Offshore Transmission Systems Planning Under Severe Uncertainty

BAINS, HENNA

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Henna Bains

Supervised By:

Dr. Behzad Kazemtabrizi, Prof. Matthias C. M. Troffaes & Dr. Ander Madariaga

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Department of Engineering

University of Durham

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Abstract

The offshore wind industry will make investment decisions regarding the electrical transmission infrastructure required to connect offshore wind farms to the onshore grid. Unfortunately, many policy, planning and operational decisions will be made under severe uncertainty due to limited data, knowledge, and expertise. There is insufficient information due to the assets' short operational history, data is usually project-specific, and future projects include advancing technologies. In particular, these uncertainties make it challenging to assign probability distributions to inputs required to assess an offshore transmission system economically. Therefore, methods based on classical probability theory may not be justified under severe uncertainty. Nevertheless, solutions must be found to handle severe uncertainty when planning future projects.

The work of this thesis designs (by setting up the methodology), tests (through applications) and validates (by comparing to conventional methods) new offshore transmission planning techniques. The main original research contributions are the development of an economic model to support offshore transmission planning, and the application of advanced statistical techniques to handle severe uncertainty in long-term decision making. This thesis presents three in-depth practical applications.

Advanced statistical methods, such as imprecise probability, are used to handle uncertainty in the input parameters. We demonstrate how to implement the techniques, as well as find and overcome challenges that may arise when applying these techniques to practical problems. Additionally, we show the benefits of these methods and, in particular, the ability to handle severe uncertainty in the input parameters more robustly than conventional methods.

Overall, the original contribution of this thesis demonstrates a framework for decision makers to handle severe uncertainty within the offshore transmission space and in the broader energy context. This enables decisions on key offshore transmission assets to take into account severe uncertainties. Ultimately, this research supports the integration of renewable technologies in a cost-effective way.

Declaration

This thesis is based on the research carried out by Henna Bains, under the supervision of Behzad Kazemtabrizi, Matthias Troffaes and Ander Madariaga at the Department of Engineering, Durham University in collaboration with the Department of Mathematical Sciences, Durham University and the Offshore Renewable Energy (ORE) Catapult. No part of this thesis has been submitted elsewhere for any other degree or qualification. The content of this thesis is all my own work unless referenced to the contrary in the text. The work of Chapter 4 closely follows [1] and the work of Chapter 6 closely follows [2]. The work of Chapter 6 was also presented as an abstract and poster at the 11^{th} international symposium on imprecise probabilities ISIPTA'19 in Ghent, Belgium.

Dedicated to my parents

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Contents

Publications

Journal Article

1. **Bains, H.**, Madariaga, A., Troffaes, M. C. M. & Kazemtabrizi, B. (2020). An Economic Model for Offshore Transmission Asset Planning Under Severe Uncertainty. Renewable Energy 160: 1174-1184.

Conference Papers

1. **Bains, H.**, Madariaga, A., Kazemtabrizi, B. & Troffaes, M. C. M. (2019), The Impact of Offshore Transmission Regulatory Regimes on Technology Choices, CIGRE Symposium. Aalborg.

2. Troffaes, M. C. M., Krak, T. & **Bains, H.** (2019), Two-State Imprecise Markov Chains for Statistical Modelling of Two-State Non-Markovian Processes, in De Bock, J., de Campos, C. P., de Cooman, G., Quaeghebeur, E. & Wheeler, G. eds, Proceedings of Machine Learning Research 103: ISIPTA'19. Ghent, PMLR, 394-403.

Abbreviations

ARMA auto-regressive moving average

CAPEX capital expenditure

ENTSO-E European Network of Transmission System Operators for Electricity

FMEA failure mode effect analysis

FTV final transfer value

GIS gas insulated switchgear

HVAC high voltage alternating current

HVDC high voltage direct current

IRR internal rate of return

LCoE levelised cost of energy

MERRA Modern-Era Retrospective analysis for Research and Applications

MOG modular offshore grid

MTTF mean time to fail

MTTR mean time to repair

NASA National Aeronautics and Space Administration

NETSO National Electricity Transmission System Operator

NPV net present value

Ofgem Office of Gas and Electricity Markets

OFTO offshore transmission owner

OPEX operational expenditure

OTS offshore transmission system

OWPP offshore wind power plant

ROI return on investment

STPR social time preference rate

SVC static var compensator

TSO transmission system operator

UK United Kingdom

VSC voltage source converter

WACC weighted average capital cost

XLPE cross-linked polyethylene

Chapter 1

Introduction

1.1 Background

Energy Challenges

Globally, there is a drive to find solutions to keep the increase in the global average temperature well below 2°C, as described by the Paris agreement [3]. This challenge involves decarbonising, among other areas, electricity generation. Subsequently, countries worldwide are keen to move to low-carbon electricity generation sources.

The United Kingdom's (UK's) current energy policy centres around energy security, decarbonisation and affordability. Accordingly, the fifth carbon budget recommends a reduction in carbon intensity to less than 100g CO_2/kWh by 2030 [4]. More recently, the United Kingdom (UK) set a target of reducing its net greenhouse gas emissions by 100% compared to 1990 levels by 2050 [5]. These targets, combined with other environmental policies, has opened a gap for renewable energy.

Due to the changing energy demand and the shift away from fossil fuels, the energy sector in the UK is evolving: the phase-out of coal-fired power stations by 2025 [6], the continued growth in renewable energy [7], and increased interconnection with Europe [8]. In addition, the movement towards the electrification of transport and potentially heat suggests that the future energy mix will be substantially changed. Although fossil fuels remain dominant in the United Kingdom's (UK) energy mix, we already see a difference, and in 2019 fossil fuels accounted for 79.4% of the energy supplied [7]. This record low value was primarily due to a continued switch from coal to renewables for electricity generation [7]. The energy mix is predicted to continue to evolve to achieve environmental targets. For these reasons, research which enables offshore wind energy to be more competitive is invaluable for the future.

Offshore Wind

Over the past decade, the amount of installed offshore wind globally has grown from 2.2 GW in 2009 to 28.9 GW in 2019 [9]. Breaking this down, the UK leads with 33% of the share of installed capacity, followed by Germany 26%, China 23%, Denmark 6%, and Belgium 4% [9]. Many other markets have plans to increase offshore wind capacity including the Netherlands, US, Taiwan and Japan. Additionally, some emerging offshore markets are Vietnam, India, Brazil and Australia [9].

In 2019, globally, a record 6 GW of offshore wind was installed [9], of which $3,623$ MW was added in Europe across ten wind farms [10]. Across Europe, wind farms have grown in size from an average capacity of 313 MW in 2010 to 621 MW in 2019 [10]. Furthermore, these projects are being installed further offshore; in 2019, the average distance offshore was 59 km, compared to 35 km in 2018 [10]. Moreover, at 1.2 GW, Hornsea One is the largest installed offshore wind farm to date (2020) [10, 11], and there are plans for larger projects such as Dogger Bank with a capacity of 3.6 GW [12]. New investments in offshore wind continue to grow, and financial markets have supported the offshore wind sector through investors and economic structures [10]. All of this information indicates that the offshore wind industry is growing, and looks to have a promising future.

Focusing on the UK status, in 2019, 37.1% of the total electricity generated was from renewable sources, an increase of 4% from the previous year (due to higher wind, solar and biomass capacity) [7]. As of the end of 2019, the UK is a world leader in terms of installed offshore wind capacity, with a total capacity of 9.9 GW spread across forty wind farms [10]. The UK has ambitious plans to increase the contribution of offshore wind, and in 2019 the offshore wind sector deal was announced [13]. Amongst other aims, the deal sets out that offshore wind will provide a third of the United Kingdom's (UK) electricity generation by 2030 [13].

The price of offshore wind energy generation needs to be reduced to enable offshore wind to be competitive with other energy generation technologies. The industry has stepped up to the challenge, and 2016/17 saw a dramatic decrease in offshore wind prices as did 2019. UK projects that reached financial investment decision status in 2019 achieved a significantly lower than expected strike price of £39.65/MWh [14]. However, there is potential for further cost reductions.

The cost reduction achieved thus far is believed to be due to the maturing of the industry, improvement of technology and management practices, increased investor confidence and the introduction of larger offshore turbines [15]. Turbine sizes are continuing to grow, as is the capacity of the wind farms connected to the grid and the distance offshore. Furthermore, these increasing trends are set to continue; the industry plans to locate offshore wind farms further offshore and in deeper water. This advancement allows the installation of offshore wind farms in more favourable and windier sites; however, it will induce technical, financial and operational issues.

Offshore Power Transmission

An offshore wind farm is connected to the onshore grid by the offshore transmission system (OTS). The requirements of an OTS are changing to accommodate the needs of the industry. As the generation capacity of offshore wind farms grows, the capital costs of the offshore transmission assets also increase since, among other factors, higher power rated equipment and more offshore platforms are required. As projects move further offshore, longer export cables are installed, and this raises the debate as to whether high voltage alternating current (HVAC) or high voltage direct current (HVDC) technologies should be installed [16, 17]. Furthermore, as the size of the wind farms grows, the greater is the importance of the OTS to be in good working order and consequently, the significance of high levels of reliability [18]. Ultimately, how we connect wind farms is an increasingly crucial question and will be the focus of this thesis.

In line with the offshore wind industry's aim of cost reduction, there is also a focus to reduce the costs associated with the OTS. Accordingly, there is active research to decrease both the capital expenditure (CAPEX) and operational expenditure (OPEX) associated with the electrical transmission infrastructure. The layout of the OTS is under consideration to reduce the capital costs of the offshore grid connection, and alternatives to radial connections, such as meshed systems are being assessed [19, 16, 20, 21]. With regards to individual assets within the transmission infrastructure, higher rated components to carry greater capacities are being explored [22].

In terms of reducing the operational costs, the electrical transmission infrastructure required to connect offshore wind farms has its particularities; especially with regards to the cable systems a key focus of this thesis. Although there have been many offshore power cables installed, the more recent offshore wind projects have introduced cables with a higher nominal voltage and power carrying capacities [23]. The relatively short operational history of the assets coupled with new projects installing advancing technologies results in a significant challenge: there are limited experience and data around which to base economic assessments [24]. As the industry matures, this situation is likely to improve; however, unfortunately, gaining sufficient information will take time.

Decision Making Under Severe Uncertainty

In the meantime, many decisions will be made in the planning and design of each new offshore wind project. These decisions will include selecting the type of technologies to install, the grid connection layout, and the level of redundancy to include in the system. While making these decisions, cost, availability, and environmental impact, among other factors, will be considered. However, as mentioned above, offshore wind grid integration, and in particular offshore transmission assets, is subject to many inherent uncertainties due to a limited amount of relevant data and expert knowledge. These uncertainties complicate decision making in terms of policy, planning and operations. Since these decisions could have a substantial impact, appropriate techniques should be implemented in the decision making analysis. This is one of the major issues we aim to address in this thesis.

When decisions are taken under severe uncertainty, it is essential to quantify this uncertainty. Uncertainty quantification is usually conducted using the classical theory of probability. When there only exists a small amount of information which is the case for offshore power transmission due to the short operational history, data confidentially, and most available data is project-specific it can be challenging to construct a model based on classical probability theory. The challenge arises since techniques based on classical probability theory require a large amount of data and knowledge; therefore, in the absence of this information, these methods have severe limitations.

In contrast, techniques based on the theory of imprecise probability are an extension of traditional probability concepts, but they allow for the more appropriate handling of severe uncertainty [25]. By severe uncertainty we mean, for example, uncertainty due to insufficient data that prevents us from accurately specifying a probability distribution. Here, insufficient data could be very little data or even no data only expert intuition. The methods within imprecise probability provide a framework to represent our knowledge more accurately and enable inferences to be made under severe uncertainty. Consequently, applying imprecise probability to support decision making under severe uncertainty could have invaluable consequences for offshore power transmission.

Summary

In conclusion, throughout the next decade, the offshore wind industry is going to be making investment decisions on strategic assets (including those in the OTS), under severe uncertainty of a technical, economic and regulatory nature. Offshore electrical transmission infrastructure projects have a short operational history, and data that is available is usually project-specific. Additionally, future projects often include advancing technologies for which there is no previous data. Nevertheless, new solutions must continue to be found to effectively connect future offshore wind farms to the onshore grid; and ultimately, to ensure that the balance between availability, affordability and sustainability is maintained.

The main focus of this research is the application of statistical methods for long-term decision making (such as investment planning) under the presence of severe uncertainty due to limited data, knowledge, and expertise. Specifically, we are dealing with uncertainty in the input parameters (required to evaluate projects economically) due to limited data, and therefore there is a limit to our knowledge when it comes to making long-term decisions. Accordingly, this thesis will formulate decision problems that are both relevant to the industry and taken under severe uncertainty. Advanced statistical techniques will be used to handle the inherent uncertainties, which could ultimately influence the decisions made. Subsequently, the main objectives of this thesis are to investigate advanced statistical methods that handle severe uncertainty and to demonstrate how implementing these techniques allows robust decision making under severe uncertainty in offshore power transmission. Finally, we aim to review the extent to which these methods are beneficial to decision makers in the offshore wind industry.

Throughout this thesis computational aspects, including simulations and figures, have been performed in `R` [26] and `Python`, using `Numpy` [27] and `Matplotlib` [28].

