,000
1	Very low	1 in 150,000 – 1 in 1,500,000

14. Based on your knowledge and/or experience, how likely do you expect the following major incidents/hazards to occur in offshore operations, on a scale of 1 to 5 (1 being extremely unlikely, 5 extremely likely)?

○ Collision	1	2	3	4	5
○ Vessel damage/drift	1	2	3	4	5
○ Ballast system failure/jack up leg failure	1	2	3	4	5
○ Crane failure	1	2	3	4	5
○ Hoist failure	1	2	3	4	5
○ Fire/explosion	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

Based on Q10, the following questions Q15 - Q21, are investigated further.

15. Considering the potential equipment faults/incidents that can lead to a collision, please rank the incidents in order of likelihood of occurrence.

○ Vessel loss of station-keeping	1	2	3	4	5
○ Malfunctioning of dynamic positioning system	1	2	3	4	5
○ Obstruction	1	2	3	4	5
○ Poorly secured cargo	1	2	3	4	5
○ Loss of secondary positioning system	1	2	3	4	5
○ Lifting point failure	1	2	3	4	5
○ Hook stabilization tool failure	1	2	3	4	5
○ Others (please specify)	1	2	3	4	5

16. Considering the potential equipment faults/incidents that can lead to vessel damage/drift, please rank the incidents in order of likelihood of occurrence.

○ Stuck monopile	1	2	3	4	5
○ Miscalculation of Centre of gravity (CoG) of removed component (e.g., tower)	1	2	3	4	5
○ Loss of stability	1	2	3	4	5
○ Crane overload	1	2	3	4	5
○ Loss of structural integrity of removal equipment	1	2	3	4	5
○ Inaccurate payload weight estimation	1	2	3	4	5
○ Excessive marine growth	1	2	3	4	5
○ Broken mooring lines	1	2	3	4	5
○ Faulty dynamic positioning system and secondary positioning system	1	2	3	4	5
○ Others (please specify)	1	2	3	4	5

17. Considering the potential incidents that can cause ballast system/jack up leg failure, rank the incidents in order of likelihood of occurrence (please select all that apply and include any incident that is not listed).

○ Centre pump failure	1	2	3	4	5
○ Ballast valve failure	1	2	3	4	5
○ Electrical fault	1	2	3	4	5
○ Mechanical fault	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

18. Considering the potential incidents that can cause crane failure, rank the incidents in order of likelihood of occurrence (please select all that apply and include any incident that is not listed).

○ Lifting failure	1	2	3	4	5
○ Rotary equipment failure	1	2	3	4	5
○ Hover failure	1	2	3	4	5
○ Boom/jib failure	1	2	3	4	5
○ Hoisting failure	1	2	3	4	5
○ Electronic component failure	1	2	3	4	5
○ Safety system failure	1	2	3	4	5
○ Crane control system failure	1	2	3	4	5
○ Loss of stability causing counterweight fall	1	2	3	4	5
○ Swing table failure	1	2	3	4	5
○ Wire sling failure	1	2	3	4	5
○ Collapse caused by extension	1	2	3	4	5
○ Toppling	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

19. Considering the potential incidents that can cause hoist failure, rank the incidents in order of likelihood of occurrence (please select all that apply and include any incident that is not listed).

○ Poor maintenance/inspection	1	2	3	4	5
○ Wear	1	2	3	4	5
○ Human error	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

20. Considering the possible incidents that can cause fire/explosion, rank the incidents in order of likelihood of occurrence

○ Ignition source close to operation area	1	2	3	4	5
○ Poor vessel housekeeping	1	2	3	4	5
○ Hot work on deck	1	2	3	4	5
○ Fuel tank or hose leak on vessel	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5

21. a. Are there any other critical incidents/hazards not listed that should be considered during offshore decommissioning operations? (Leave blank if not applicable)

b. For one of the listed incidents/hazards, what would you consider the likelihood of occurrence of the critical hazard/incident mentioned in Q17a to be? Please specify the hazard below

Likelihood of occurrence of	1	2	3	4	5

Rank	Magnitude of consequence
5	Very high
4	High
3	Moderate
2	Low
1	Very low

22. What do you consider the magnitude of the consequence of collision to be, based on the indices below?

Personnel Safety	1	2	3	4	5
Environmental Impact	1	2	3	4	5
Asset Integrity	1	2	3	4	5
Operational safety	1	2	3	4	5

23. What do you consider the magnitude of the consequence of vessel damage/drift to be, based on the indices below?

Personnel Safety	1	2	3	4	5
Environmental Impact	1	2	3	4	5
Asset Integrity	1	2	3	4	5
Operational safety	1	2	3	4	5

24. What do you consider the magnitude of the consequence of ballast system failure to be, based on the indices below?

Personnel Safety	1	2	3	4	5
Environmental Impact	1	2	3	4	5
Asset Integrity	1	2	3	4	5
Operational safety	1	2	3	4	5

25. What do you consider the magnitude of the consequence of crane/hoist failure on the following?

Personnel Safety	1	2	3	4	5
Environmental Impact	1	2	3	4	5
Asset Integrity	1	2	3	4	5
Operational safety	1	2	3	4	5

26. What do you consider the magnitude of the consequence of fire/explosion to be, based on the indices below?

Personnel Safety	1	2	3	4	5
Environmental Impact	1	2	3	4	5
Asset Integrity	1	2	3	4	5
Operational safety	1	2	3	4	5

If Q21a and Q21b was unanswered, Q27 will be skipped.

27. Based on the additional hazard/incident you mentioned in Q21a, what do you consider the magnitude of consequence of the event to be, based on the indices below?

Personnel Safety	1	2	3	4	5
Environmental Impact	1	2	3	4	5
Asset Integrity	1	2	3	4	5
Operational safety	1	2	3	4	5

28. Please distribute the contribution of the following removed components with respect to Effort (man-hours, h or equipment days, d) in percentage (%).

Blade removal	___%
Hub and Nacelle removal	___%
Tower removal	___%
Foundation removal	___%

Cable removal	___%
Mast removal	___%
Offshore substation removal	___%

29. Please distribute the contribution of the following removed components with respect to Cost (£) in percentage (%).

Blade removal	___%
Hub and Nacelle removal	___%
Tower and transition piece removal	___%
Foundation removal	___%
Cable removal	___%
Mast removal	___%
Offshore substation removal	___%

30. In terms of reducing/preventing operational/human error, rank the following recommendations in terms of potential impact.

○ Improvement in lifting work plan design and approach	1	2	3	4	5
○ Supervisory training	1	2	3	4	5
○ Improved training for personnel	1	2	3	4	5
○ Use of simulations for training	1	2	3	4	5
○ Disclosure of potential risks associated with decommissioning operations	1	2	3	4	5
○ Improvement of safety regulations	1	2	3	4	5
○ Improvement of equipment and vessel maintenance	1	2	3	4	5
○ Installation of cameras at critical operational angles	1	2	3	4	5
○ Weight of removed component must be accurately checked against maximum crane lifting capacity	1	2	3	4	5
○ More Intelligent tools used (e.g. robotics)	1	2	3	4	5
○ Other (please specify)	1	2	3	4	5