1.2 Original Research Contribution

The work of this thesis designs (by setting up the methodology), tests (through applications) and validates (by comparing to conventional methods) a new power systems planning technique to support the decisions taken under severe uncertainty in offshore transmission. Advanced statistical methods, such as imprecise probability, are used to address the inherent uncertainties (of a technical and economic nature) due to limited data. These uncertainties make it challenging to assign probability distributions to inputs required to assess a particular OTS economically.

The application of advanced statistical techniques to offshore power transmission is the original contribution of the work conducted in this thesis. This thesis uses three applications to demonstrate the utilisation of the techniques, and each decision problem addresses a relevant research question. Exploring these questions alone is of interest to those in the offshore wind transmission field. However, the main aim of this thesis is to demonstrate the extent to which advanced statistical methods can be beneficial to decision making under severe uncertainty in offshore power transmission. Accordingly, the implementation of these techniques serves the following purposes: to demonstrate how the techniques can be applied in the analysis of a practical decision problem; to find and overcome challenges that may arise in the use of these techniques to practical problems;

to show the benefits of taking this alternative approach and, in particular, its ability to handle severe uncertainty in the input parameters more appropriately than conventional methods; and to discuss any limitations.

Looking at the bigger picture, this thesis's original contribution will provide decision makers in offshore power transmission (and in the broader energy context) a framework to handle severe uncertainty, and base their decision on analysis that addresses the uncertainty involved. Consequently, developing and implementing a methodology that handles severe uncertainty will be invaluable to the future of the offshore wind industry.

1.3 Research Aims and Questions

The research aims and questions of this thesis are divided into three areas: motivation, methodology and application.

Motivation

1. To develop a methodology to assess the economic impact of severe uncertainty on offshore transmission planning. What information and methodology are required to assess the economics of an OTS effectively?

2. To identify areas of the economic model developed in Aim 1 that, for a future OTS, contain significant uncertainty. Consequently, applying statistical models to these areas will enable better risk-informed decisions to be made. What areas of the economic model contain significant uncertainty that results in significant uncertainty in the expected net present value of an OTS?

Methodology

3. Advanced statistical methods, such as imprecise probability, have been suggested in the literature to handle severe uncertainty due to limited information. This work aims to use these techniques to address severe uncertainty in the formulated decision problems. We aim to identify which techniques are required to handle the identified severe uncertainty appropriately in the formulated decision problems. Additionally, we aim to understand how these techniques could be applied.

4. To understand and overcome challenges that arise during the application of advanced statistical methods to practical applications in offshore power transmission. In particular, how do we overcome the issue of act-state dependence in a practical decision problem?

5. How do we effectively communicate the handling of severe uncertainty? In particular, we set out to explore how to clearly communicate advanced statistical modelling and the results of this analysis.

Application

6. The main aim of this thesis is to investigate the extent to which advanced statistical methods can be beneficial to decision making under severe uncertainty in offshore power transmission. To achieve this, we demonstrate how the methods proposed can be implemented in the analysis of a practical decision problem that is made under severe uncertainty. Furthermore, we aim to show how to address and quantify the uncertainty in three applications.

7. To demonstrate the application of advanced statistical methods to practical decision problems, we investigate the three questions outlined below. These questions act as case studies to illustrate and understand the implementation of the techniques.

    (a) For an emerging market, what regulatory regime and technology choice is optimal under severe uncertainty?

    (b) From the perspective of different stakeholders, should they invest in an interlink between two offshore substations to provide increased redundancy?

    (c) Given the components available in the market, what is the optimal OTS for different project capacities and distances from shore?

8. To show how the novel approach presented in this thesis to handle uncertainty in offshore transmission decision problems compares to conventional methods. To illustrate the benefits of taking this alternative approach and, in particular, its ability to handle severe uncertainty in the input parameters (required to evaluate projects economically) more appropriately. Finally, we will discuss any limitations to the proposed methodology.

1.4 Thesis Outline

This thesis presents the research that addresses the aims outlined above and is organised in the following way. Additionally, Fig. 1.1 visually shows the thesis structure. To begin, Chapter 1, explains the broader context in which the research of this thesis sits. We also present the research aims of this thesis and its original contribution. In Chapter 2, we discuss the current knowledge about OTSs, as well as review and summarise the literature in this field. In particular, we identified that there is a limited amount of relevant data about offshore wind transmission systems to make long-term investment decisions.

Although we may not have enough data to accurately perform economic evaluations and make decisions under severe uncertainty adequately, there does exist some data. In Chapter 3, we collect and present data that is available in the public domain associated with OTSs. In Chapter 4, we confirm the need for advanced statistical methods to handle uncertainty in offshore transmission by developing an economic framework to assess an OTS (we will use this framework throughout the thesis), identifying uncertain model variables, and, finally, evaluating their impact on project performance. Since some uncertain inputs have a significant impact on the economic benefit of a project, and these projects require considerable investments, there is a need to handle uncertainty appropriately.

In Chapter 5, we revisit conventional techniques currently implemented in decision making analysis (based on the classical theory of probability), discuss their limitations when applied to problems that involve uncertainty and subsequently, explore more robust techniques under severe uncertainty. These advanced statistical techniques are applied in Chapters 6 to 8, which are the application chapters of this thesis.

In Chapter 6, we investigate economically preferable regulatory regimes and technology choices for emerging markets from an investor's point of view. In Chapter 7, we explore, from the perspective of different stakeholders, whether they should invest in an interlink between two offshore substations to provide increased redundancy. The final application is presented in Chapter 8, where we demonstrate a more comprehensive application by extending the decision problem to include a framework to construct the decision space. Therefore in Chapter 8, the application investigates and designs optimal OTS for varying distances offshore and wind farm generation capacities. All three application chapter serve the purpose of demonstrating and understanding how to implement the proposed advanced statistical methods to ultimately show how they can be beneficial to decision makers in offshore power transmission. Finally, in Chapter 9 we give chapter summaries, and in Chapter 10 we present the conclusions of this thesis and discuss further work.

Before moving to the next chapter, it is important to make two notes. Firstly, in this thesis, although the case studies have been designed as accurately as possible based on the available information, there may be limitations to the problem formulation or data inputs. However, as this work's primary aim is to demonstrate the ability of advanced statistical techniques to support decision making under severe uncertainty, accurately arriving at decisions to the three applications is not the priority. In summary, these applications act as case studies to demonstrate the application of advanced statistical methods to practical decision problems. Secondly, the notation for variables should be contained within each

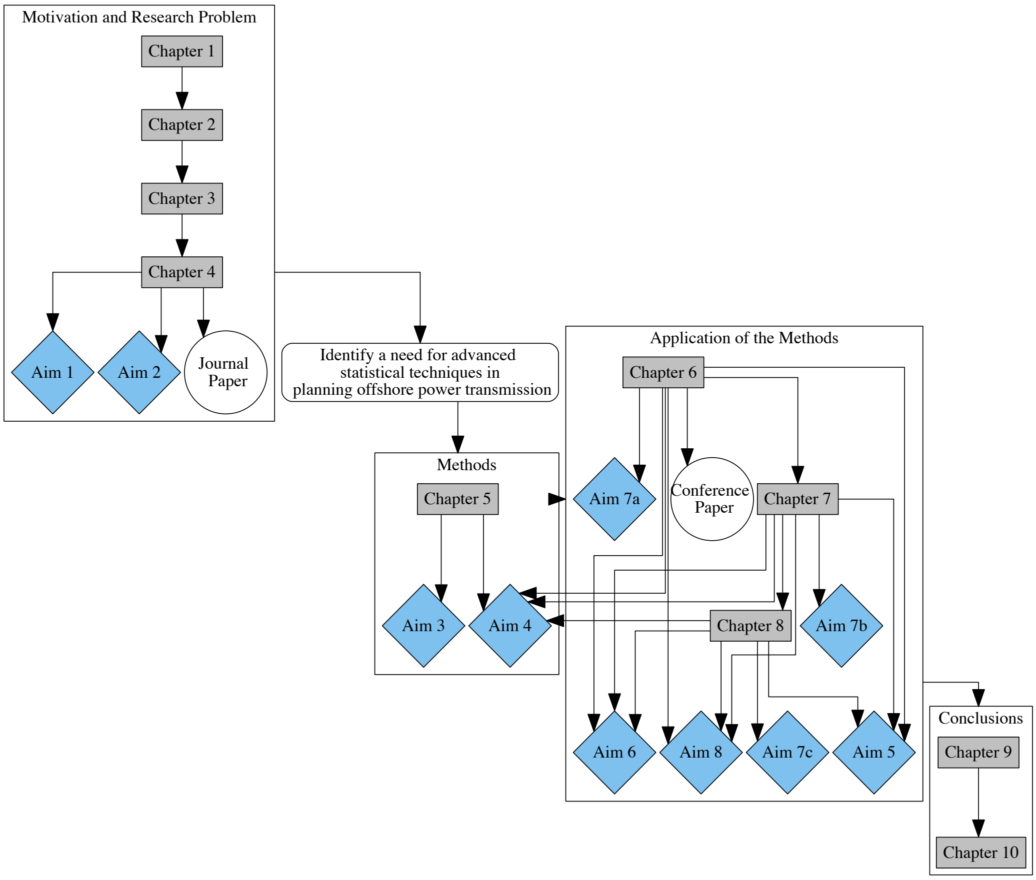


Figure 1.1: Thesis structure showing the links between chapters, research aims and publication outputs.

chapter, and be consistent for variables that appear in multiple chapters. Some symbols have been reused for variables that do not appear in multiple chapters due to limited symbols.

Chapter 2

Offshore Transmission Systems State of the Art

2.1 Introduction

In Chapter 1, we established the need for methods to handle uncertainty when making long-term investment decisions regarding the offshore transmission system (OTS). This chapter discusses the current knowledge about OTSs and reviews the literature in this field. The aims of this chapter are:

1. To gain a deeper understanding of the role of an offshore transmission system (OTS) and its key components.
2. To investigate current challenges faced by the offshore wind industry, and in particular, the problems that need to be addressed to support offshore transmission.
3. To review current studies that assess policy, planning or asset management decisions in offshore transmission. Furthermore, to advance our knowledge about the types of decisions that are currently being made by project planners in offshore transmission.
4. To understand the challenges that uncertainties bring to offshore transmission planning, and review current approaches to handle these uncertainties.

This chapter begins by defining the offshore transmission system (OTS) before detailing the components that constitute the system. This explanation is followed by a review of the different ownership structures of the OTS adopted by individual countries. As the OTS is one part of the offshore wind power plant (OWPP), we go on to discuss challenges faced by the offshore wind industry. In particular, we focus on cost reduction. We also review obstacles associated explicitly with the OTS. This aim of cost reduction is crucial in many of the decisions taken throughout the lifetime of the OTS. Therefore, we look at the long-, medium- and short-term decisions currently being investigated in the literature. We

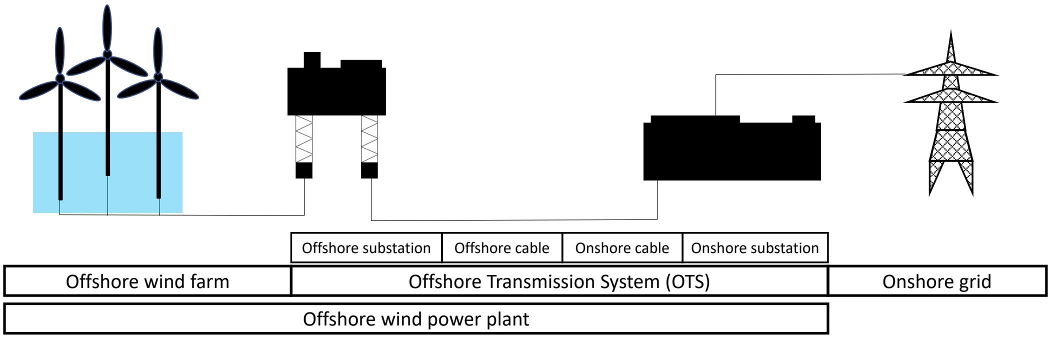


Figure 2.1: Breakdown of an OWPPs into an offshore wind farm and an offshore transmission system (OTS), as well as detailing typical assets within the OTS.

identify that uncertainty due to a limited amount of data and expert knowledge impacts the decision making process, and go on to review current approaches to handle uncertainty in offshore transmission. Conclusions are drawn about current challenges and limitations in offshore transmission; specifically, handling uncertainty in the decision making process when planning and designing these systems.

2.2 Definition: Offshore Transmission System (OTS)

An offshore wind power plant (OWPP) is made up of an offshore wind farm and an offshore transmission system (OTS) as shown by Fig. 2.1. An offshore wind farm consists of many turbines along with the associated electrical equipment that is required to generate the electricity. Electricity is generated offshore with the intent of it being sold to the onshore grid. Therefore, the wind farm needs to be connected to the onshore network. This connection is the role of the OTS. The exact assets that constitute an OTS will be project dependent; however, the system will usually include offshore substations, offshore cables, onshore cables, onshore substations and the electrical equipment associated with each of these. We will detail each of these components in Section 2.3.

In technical terms, often, the offshore transmission assets are between the following two boundary points as detailed in [19]:

1. The boundary point on the offshore wind farm side is located on the offshore substation platform at the incoming low-voltage transformer circuit breaker cable termination.
2. The boundary point on the onshore network side is located in the onshore substation between the high-voltage busbar disconnectors and the high-voltage circuit breaker. This is known as the point of common coupling and is where the OWPP meets the onshore grid.

The expenditure associated with the OTS usually accounts for around 15% to 20% of the capital costs of an offshore wind project which is equivalent to 10% to 15% of the levelised cost of energy (LCoE) [29]. In 2019, transmission asset investments in Europe amounted to €0.5 billion [10]. In the UK, the first wind farm was installed in 2000 at Blyth offshore wind farm. This project, and many of the other early projects and demonstration projects, are located close enough to shore that a full OTS was not required. Since these projects, many offshore wind farms have been installed at a sufficient distance from shore that an OTS is justified. In the UK, projects to date are located between 9 and 120 km from shore with a capacity between 64 and 1200 MW [30, 31]. Of these projects, fourteen projects (that have a capacity between 90 and 630 MW) have detailed costing data available in the public domain and suggest that, up until now, the capital costs of an OTS (for varying project sizes) are between £25 million and £350 million [32]. This value is likely to increase as project capacity grows.

Thus far, in the UK, the connection between the wind farm and the onshore network is usually radial (point-to-point) and using HVAC technologies. Elsewhere, for example, Germany has installed some HVDC offshore transmission systems (OTSs). However, as the industry moves further offshore, alternative transmission connections, such as a more coordinated approach or designing a wind farm that could accommodate a future wind farm, are being considered [19, 16, 20, 21]. These alternative connections come as a suggested solution to the need for an increased transmission network capacity. As offshore transmission advances to accommodate the needs of the industry, questions around designing electrical transmission infrastructure arise.

2.3 Components in an Offshore Transmission System (OTS)

An offshore wind farm can be connected back to the onshore grid using one of two technology types: HVAC technologies or HVDC technologies. In this section, we detail the key components that make up an offshore transmission system (OTS) for both connection approaches. We start by describing the offshore platform, where the OTS begins, before explaining both the onshore and offshore cables. Finally, we discuss the onshore substation where the OTS ends and meets the onshore grid.

- **Offshore Platform**

  The offshore platform (or platforms) are where the array cables from the turbines meet. Additionally, the platforms host the electrical equipment required to collect the generated electricity and transmit this to the onshore grid [33]. An offshore platform hosts the offshore transformer that transforms the voltage from 33 kV (in older projects) or 66 kV (in recent projects) to higher voltages of 132 kV (in older projects) or 220 kV (in recent projects). This higher voltage (132 kV or 220 kV) is required for transmission back to shore. To give an example, Race Bank offshore wind, which became operational in 2018, has a capacity of 578 MW and consequently has two offshore platforms. Each offshore platform in the Race Bank project is 20 m by 30 m by 38 m, and the overall height is 35 m [30].

If the offshore transmission system (OTS) is using HVDC technologies, then a separate offshore platform may be needed to host the voltage source converter (VSC). This VSC converts the power from HVAC to HVDC for the transmission back to shore. Recently, research by [34] investigates combining the transformer and converter platforms to reduce costs. The study by [34] found that a 1 GW combined HVAC and HVDC platform topside can be achieved; furthermore, this asset can weigh less than $10,000$ tonnes which brings cost reductions. This is discussed further in Section 3.8.2.

The use of HVDC grid technologies allow multi-terminal connections to be considered as an alternative to point-to-point connections. The study by [20] finds that point-to-point HVDC options are economically favourable (with regards to CAPEX), however multi-terminal HVDC options have security of supply advantages.

The offshore platform also hosts other electrical equipment such as switchgear, shunt reactors and auxiliary transformers. A project may require more than one platform if it is sufficiently large in capacity. The size of the platform is limited by the weight of the equipment on the platform. Once the power is in the correct form for transmission, the platform connects to the offshore cable (or cables).

- **Offshore Cable**

  The offshore cable, usually installed below the seabed and therefore called a subsea cable, transmits the power back to shore. The combined offshore and onshore cable system is sometimes referred to as the export cable. A larger project may require more than one export cable; the capabilities of the cables available in the market determines this. Depending on the technology chosen for the OTS, the offshore cable will either be a HVAC or HVDC cable.

  The majority of HVAC cables used in operational projects are three-core HVAC subsea cables with cross-linked polyethylene (usually referred to as XLPE) insulation [35, 33, 36, 37]. Some HVAC cables include a fibre optic cable for communications [37]. A three-core cable is installed in a single trench, typically buried at a depth of one to four metres below the seabed [38]. Cables installed between 2013 and 2016 were usually rated at 132 kV. However, advancement in cable design and growth in project capacity means that 220 kV are becoming the standard in more recent projects [30, 38]. Currently, HVAC cables have the ability to transfer 350 to 400 MW per cable [38] and even 550 MW per cable as suggested in [37]. Should HVAC approaches be considered for very far offshore projects, reactive power can become problematic. Therefore, HVAC cables of such considerable lengths will require reactive compensation units around the midpoint of the cable [16, 11].

Next, we move on to discuss HVDC cables, which are typically used for longer distances to solve issues related to reactive power flow that occur in HVAC systems. HVDC cables can be bipolar with two single-core cables, and currently a pair of single-core 320 kV cables can export 1200 MW [38]. Some of the advantages of a HVDC approach stem from the reduced weight and size of HVDC cables, as well as being free from reactive power [39].

To compare costs, a 400 MW (220 kV) HVAC cable costs around £0.7 million per km whereas a 1200 MW (220 kV) HVDC cable costs around £0.8 million per km [33, 36, 37]. In 2019, NKT Group supplied 55% of the cables energised in Europe, followed by Nexans (18%), Prysmian (18%) and LS Cable and System (9%). JDR is another key manufacturer; however, they did not supply any of the cables that were energised in 2019 [40]. When the offshore cable meets the landfall, a cable joint connects the subsea cable to the onshore cable.

- **Onshore Cable**

  The onshore cable, usually buried underground, takes power from the landfall to the onshore substation. The length of the onshore cable depends on the onshore substation's location and the route from the landfall to the onshore substation. Similar to the offshore cable, the onshore cable is usually a cross-linked polyethylene (XLPE)-insulated cable. In line with the advancement of higher voltage offshore cables, the onshore cables have also moved from 132 kV to 220 kV in more recent projects [38, 37].

- **Onshore Substation**

  The onshore substation houses the equipment required to transform the voltage up to the level of the onshore grid and to connect to the onshore transmission system [38]. In the UK, the onshore grid has a voltage level of 400 kV. The equipment in the onshore substation may include transformers, switchgear, shunt reactors, harmonic filters, and metering equipment to measure the amount of electricity exported to the grid [30, 38]. If HVDC technologies have been chosen, the onshore substation may also host the onshore VSC which converts the power back from direct current to alternating current. The estimated cost of an onshore substation is £30 million for a 1 GW wind farm [38].

2.4 Ownership Structures

Currently, the responsibility of owning and operating the offshore transmission system (OTS) varies between countries this section details individual countries' set-ups for nations leading in the offshore wind industry. We discuss the ownership structures for Belgium, China, Denmark, Germany, the Netherlands and the UK. However, we note that these structures may evolve to suit the needs of a country's offshore wind market.

- **Belgium**
  Previously, each offshore wind farm operator had to build their OTS. In 2017, Elia (Belgium's onshore transmission system operator (TSO)) announced that they would connect the next four offshore wind farms to the onshore grid by investing in a modular offshore grid (MOG) [41]. Each wind farm would connect to the MOG for transmission to the onshore grid [41, 42].

- **China**
  In earlier projects, offshore wind projects were located close to shore and connected directly to the onshore substation by 35 kV cables [43]. Therefore, offshore substations, higher voltage cables and ownership structures for the transmission assets were not required [43]. For more recent projects requiring a more substantial grid connection, the developers are responsible for financing and constructing the OTS [44]. However, ownership structures that split the responsibility are being considered [44].

- **Denmark**
  In Denmark, there are two ways to obtain a permit to build an offshore wind farm: open door procedure and tender procedure [42]. Under the open door procedure, the grid connection is located onshore and therefore, the wind farm developer pays for the OTS. Under the tender procedure, the developer is only responsible up to the grid connection, which is placed offshore. In this case, the Danish onshore TSO are responsible for the connection to shore [42]. However, in 2018, for three offshore wind projects, Denmark decided to switch to a developer build model for the OTS [44].

- **Germany**

  In Germany, the responsibility to connect offshore generation assets falls either to TenneT TSO or 50 Hertz Transmission GmbH. TenneT is legally obliged to connect all offshore wind farms in the German North Sea to the power grid [45, 46].

- **The Netherlands**

  In the Netherlands, for recent offshore wind farms, the government appointed the Dutch onshore TSO, TenneT, as the Dutch offshore grid operator [47]. TenneT has the responsibility to connect offshore generation assets to the onshore grid. Currently, TenneT is developing five offshore grid connections that could each connect multiple wind farms, via an offshore substation and two 220 kV cables, to the onshore grid [47]. In 2015, Gemini was a pioneering project, and the wind farm owner had to install its offshore grid [48].

- **United Kingdom**

  In the UK, usually, a developer builds the entire power plant but must hand the OTS (when it is operational) to a third-party entity termed an offshore transmission owner (OFTO). An OFTO finances, operates and owns the OTS assets, under long-term licences that guarantee a revenue stream subject to satisfying performance requirements [49, 50, 51, 19].

From the countries' set-ups, we see that ownership usually falls to either a third-party entity, the offshore wind farm developer or the onshore TSO [52]. The industry as a whole appears to prefer onshore TSO ownership.

When conducting an economic evaluation, a specific stakeholder's perspective should be taken. In the work of this thesis, due to the information available, we usually focus on the UK market and analyse from the offshore transmission owner's (OFTO) perspective. The rest of this subsection will focus on and discuss in more detail the OFTO regime.

In the UK, currently, a developer builds both the wind farm and the OTS but will only own the wind farm during its operational phase [50]. When the transmission system assets can transfer electricity to shore, the developer must hand these assets over to an OFTO. This transfer of assets is regulated by the Office of Gas and Electricity Markets (Ofgem) who run a competitive tender process to select and award an OFTO licence to a particular company [51].

During the competitive tender process, a cost assessment is carried out to determine the transfer value of the assets. The developer provides Ofgem with figures and estimates of their costs and Ofgem regulate these [50]. Throughout the assessment process, Ofgem presents three numbers: the initial transfer value, the indicative transfer value and the final transfer value (FTV) [51]. The FTV is the payment that the OFTO makes to the developer for the transfer of the transmission assets. The tender process also results in an agreed revenue stream (including details about the base revenue) for the OFTO that receives the assets.

In the United Kingdom's (UK) regulatory regime, OFTOs are incentivised to maintain very high levels of asset availability to limit financial losses to generators from network outages. The reward or penalty that the OFTO receives depends on the availability of the OTS to transmit electricity. Specifically, it is a result of whether the yearly availability has reached the target of 98%. Only 10% of the offshore transmission owner's (OFTO) base revenue is at risk due to availability, hence should the availability fall below 94% the OFTO would obtain 90% of the base revenue. For an availability value greater than 94%, the revenue increases linearly from 90% of the base revenue at 94% availability to 105% of the base revenue at 100% availability [53].

The work by [52] suggests that the United Kingdom's (UK) approach is flexible, which has allowed the UK to deliver timely offshore projects that economically and efficiently connect offshore generation assets to the onshore grid. Furthermore, the report by [54] indicates that this approach has a predictable revenue stream which attracts private investment in these assets.

2.5 Offshore Wind Industry Challenges

As the offshore transmission system (OTS) is part of the offshore wind power plant (OWPP), it is necessary to understand the main challenges faced by the offshore wind industry. In this section, we discuss those challenges. The offshore wind industry looks to have a promising future, but it still faces a plethora of technical, environmental, social, regulatory and financial challenges.

Possibly the most crucial challenge for offshore wind is cost reduction, and there is potential for significant work in this area [55]. Dramatic progress has already been made to reduce the cost of offshore wind; however, the industry must ensure that it is competitive with other energy sources. The challenge of cost reduction is revisited in more detail in Section 2.6.

There exist many investment, design and operational decision problems that require answering to allow offshore wind to continue to progress. Some of these decision problems are investigated in the literature: whether investors should expand, continue or abandon projects [56]; operational decisions to optimise the maintenance strategy [57]; lifetime extension of wind turbines [58]; optimising the wind farm layout [59]; selecting an optimal access point for the wind farm to connect back to the onshore grid [60]; the selection of suitable support structures for offshore wind turbines in deeper waters [61].

Furthermore, the offshore setting of an offshore wind farm adds additional complexity to the maintenance and repair of these assets; specifically, logistical, time and cost challenges that need to be addressed. Several works in the literature review operation and maintenance practices for the offshore wind farm [62], usually focusing on the maintenance and repair of the turbines. The work by [63, 64] compares the following maintenance strategies: preventative, corrective, scheduled and unscheduled maintenance. Operational strategies are vital to the success of a project, and therefore indicates the importance of these asset management decisions.

The increasing size of offshore wind farms, coupled with more distant locations brings additional maintenance challenges. Vessels will be required to travel further distances in potentially harsher conditions, and therefore, research into robotics and drones for operations and maintenance is attracting increasing attention [65]. Research into asset management has led to the development of operations and maintenance tools [66, 67, 68, 69], and tools to aid in specific maintenance problems such as vessel routing [70].

Vessel hire is a significant contribution to the repair cost. Accordingly, the work of [71] investigates different vessel capabilities and charter periods, and as a result, identifies the advantage of hiring vessels for a more extended charter period. The study conducted by [57] investigates three operations and maintenance decisions regarding vessel hire. Furthermore, the work by [72] notes that acquiring effective and efficient asset management processes facilitates structured and supported decision making throughout the lifetime of the asset, and leads to a reduction in the cost of energy.

Another challenge arises due to uncertainty. Several studies have investigated the uncertainties associated with the entire offshore wind power plant and their impact on economic metrics [73, 74, 75]. In particular, the impact of variations in the power generated by the wind farm is assessed. With the maturing of the industry, the situation will improve, but this will take time. Therefore, appropriate techniques must be developed to deal with this limited information.

In summary, one of the greatest challenges that the offshore wind industry faces is its higher development and operational costs which are primarily due to the location of the wind farm sites. Furthermore, the transmission system plays a significant role in this, especially as projects grow in capacity and are installed further offshore. Due to the increased importance of offshore transmission systems (OTSs), this work focuses on them.

2.6 Cost Reduction Motivation and Progress

As highlighted in the previous section, one of the biggest challenges faced by the offshore wind industry is cost reduction. As a result, research within the sector has a strong focus on reducing the cost of energy. In this section, we explore the motivation behind cost reduction and review the literature that suggests areas to address this issue.

As previously mentioned, across Europe, offshore wind farms have grown in size from an average capacity of 313 MW in 2010 to 621 MW in 2019 [10]. This increase is partly due to achieving economies of scale within the offshore wind energy sector, which has enabled cost reduction. In particular, the increasing turbine size from an average of 3 MW in 2009 to almost 8 MW in 2019 [10]. Furthermore, in April 2020, Siemens Gamesa released a 14 MW offshore wind turbine which they plan to introduce by 2024 [76].

The cost reduction monitoring framework outlined in [77] evaluates the progress of cost reduction in UK offshore wind projects against key milestones. Considerable cost reduction has already occurred, and the report by [77] suggests that this is predominately driven by technology developments, including higher power rated turbines. The report by [77] also outlines that increased competition at the developer level (leading to lower supply chain costs) and the improved confidence in the sector (ultimately reducing risk profiles and capital costs) have supported cost reduction aims. The report by [77] suggests that there is expected to be further cost reductions over the next decade through technology innovation and collaboration across the sector.

Some areas of potential research to address cost reduction are suggested in [78]: erection and installation of turbines, the construction of platforms, the laying of subsea cables, operations and maintenance, and decommissioning of the site. The work by [79] indicates that operating costs are significantly influenced by labour costs and the availability of the components. [79] goes on to detail key drivers for operational expenditure in offshore wind: availability of vessels, crew, helicopters and parts, network charges, vessels for larger equipment, production facilities of jackets, and lead time for cables. The work by [79] also suggests that research into lead times for cables could result in substantial consequences for the offshore wind industry.

Several initiatives are already in place to address the cost reduction challenge with regards to the grid connection. These initiatives include the development of a coordinated network and improvements to the offshore transmission owner process [55]. However, the work by [55] suggests that such actions may lead to uncertainty about future policy frameworks for offshore transmission, consequently making standardisation and other cost reduction opportunities more difficult to reach. [80] describes offshore transmission infrastructure development in a timely and cost-effective way to be essential to deliver offshore wind generation.

2.7 Offshore Transmission Challenges

Cost reduction

In line with the aim of reducing the cost of offshore wind energy, the offshore transmission system (OTS) also has a cost reduction focus. Delivering value for money offshore transmission projects is discussed in [81] as one of the barriers to achieving the United Kingdom's (UK) Offshore Wind Sector Deal target of 30 GW by 2030. The industry has already progressed in this area by advancing technologies; however, there is still work to do, in particular with increasing the reliability of OTSs [18] and handling the uncertainties involved in project assessments [82, 83].

Distance offshore

To enable wind farms to be deployed even further offshore requires technological innovation regarding the OTS. The length of cable required, so far, has not been long enough to cause significant problems. Project planners have to decide whether the transmission topology should be HVAC or HVDC, taking into consideration that HVDC becomes the more economical option after a certain length of cable. This cable length is disputed in the literature; for example, the work by [16] suggests between 50 km and 80 km, whereas the study by [84] suggested between 120 km and 160 km. Projects currently being planned and installed are at distances within these ranges.

As offshore wind projects are installed at greater distances offshore and longer cables are required, reactive power in HVAC grid connections becomes an issue. HVAC cables of such considerable lengths will require reactive compensation units around the midpoint of the cable, and this will inevitably come with higher costs [16]. [85] compares the investment cost of two reactive compensation strategies: concentrated (a dedicated reactor unit) and distributed (using the power converters in the offshore turbines). The work of [85] finds that usually, a mix of both strategies is economically optimal.

Another challenge that the OTS has to overcome is due to the losses in the electrical equipment. Models to calculate the power losses of the offshore cables, transformers and converters are developed in [86]. This work finds that cables are the main contributors to losses for HVAC connections, whereas converters and offshore transformers are the primary source of power losses for HVDC connections [86].

Uncertainty

Unfortunately, many of the decisions taken in offshore transmission are under severe uncertainty which complicates the decision making process. In this section, we discuss the nature of these uncertainties. In the context of offshore wind, uncertainty arises from the need to predict the future, or due to a limited amount of relevant data and expert knowledge.

The work by [87] describes uncertainty analysis to be an essential topic of research in the wind power sector. The unpredictable nature of wind is also emphasised in the study by [88], who analyses four wind speed distribution models. Similarly, the work by [89] points out that uncertainty in the input parameters impacts the predictions, and unfortunately, many variables in the design stage of an offshore wind farm contain uncertainty.

The methodology to assess the economics of offshore transmission projects usually involves economic metrics such as net present value (NPV) or levelised cost of energy (LCoE). These metrics rely on forecasts [87], and unfortunately, in offshore transmission, the input parameters required are often uncertain. As a result, investment decisions are taken based on uncertain variables, such as unknown costs associated with the capital, operational, decommissioning and financing of a project, as well as wind farm availability and losses predictions [90]. Uncertainties affect the financial stability of an offshore wind project and [87] suggests that the main factors contributing to the uncertainty are wind resource, discount rate, electricity price and future variable costs.

Some of the uncertainty in economic evaluations is due to limited costing data for emerging technologies. The work of [91] reviews data in the public domain for HVDC grid connections, and finds large variations between data sets. Perhaps an even larger challenge is the uncertainty around predicting operational costs of these assets. As a result of the short operational lifetime of offshore wind combined with the confidentiality surrounding operational experience, expert information and data are scarce.

For these reasons, the data used to estimate the OPEX in [59] was taken from a two year period where very few repairs took place and thus was not representative of the average operational year. Uncertainty in evaluating the OPEX has also been investigated by [92]. The work by [92] focuses on the uncertainty surrounding the failure behaviour of the electrical equipment and explores their impact on maintenance strategies. Unfortunately, information regarding the availability of components is limited due to the short operational history of the industry. Furthermore, a breakdown of the variables that impact the OPEX are presented in [93] and it is suggested that some of these variables, such as meteorological conditions, turbine reliability, staff and vessel costs, capacity factors and availability, contain uncertainties.

Reliability

Unfortunately, some offshore transmission projects have experienced costly (in terms of time and money) cable failures [82]. These cable failures occurred more frequently than initially expected [83, 82]. A review of the reliability of offshore wind transmission systems is conducted in [83] and finds that the failure rate experienced in operational projects is higher than the value used in industry practice. Consequently, [83] suggests that an intervention is required as there is insufficient data to carry out accurate failure analysis.

The report by [82] compares the operational failure experience of export cables to the failure rate value used in industry assessments, and finds, like [83], that operational systems are experiencing more failures than expected. Therefore, steps should be taken to reduce the number and impact of offshore cable failures when planning future projects. Consequently, research into cable reliability, proactive cable maintenance, cable installation practices, cable testing, cable fault detection methods, and redundancy has emerged.

The reliability of offshore wind systems is studied in [94, 95, 96, 18, 97, 16]. Offshore grids are sensitive to low probability high impact failures such as cable failures [95], and the reliability of an offshore grid impacts the security of supply of the onshore grid [18]. However, most studies in the field focus on evaluating offshore network reliability from a wind farm owner's perspective [18]. Therefore, little research has been done to evaluate the impact of cable failures from a transmission owner's perspective.

The reliability of HVDC transmission systems has been explored extensively [98, 99, 100]. The work of [98] uses Bayesian networks to advance techniques for reliability assessments of HVDC onshore and offshore transmission systems. The availability of HVDC systems is explored in [99] and finds that the subsea cable has the most significant impact on the availability of the system. The study by [100] presents a methodology to assess the reliability of a HVDC link and investigates the benefits of modelling the modular multilevel converter (MMC) in an additional third state (called the derated state). The work by [100] finds that this additional modelling reduces the downtime of the system, however only slightly increases the revenue of the system.

From the literature, it is quite clear that the reliability of OTSs is an open area of research and the operational experience indicates that improving the availability of these systems is crucial. The work by [18] raises many open research questions around the reliability of the offshore grid, such as, since the usual $n-1$ redundancy criterion often adopted is not economical offshore, what level of redundancy is required for offshore grids? Further work is necessary to ensure that offshore networks can manage increased capacity reliably.

Cable failures

As previously discussed in this subsection, industry experience is suggesting that it is challenging to assign an accurate value to the failure rate of offshore cables. The economic impact of a cable failing is estimated to be on average £12.5 million, and this includes the cost to repair the cable, loss of production, and any extra maintenance required as a result of the cable failing [82]. Since an outage results in a substantial loss of revenue, uncertainty in the failure rate could have a significant impact on the companies involved [24]. The report by [82] presents the United Kingdom's (UK) experience of seven post-commissioning failures significantly higher than expected. £160 million has been spent due to these seven failures [82], and thus cable failures seem to be an obvious avenue to explore with regards to cost reduction and risk mitigation for future projects.

The experiences in the UK thus far have resulted in a failure rate of 0.0016 failures/km/year; however, a commonly used value is quoted in the literature to be 0.0007 failures/km/year [82]. The latter value is based on $60 - 100$ kV single-core cables with no additional details as to whether the cable has a fibre optic or if it is buried [82]. Therefore, it is not representative of the current offshore cables in operation in the offshore wind industry and any extrapolation should be treated with care. Using a failure rate lower than is realistic in economic assessments that underpin investment decisions could be detrimental to the companies involved.

In this subsection, we have reviewed the main challenges faced when developing and operating OTSs. These barriers centre around cost reduction, reliability, cable failures and uncertainty in input parameters that feed into economic evaluations.

2.8 Decision Making in Offshore Transmission

Despite the challenges described above, different stakeholders, together and separately, have to make decisions as to the best way to connect offshore wind farms to the onshore grid. In this process, many long-, medium- and short-term decisions will be made. In the long-term, governments and regulatory bodies will design frameworks and regulations to facilitate the fair development of offshore transmission. In the medium-term, decisions about the design of individual projects will be made. Finally, in the short-term, operational decisions will be taken. The decision maker in each of these time scales may be different. The industry aim of cost reduction is crucial in all of these types of decisions. In this section, the literature surrounding each of these classes of problems is discussed.

Some of the critical questions that must be addressed when designing offshore systems are discussed in [16]. These questions include who pays for the connection? Who benefits from the link? Should overdesign of the grid connection be considered to allow a second wind farm to be added at a later date? Should the system be HVAC or HVDC?

Similarly, challenges that should be addressed to enable the US offshore wind market to realise its potential are discussed in [101], and include how and where would an offshore grid integrate with the onshore network? What onshore grid upgrades are required? Who is responsible for transmission development? How will different regions coordinate? How will offshore transmission be regulated? Many of these questions are relevant to other emerging markets. In the UK context, to work towards the targets of the Offshore Wind Sector Deal, [81] identifies grid-related challenges. These include the impact of onshore infrastructure on communities, the capabilities of the onshore grid, further cost reduction, and the need for a more coordinated approach between the onshore grid, offshore grid, and interconnectors.

Long-term decisions

In the case where a country or region does not have an established offshore market, there is a need to formulate regulations, regimes and frameworks to allow the development of grid connections. Several studies in the literature explore issues around who should design, build, own and operate the OTS and what regulations should be implemented to support this. The report by [52] gives an in-depth review of current regulatory regimes in a view to increasing the amount of offshore wind generation in the North and Irish Sea.

Similarly, the work by [102] compares two options to develop the offshore grid: developer build and TSO build. Benefits to the transmission system operator (TSO) build are suggested in [102] to be the opportunity for early planning, central coordination and the ability to consider a modular grid connection that has economies of scale advantages. In terms of the developer build option, [102] identified that costs for individual projects could be optimised. The research by [103] takes a consumer perspective to assess the value for money of third-party ownership compared to TSO ownership. The work by [103] suggests TSO ownership to be beneficial in small- and medium-scale projects. However, for more substantial projects, the work by [103] suggests that a third-party approach may be beneficial.

Medium-term decisions

In the case where an established offshore market exists, project planners will make decisions regarding the optimal design of the electrical transmission infrastructure. One major consideration is whether to use HVAC or HVDC technologies. There has been a history of interest in comparing HVAC and HVDC approaches for offshore wind connections, for example, [104] economically compares HVAC and HVDC approaches for a 100 MW offshore wind farm. The study by [104] assesses the impact of distance, component cost, converter reliability and converter losses on the decisions made. Similarly, the work by [17] investigates the economic value of VSC-HVDC connections and compares this approach to HVAC connections for a 300 MW wind farm. The study by [17] considers different cable lengths between 25 and 100 km.

Assessing projects more representative of offshore wind farms planned for post-2020, [84] compares HVAC and HVDC approaches for the connection of larger offshore wind farms. The study by [84] considers the technical and economic benefits of each option, as well as discussing how each technology option complies with industry standards. The research in [84] makes important insights on the need to carefully consider the reactive power produced by long HVAC cables, and consequently, finds that the costs associated with energy lost during transmission are larger for HVAC systems. However, [84] notes that the cost of VSCs are significant in the HVDC approach.

To allow HVAC approaches to be used at longer distances from shore, [105] investigates non-conventional AC frequency approaches and finds that a frequency of 10 to 16.7 Hz is comparable to the cost of VSC-HVDC up to 200 km. A comparison of HVAC and HVDC technologies for large ($80,000$ MW) offshore wind developments in the United States is carried out in [106] with a focus on power losses. The results of [106] shows that for a project 120 km offshore, losses in the HVDC approach is roughly 1% to 2% lower than a HVAC system.

In more recent work, [107] compares different technologies to connect two offshore wind farms: two separate HVAC links, two separate HVDC links and two separate HVDC links with an interlink between the two links. The study by [107] uses a probabilistic transmission expansion planning model and concludes that the HVDC topologies are more efficient, are becoming a cost-effective solution for large offshore wind farms, and combined with an interlink offers greater flexibility.

Another consideration in the planning of an OTS is the layout of the system which is a highly discussed topic [20, 21, 95, 18, 108, 109, 110, 111, 112]. In particular, the work by [113] investigates the design and planning of offshore transmission based on NPV assessments. Although the UK has so far preferred radial systems, the question arises of whether a coordinated or meshed network is more suitable as we move to larger projects that are further offshore.

The literature often compares radial, coordinated and meshed layouts. For example, [21] compares the economic benefit of a more coordinated transmission approach to managing increasing network capacities. The work by [112] compares radial, ring and meshed transmission topologies for connecting multiple offshore wind farms to multiple onshore connection points, using a rule-based genetic algorithm to find the best economical and technical grid solution. The approach adopted in [112] is developed into an optimisation tool and is shown to find solutions with lower investment costs.

Looking at layout options when connecting more than one wind farm, the work by [20] investigates three HVDC topologies to join 2.4 GW of power from two separate wind farms. Additionally, the study by [95] compares different HVDC configurations (radial, multi-terminal, meshed and bipole) based on their reliability and finds that bipole transmission helps to reduce the impact of cable failures. Finally, the study carried out in [111] examines the benefits of integrated projects and investigates cost-benefit sharing mechanisms between the integrated countries. The work by [111] shows that a coordinated approach is optimal and highlights that it has yet to be adopted, perhaps due to on occasion, generating countries will be at a loss.

Once the general topology has been chosen, the focus of decision making shifts to consider specific components. Project planners make many decisions, such as selecting the number, rating, and manufacturer of each component in the system. The study by [89] presents a methodology to design, under risk, the transmission system, including choosing HVAC or VSC-HVDC technologies, and the number and size of cables and transformers. The work in [89] uses a Monte Carlo simulation to evaluate each design option economically. Additionally, the work by [89] selects the optimal configuration using a criterion that incorporates the decision maker's risk tolerance through a risk tolerance parameter. The study considers energy generated by the wind farm, energy losses in the system and the capital costs of the system.

Although the main focus of the work by [114] is the array cables, the study discusses some vital design decisions that affect the OTS; they include the allocation of wind turbines to an offshore substation, the number and location of the offshore substations and the interconnection of offshore substations and onshore connection points. A decision about the design of the system must be compliant with industry standards, and accordingly, the work by [115] conducts a review of single transformer substations. The report by [115] concludes that offshore platforms greater than 90 MW with single transformers are compliant with industry standards, provided that at least two transformers are installed in the OTS.

Short-term decisions

In regards to short-term planning, decision problems arise relating to the day-to-day operations of the OTS. The work by [116] investigates the impact of uncertainties on the performance evaluation of short-term reliability management. Furthermore, as discussed in Section 2.5, a decision support tool for the routing of vessels to conduct maintenance of wind turbines is presented in [117]. Other operation and management tools have been developed by the research and development community, for example, NOWIcob [67], University of Strathclyde [66], and ECUME model [68].

The operations and maintenance of OTSs are not as prominent as offshore wind farms in the literature. However, the work of [118] reviews the operational experience of six OTSs and makes recommendations to improve performance. These suggestions centre around routine inspections, the need to focus on offshore specific requirements, contingency planning and the availability of access vessels [118].

This subsection has reviewed important policy, planning and operational decisions that are explored in the literature. From this review, we conclude that these decisions centre around a few topic areas: regulation, technology choice, electrical system layout and maintenance planning. As discussed and identified in Section 2.5, the offshore wind industry faces a significant challenge due to the many uncertainties involved. In line with Section 2.7 and Section 2.8, decision making associated with the OTS is no exception, and therefore techniques to quantify and handle these uncertainties are critical in these types of analyses. In the next subsection, we review the current methods used in the literature to handle uncertainty in energy-related problems.

2.9 Current Approaches to Handling Uncertainty in Offshore Transmission

As previously discussed, there are many uncertainties associated with offshore wind. These uncertainties are usually identified in the literature but not always addressed. In the studies that do address uncertainty, a range of techniques are applied depending on the situation at hand. Examples of some of the methods used to handle uncertainty in energy-related problems are discussed below.

The report by [119] notes that if future events are uncertain, requiring precise predictions to make strategic business decisions can be dangerous. Moreover, [119] categorises four levels of uncertainty: a clear enough future in which precise probability is sufficient, given the high amount of information available; alternative futures, where a small set of discrete scenarios can describe the future; a range of potential prospects that could be possible; and finally, true ambiguity in which it is challenging to identify possible scenarios. These varying levels of uncertainty require different techniques.

The work by [120] identifies areas of uncertainty in electric power systems and reviews techniques to handle these uncertainties. The study splits the sources of uncertainty into technical parameters (load, generation and component outages) and economic parameters (inflation, interest rate, electricity price, investment costs and operational costs). The following techniques to handle uncertainty are discussed in [120]: probabilistic approaches (Monte Carlo simulation, scenarios based analysis and point estimate method), possibilistic approaches and hybrid probabilistic-possibilistic approaches. The review by [120] concludes that novel techniques that handle uncertainty and have a lower computational time could be an area of future work.

Focusing on decision making under uncertainty in energy systems, [121] reviews state-of-the-art techniques in this field. In a similar way to [120], the work by [121] splits the uncertain input parameters into technical and economic parameters. The methods to handle uncertainty reviewed by [121] include probabilistic approaches (Monte Carlo Simulation, point estimate and scenario-based modelling), possibilistic approaches, hybrid probabilistic-possibilistic approaches (fuzzy-scenario and fuzzy Monte Carlo), information gap decision theory, interval-based analysis and robust optimisation. The study by [121] indicates that a method's suitability depends on the level of uncertainty in the decision problem.

When modelling a system, the stochastic nature of that system should be considered; however, as noted by [122], this cannot be achieved using deterministic methods and fixed values that artificially constrain the system. This problem establishes the requirement for probabilistic methods. Although some of the literature in offshore transmission analysis (and broadly speaking energy) uses a deterministic approach, there has been a shift to using probabilistic methods. Some examples include the work by [123] (discussed in more detail below), and the study by [96] which applies probabilistic reliability methods to investigate the impact of the grid connection on the overall wind farm's reliability.

When taking a probabilistic approach, the underlying assumptions of any statistical model should be validated, and where this is challenging the assumptions should be stated. The study by [124] illustrates this. In particular, [124] uses historical data and intuition about the real-world processes to validate statistical assumptions required to model the long-term reliability of demand and supply of electrical power.

Numerous reliability studies in the literature stem from the work by [125], who makes a significant contribution to power system reliability research. In particular, the need to apply probabilistic methods to assess the reliability of power systems. There have been many advancements in this field [123, 126, 127, 123], including the development of techniques to evaluate the reliability of both simple and complex systems, the economics of power system reliability, and hierarchical system analysis (generation, transmission and distribution). Notably, the work of [128] utilises Markov analysis to include component repair and spare parts into the reliability analysis. The use of Markov models in power system reliability analysis is now, and has been for some time, very popular.

A number of energy studies take a sensitivity analysis approach (where one input at a time is varied over several values), to consider the impact of uncertainty on the outputs [129, 130, 88, 93]. This approach is taken by [130], who investigates the effect of input variables on the life-cycle costs associated with a floating offshore wind farm, and finds that the number of wind turbines and distance from shore have the most significant impacts. The work of [93] also conducts a sensitivity analysis, and identifies the most critical factors that contribute to operational costs to be access and repair costs, as well as failure rates. A further example of using sensitivity analysis, but this time focused on the offshore transmission system (OTS), is presented in [129]. The work of [129] compares (through a cost-benefit analysis) three transmission grid topologies in the North Sea that connect six countries. A sensitivity analysis is carried out to assess the impact of wind speed, load and industry development on the cost-benefit analysis.

Similar to conducting a sensitivity analysis, some work in the literature handles uncertainty by considering the study in different defined scenarios. This approach is sometimes referred to as taking a scenario-based approach to handling uncertainty. The work by [92] uses this approach to investigate four operational strategies under different failure rate scenarios: fix on fail, batch repair, annual charter, and vessel purchase. The study in [92] finds that if the failure rate is low, fix on fail or batch repair are preferred, whereas if the failure rate is high, the vessel purchase strategy is optimal.

A strategy used in engineering for risk and reliability analysis is failure mode effect analysis (FMEA). The work by [131] compares FMEA to a fuzzy-FMEA for the risk assessment of offshore wind turbines. The study by [131] motivates the need for fuzzy-FMEA by pointing out that the failure data for offshore wind turbines can be missing or unreliable, and therefore, is often based on expert judgement.

Monte Carlo simulations are used to tackle a range of problems across many fields, in particular when predictions are desired. Monte Carlo simulations use repeated sampling to obtain numerical results. Markov chains (or processes for continuous-time modelling) are stochastic models used to describe a sequence of events that are Markovian (the transition probability to the next event depends only on the current state of the process). Monte Carlo Markov chain is a popular sampling method that combines Monte Carlo properties and Markov chain properties.

The work of [132] uses a Monte Carlo simulation approach to assess the profitability of wind energy investment in four regions of China, [122] uses Monte Carlo simulations to evaluate the reliability of an offshore wind farm, and the work of [90] uses Monte Carlo simulations for levelised cost of energy (LCoE) estimation. Markov chains are implemented by [133], who aims to automate the maintenance planning of offshore wind turbines. Specifically, [133] uses a semi-Markov decision process to allow a failure rate that varies with time.

Additionally, a Monte Carlo based reliability analysis is presented in [20]. Specifically, the work by [20] explores three HVDC topology options to connect 2.4 GW from two wind farms at Dogger Bank (situated in the North Sea), to the onshore network. Repairs can only occur when site conditions allow, which depends on wind speed (which affects energy not supplied) and wave height (which affects repair times). Data for mean time to fail, fixed delay and required time to repair for HVDC network components are presented in [20] as single values. This data is used in the Monte Carlo simulation. Assigning single values to inputs may be challenging given limited data.

Bayesian methods are also implemented in the literature to handle uncertainty in offshore wind applications. Bayesian methods are used by [134] to plan the operation and maintenance of offshore wind turbines, by [135] to consider the uncertainty of extreme natural hazards on offshore wind structures, and by [136] when conducting a risk assessment of decommissioning options. The work by [66] also uses Bayesian techniques, namely Bayesian belief networks, to aid with decision making about operational strategies for offshore wind turbines. One advantage of this approach that is discussed by [66] is the ability to take dynamic decisions by updating beliefs throughout the lifetime of the project as more information is gained.

Additionally, information gap decision theory is used to handle uncertainty in the literature. The study by [137] reviews the research that uses this approach for uncertainty modelling in energy and power systems. Information gap decision theory uses functions (termed robustness and opportunity functions) to assess the negative and positive aspects of the uncertainty involved [137]. The final approach to uncertainty handling that we discuss is called interval analysis. In particular, this is utilised in the literature for reliability and availability applications. The work of [138, 139] conducts reliability analysis by using intervals to represent uncertain inputs. Also, the work of [140] demonstrates the use of Markov chains and interval analysis techniques to study the availability of multi-state systems.

In this subsection, we explored different techniques implemented in the literature to handle uncertainties in energy-related problems. We find that various methods are suitable for a given level of uncertainty in a specific problem. Therefore, it is vital to implement an appropriate approach for each given problem. Furthermore, from the techniques reviewed, there is a need for methods that can handle severe uncertainty in energy-related problems.

2.10 Conclusions

In this chapter, we defined what is meant by an offshore transmission system (OTS) and reviewed the components that make up this system. We detail the state-of-the-art technologies for both HVAC and HVDC connections. We move on to review the ownership structures of the OTS implemented by the leading nations in offshore wind. We observe that the different ownership structures fall into three broad categories: third-party entity ownership, offshore wind farm ownership and onshore transmission system operator (TSO) ownership.

As the OTS is part of the offshore wind power plant (OWPP), we investigated the challenges faced by the offshore wind industry. From reviewing the literature, we identified that cost reduction is one of the most significant challenges. We next reviewed the obstacles specific to offshore power transmission. We established that as offshore wind projects grow in capacity and move further offshore, the role of the OTS becomes even more crucial. This advancement brings additional challenges, and we discovered that the main difficulties centre around reliability, cost and uncertainty.

Furthermore, we see that a common theme amongst the literature reviewed is that there is a considerable variation in the available data. This challenge leads to uncertainty when economically evaluating projects, and this uncertainty can have substantial impacts on operational projects. Despite the challenges, many policy, planning and operational decisions will be made to support the development and installation of the electrical transmission infrastructure required to connect future offshore wind farms. Therefore, we reviewed the decisions taken surrounding these assets to gain an understanding of the relevant decision problems. Finally, given the identified challenge of uncertainty, we reviewed current methods to handle uncertainty that have been applied to energy problems.

We concluded from the literature reviewed that there exists the need for research into decision making under severe uncertainty for offshore transmission applications. This research attention is on account of the industry challenge of uncertainty, the growing importance of the OTS, the need to make decisions to plan future OTSs, and the limited amount of techniques applied to energy-related problems that adequately handle severe uncertainty. Therefore, there is a need to conduct research that investigates suitable methods that can be applied to decision problems under severe uncertainty, explore applying these techniques to decisions made in offshore power transmission, and assess the benefits and drawbacks of using these techniques.

Chapter 3

Current Status: Data Collection

3.1 Introduction

In this chapter, we collect and present data associated with offshore transmission systems (OTSs) from a variety of sources, including academic papers and industrial reports. In Chapter 2, we identified that there is a limited amount of relevant data about offshore wind transmission systems. Although we may not have enough information to perform economic evaluations of future projects adequately, there does exist some data. This data may be for older projects with previous technologies. Nonetheless, this data can be useful to identify industry trends and, as a starting point, is better than no data. Due to access to data, the majority of the data presented in this chapter is for UK projects. The aims of this chapter are:

1. To collate operational and costing data associated with OTSs.
2. From this data, gain a greater understanding of costs, operational project and component trends, operational behaviour, component availability and future projects.

This chapter begins by presenting general characteristics of operational UK projects: project start date, capacity, asset summary, cable details, availability values, project costs and revenue streams. The chapter then goes on to present individual component costs in more detail. This costing data is followed by component failure and repair data. Many lessons can be learnt from power transmission in offshore interconnectors, and therefore we include outage data from an interconnector. Analysis in offshore wind transmission may require data about the amount of power transmitted through the system, which depends on wind speed. Consequently, we discuss a tool that allows wind speed to be used in this type of assessment. Finally, the chapter gathers information about future technologies for offshore wind transmission systems.

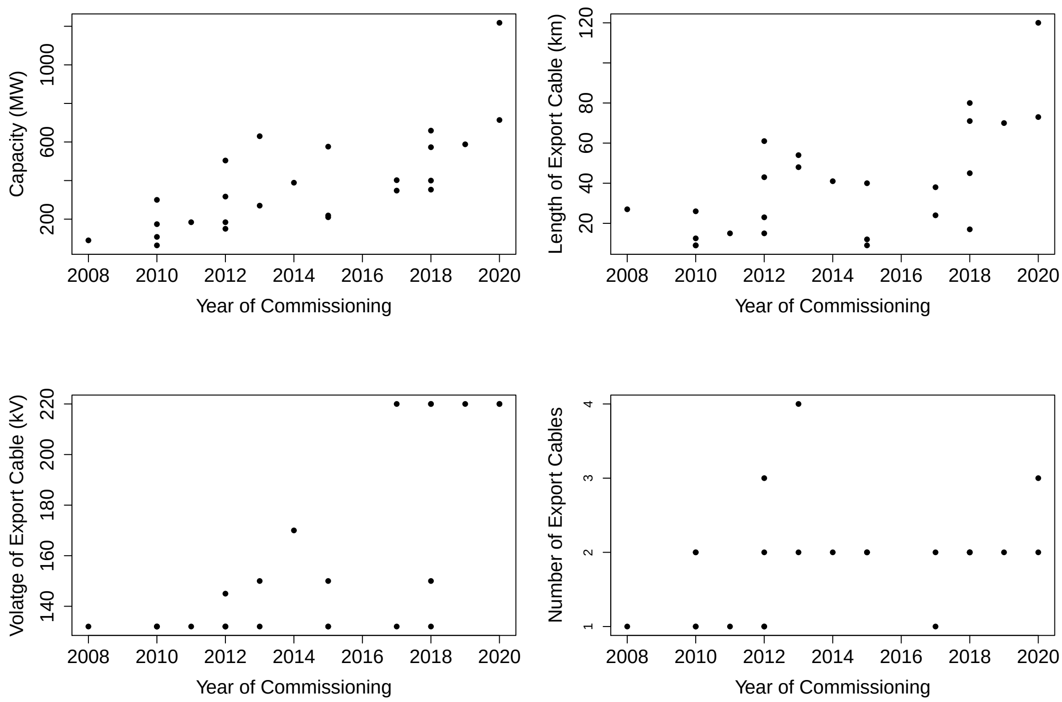


Figure 3.1: Characteristics (capacity, export cable length, export cable voltage and number of export cables) over time for projects in OFTO tender rounds (TR) 1 to 6.

3.2 UK Offshore Wind Transmission Project Details

3.2.1 Project Characteristics

Although offshore wind is still in its infancy, there are some trends we can observe from current and planned projects. Characteristics of operational and planned UK offshore wind projects, including project capacity, export cable length, export cable voltage and the number of export cables have been collected in Table 3.1 and graphically presented in Fig. 3.1. The information has been gathered from an individual UK project's preliminary information memorandum [30, 31]. These documents are discussed in more detail below. Fig. 3.1 shows that over time projects have increased in capacity, and more recent projects have been installed further offshore. Furthermore, more recent projects have installed cables with a higher nominal voltage of 220 kV. The final plot in Fig. 3.1 suggests that there is no overall trend in the number of cables installed at each project against time.

3.2.2 Component Breakdown

For each offshore transmission project, the Office of Gas and Electricity Markets (Ofgem) prepares a Preliminary Information Memorandum (PIM) document [30]. Ofgem are the regulator for gas and electricity markets in Great Britain. These documents, [30],

Name	TR	Year	Capacity (MW)	Length (km)	Voltage (kV)	Export Cable
Barrow	1	2008	90	27	132	1
Greater Gabbard	1	2012	504	61	132	3
Gunfleet Sands 1	1	2010	108	9	132	1
Gunfleet Sands 2	1	2010	64	9	132	1
Ormonde	1	2012	150	43	132	1
Robin Rigg	1	2010	174	12.5	132	2
Thanet	1	2010	300	26	132	2
Sheringham Shoal	1	2012	317	23	145	2
Walney 1	1	2011	184	15	132	1
Walney 2	1	2012	184	15	132	1
Lincs	2	2013	270	48	132	2
London Array	2	2013	630	54	150	4
Gywnt Y Mor	2	2015	576	40	132	2
West of Duddon Sands	2	2014	389	41	170	2
Westermost Rough	3	2015	210	12	150	2
Humber Gateway	3	2015	219	9	132	2
Burbo Bank Extension	4	2017	348	24	220	1
Dudgeon	5	2017	402	38	132	2
Galloper	5	2018	353	45	132	2
RaceBank	5	2018	573	71	220	2
Rampion	5	2018	400	17	150	2
Walney Extension	5	2018	659	80	220	2
Beatrice	6	2019	588	70	220	2
Hornsea 1	6	2020	1218	120	220	3
East Anglia 1	6	2020	714	73	220	2

Table 3.1: UK project details: project name, TR (tender round), year (project operational date), project capacity, length (of the export cable), nominal voltage (of the export cable) and the number of export cables in the project. Data from [30, 31].

Name	Capacity (MW)	Number of Cables Offshore	Number of Cables Onshore	Number of Transformers Offshore	Number of Transformers Onshore
Westermostrough	210	1	1	2	2
Humber Gateway	219	2	2	2	2
Burbo Bank	258	1	1	2	2
Galloper	336	2	2	2	2
West Of Duddon Sands	382	2	2	2	2
Dudgeon	400	2	2	2	2
Rampion	400	2	2	2	2
Race Bank	574	2	2	4	2
London Array	630	4	4	4	4
Walney Extension	659	2	2	4	2
Greater Gabbard	504	3	3	5	3
Gwynt Y Mor	576	4	4	4	2
Lincs	270	2	2	2	2
Sheringham Shoal	317	2	2	4	2
Thanet	300	2	2	2	2

Table 3.2: The number of cables (onshore and offshore) and transformers (onshore and offshore) in UK projects. Data from [30].

include details of each project, such as a simplified single line diagram, breakdown of transmission assets and characteristics of the components. Using this information, a summary of the components for the larger UK OTSs is presented in the following tables and figures. Table 3.2 shows the number of cables (onshore and offshore) and transformers (onshore and offshore). Table 3.3 goes on to detail the ratings of the transformers, and Tables 3.4 and 3.5 present details of the offshore substation platforms installed at operational projects. Finally, Fig. 3.2 shows project capacity, export cable length, export cable voltage and the number of export cables.

3.2.3 Offshore Wind Transmission Cable

This section analyses export cable data and makes summary conclusions about current export cable trends. In particular, cable length, number of export cables, cable voltage, and failure rates are explored. Information from National Grid performance reports [141], including outage description and duration, for the export cable were analysed to provide

Project	Capacity	Offshore Transformers			Onshore Transformers		
	(MW)	Quantity	Rating (kV)	MVA	Quantity	Rating (kV)	MVA
Westermost Rough	210	2	150/34	140	2	275/150	
Humber Gateway	219	2		140	2	275/132	160
Burbo Bank extension	259	2	220/34		2	400/200/15.5	
Lincs	270	2	132/33	240	2	132/400	300
Thanet	300	2	132/33/33	180			
Sheringham Shoal	317	4	132/33				
Galloper	353	2	132/33/33				
West of Duddon Sands	389	2	155/34	240	2	400/155	240
Rampion	400	2	150/33	240	2	400/150/33	
Dudgeon	402	2	132/33	200	2	400/132/33	200
Greater Gabbard	504	5	132/33				
Race Bank	573	4	200/34	200	2	400/220	360
Gwynt Y Mor	576	4	132/33		2	400/132/13.9	
Walney Extension	659	4	220/36	200	2	400/220	
East Anglia ONE	714						
London Array	630	4	150/33	180	4	400/150	180

Table 3.3: Details of offshore and onshore transformers including quantity, rating and MVA. Data from [30].

Project	Project Capacity (MW)	Number of Platforms
Westermost Rough	210	1
Humber Gateway	219	1
Burbo Bank extension	259	1
Lincs	270	1
Thanet	300	1
Sheringham Shoal	317	1
Galloper	336	1
West of Duddon Sands	389	1
Rampion	400	1
Dudgeon	402	1
Greater Gabbard	504	2
Race Bank	573	2
Gwynt Y Mor	576	2
Walney Extension	659	2
East Anglia ONE	714	1
Hornsea 1	1218	3
London Array	630	2

Table 3.4: The capacity of each project and the number of offshore platforms installed at each project. Data from [30].

Project	Capacity (MW)	Number of Platforms	Dimensions Height (m)	Width (m)	Length (m)
Westermost Rough	210	1	15	30	15
Burbo Bank extension	259	1	20	30	40
Race Bank	573	2	20	30	38
Walney Extension	659	2	20	30	40

Table 3.5: Further details about some offshore platforms such as project capacity, number of platforms and dimensions. This information is shown for selected projects depending on the availability of this data in [30].

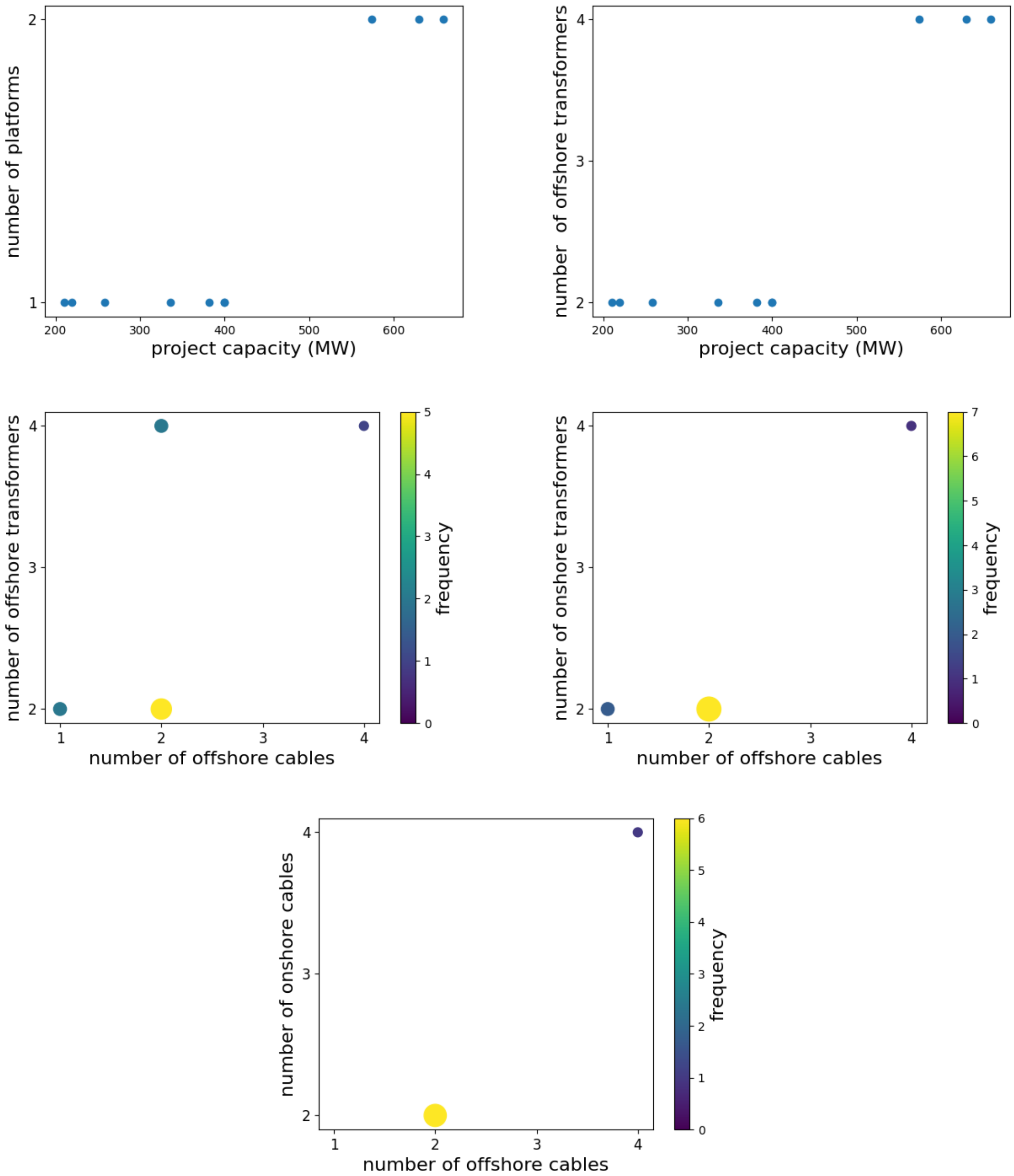


Figure 3.2: Characteristics (capacity, export cable length, export cable voltage and number of export cables) over time for projects OFTO tender rounds (TR) 1 to 6. Data from [30].

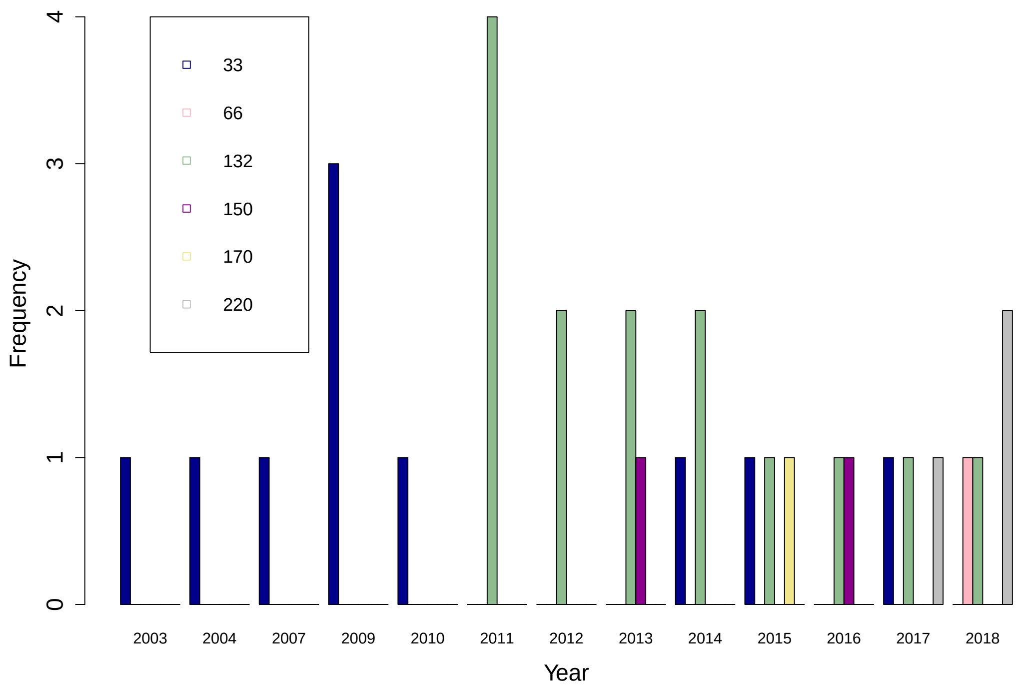


Figure 3.3: Number of cables installed each year split by voltage. Data from [141] and [30].

the summary information below. National Grid in the UK transports energy from producers to local network operators. In the following analysis, we use the National Grid performance reports that give data from 2011 to 2018. This data provides information on twenty-one OTSs that have been operational between one and seven years.

In this section, we aim to find overall trends for export cables and ultimately ways to quantify the failure rate of the export cable. In Chapter 2, we identified that current industry practice uses the failure rate given in [142] of 0.000705 fails/year/km. This value has been acknowledged in the literature, such as [82], to be low compared to operational experience.

We begin by presenting a summary of operational subsea export cables. Figs. 3.3 and 3.4 show that the majority of installed cables are 132 kV. The amount of 220 kV cables installed in 2018 suggests a potential shift towards higher voltage rating cables. This advancement is in line with projects that are currently planned and under construction.

From here, the analysis only considers twenty-four 132 kV export cables that are operational in UK waters. This subset has been selected for the following reasons:

1. Voltage ratings less than this are not planned to be installed in the future as project capacity grows.
2. Export cables with a voltage level of 220 kV have been omitted as they are new

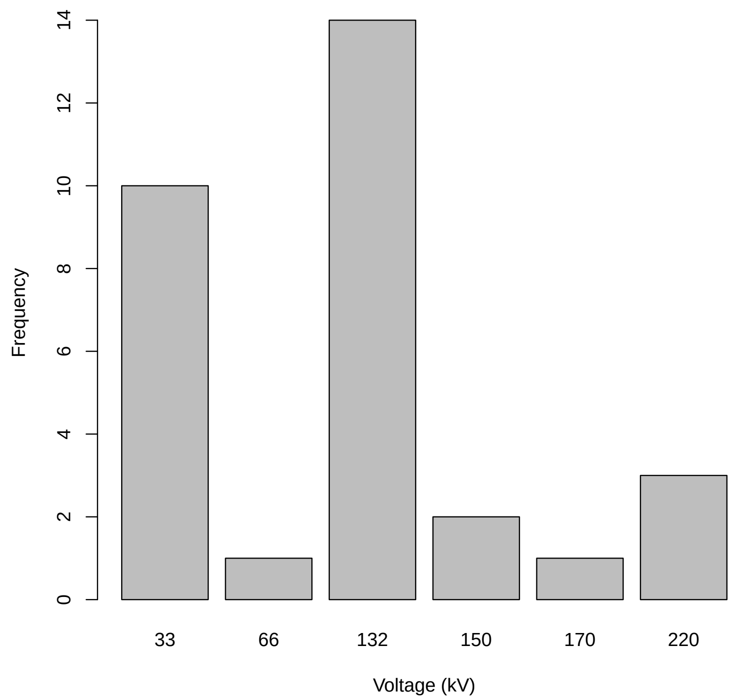


Figure 3.4: Number of projects installed at each export cable voltage rating. Data from [141] and [30].

projects and consequently, the National Grid transmission performance reports [141] do not (at the time of writing) have sufficient operational data for them.

3. Export cables at Dudgeon and Galloper have also been omitted as they too are new projects (at the time of writing). Therefore, National Grid performance reports [141] do not contain sufficient operational data for these projects.

For the twenty-four 132 kV export cables considered, we explore the number of years each export cable have been operational for (see Fig. 3.5), the number of export cables installed at each project (see Fig. 3.6) and the length of cable installed (see Fig. 3.7). Fig. 3.5 shows that so far, between two and four 132 kV export cables are installed each year. As shown by Fig. 3.6, the majority of operational wind farms have one or two export cables connected radially. For the data considered, export cables range between two and seven years old. Fig. 3.7 suggests that the majority of installed export cables, considered in this analysis, are between forty and fifty kilometres long.

We now investigate available data [141] for the experiences of cable failures. We look at the number of cable failures in each calendar year (see Fig. 3.8) and the number of cable failures in each year of operation for each cable (see Fig. 3.9). There is very little to conclude from Fig. 3.8, other than that 2015 was a particularly bad year. Fig. 3.9 shows

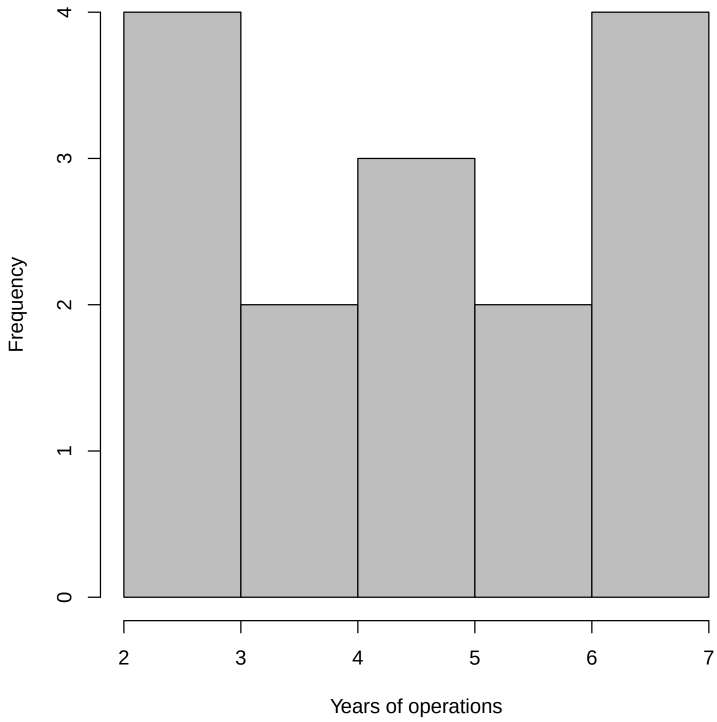


Figure 3.5: Histogram of operational years for each export cable. Data from [141].

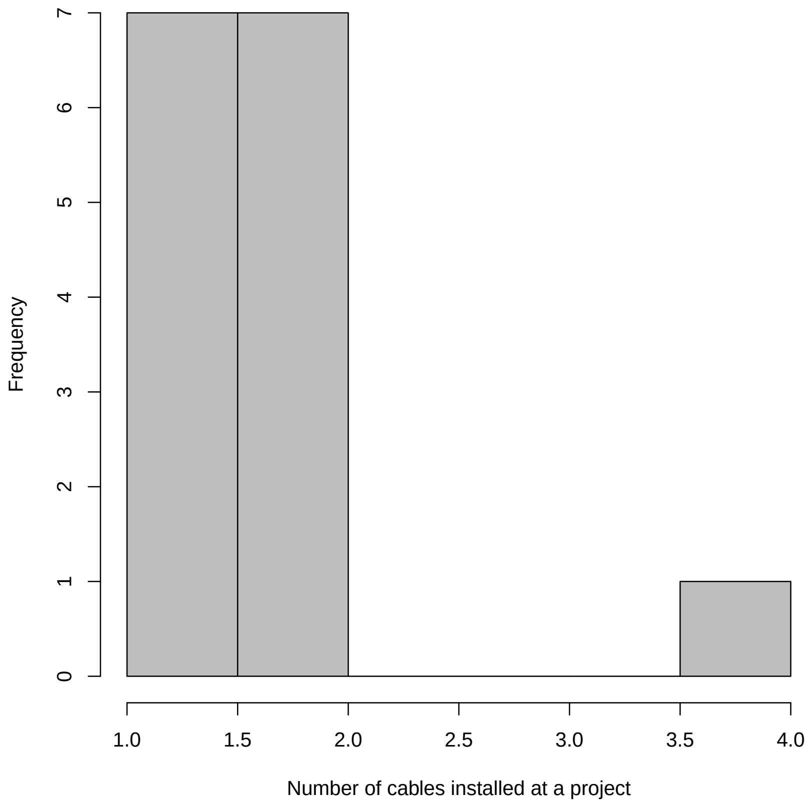


Figure 3.6: Histogram of the number of subsea export cables at each wind farm. Data from [141] and [30].

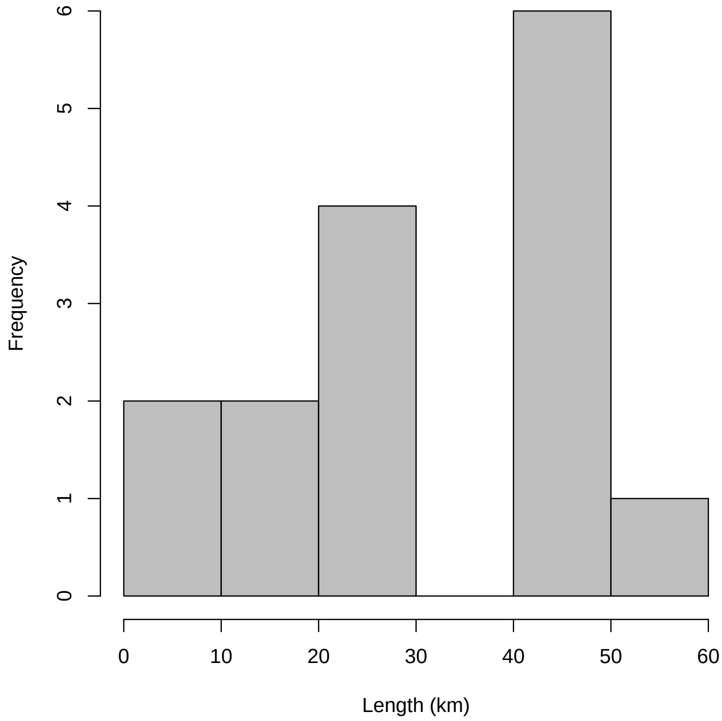


Figure 3.7: Histogram of subsea export cable length. Data from [141] and [30].

the number of failures in each year of operation (year one represents how many cables failed in their first year of operation) and suggests that failures in the first and second year of service are more common than in later years. One leading cause of cable failures is thought to be poor cable installation [83]. Fig. 3.9 shows that the latter years only have one or two cable failures a year. This low occurrence could be influenced by there being fewer operational cables that are six years old in the data set.

Next, we look at the operational data surrounding cable failure rates. The failure rate of offshore subsea cables is often quoted as the number of failures per year per kilometre. A failure rate with these units implies that longer export cables experience a higher number of failures per year. As used in the literature, including by [83], the observed failure rate of an operational cable could be evaluated by Eq. (3.1).

$$\text{failure rate} = \text{number of failures observed} \,/\, \text{operational years} \,/\, \text{export cable length} \tag{3.1}$$

Using data from [141], Fig. 3.10 shows the number of failures per year against cable length for the twenty-four export cables analysed. Similarly, Fig. 3.11 shows the number of failures per year per kilometre against cable length for the twenty-four export cables. Fig. 3.12 shows a histogram of the observed cable failure rates evaluated using Eq. (3.1).

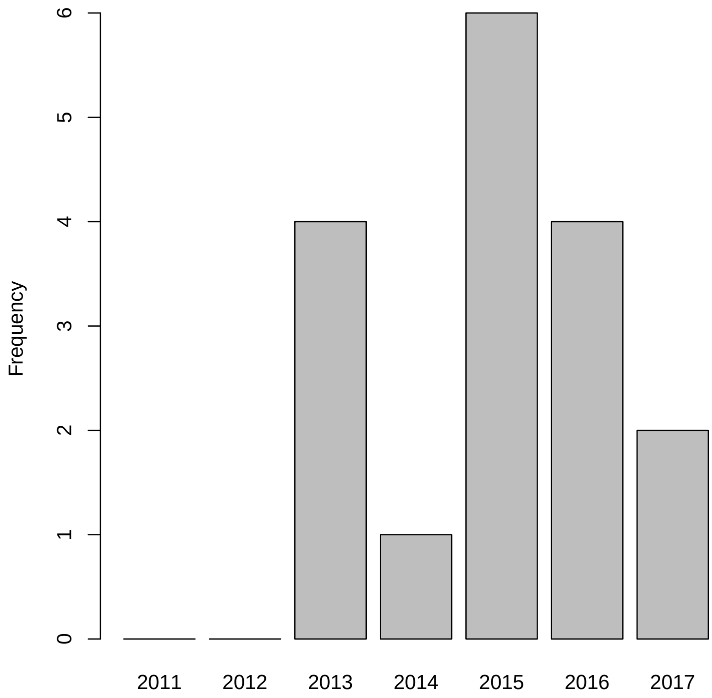


Figure 3.8: Number of failure in each calendar year. Data from [141].

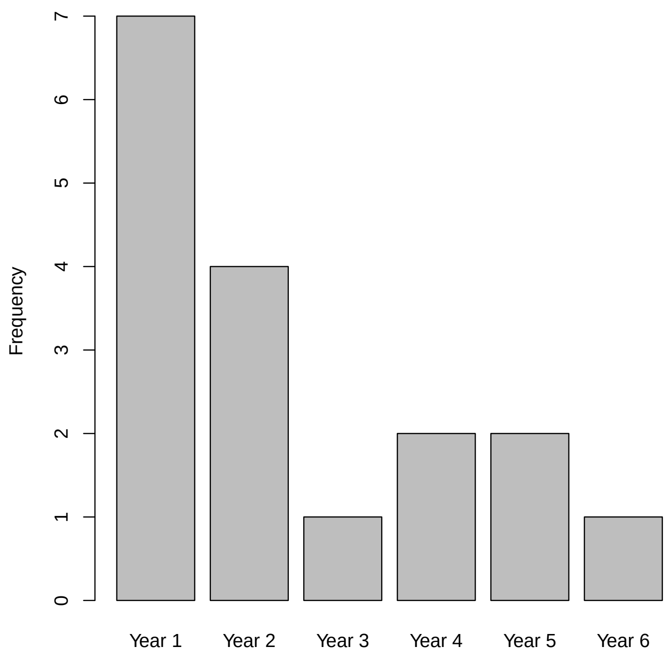


Figure 3.9: Number of failures in each year of operation for each cable. Using data from [141].

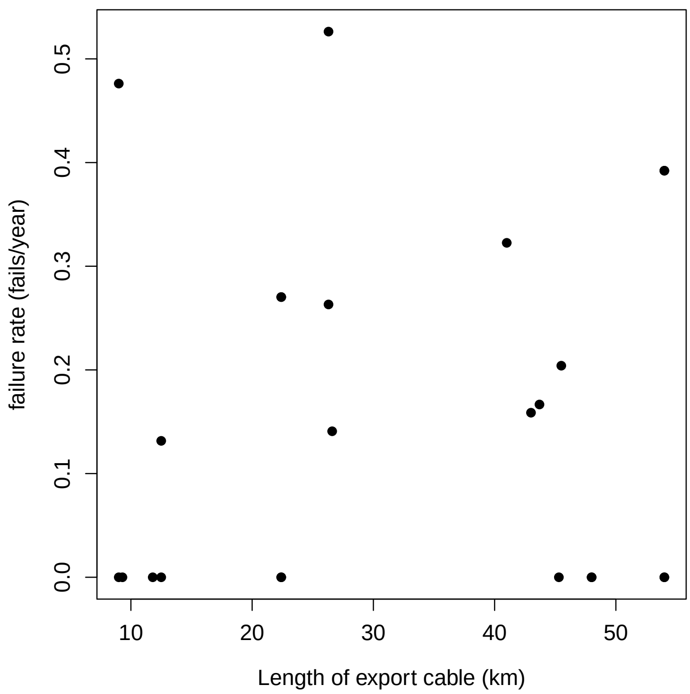


Figure 3.10: Number of failures per year against the length of the cable for the twenty-four export cables. Using data from [141].

From Fig. 3.12 we see that a lot of the mass lies between 0 and 0.01 fails per year. This low failure rate is influenced by ten of the twenty-four export cables that are yet to fail. As it may be useful to look at how the failure rate changes over time, Fig. 3.13 shows the failure rate for each project in each of its operational years.

3.2.4 Offshore Wind Transmission System Availability

Next, we study the availability of operational offshore transmission projects. National Grid reports the availability of UK offshore transmission systems (OTSs) in performance reports [141]. In this section, this data is visualised. Fig. 3.14 shows the monthly availability for seventeen UK OTSs between 2011 and 2019. Fig. 3.15 shows the yearly availability of these same wind farms, and Fig. 3.16 shows the annual availability indexed by the year of operation.

The data shown in Appendix A.1 provides more detailed information on the cable outages experienced by UK offshore wind cable systems. This information includes the date the fault occurred, the project involved, a brief description of the fault, and the downtime caused by the fault. This data is from [141].

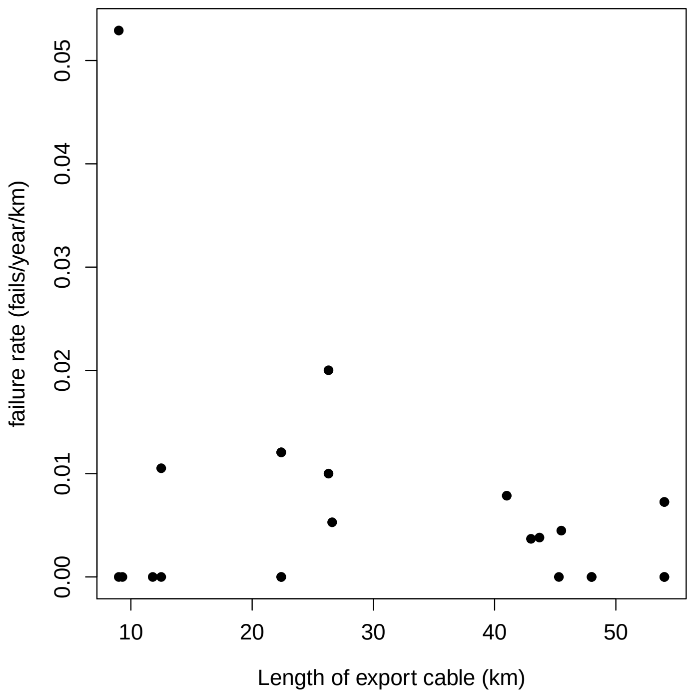


Figure 3.11: Number of failures per year per kilometre against the length of the cable for the twenty-four export cables. Using data from [141].

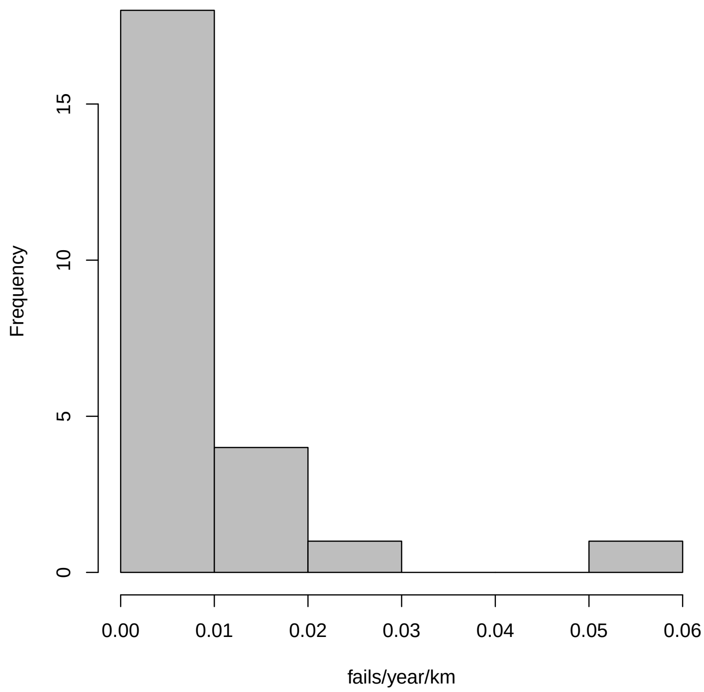


Figure 3.12: Histogram of observed failure rates for each export cable. Using data from [141].

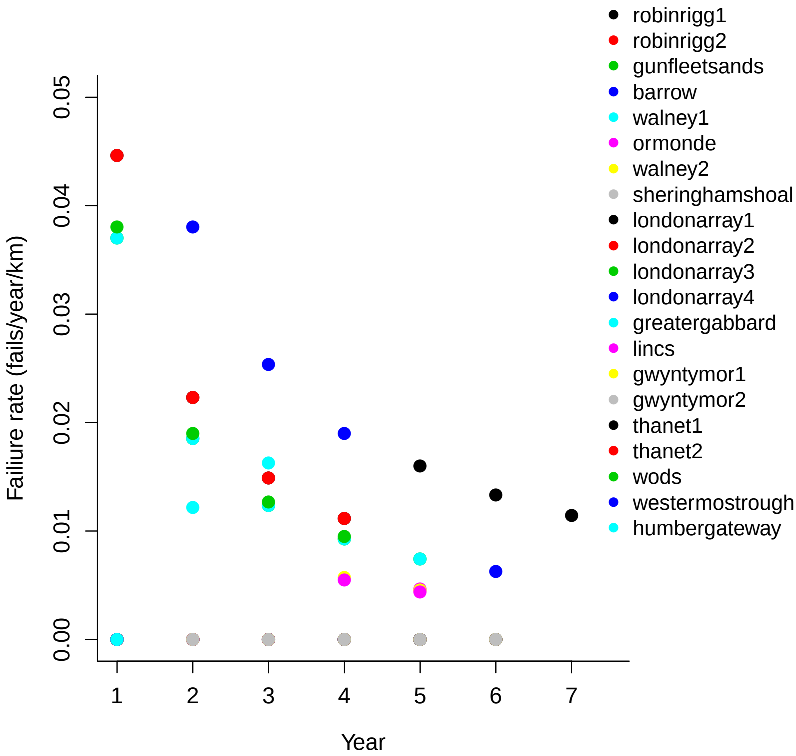


Figure 3.13: The failure rate for each project in each operational year. Using data from [141].

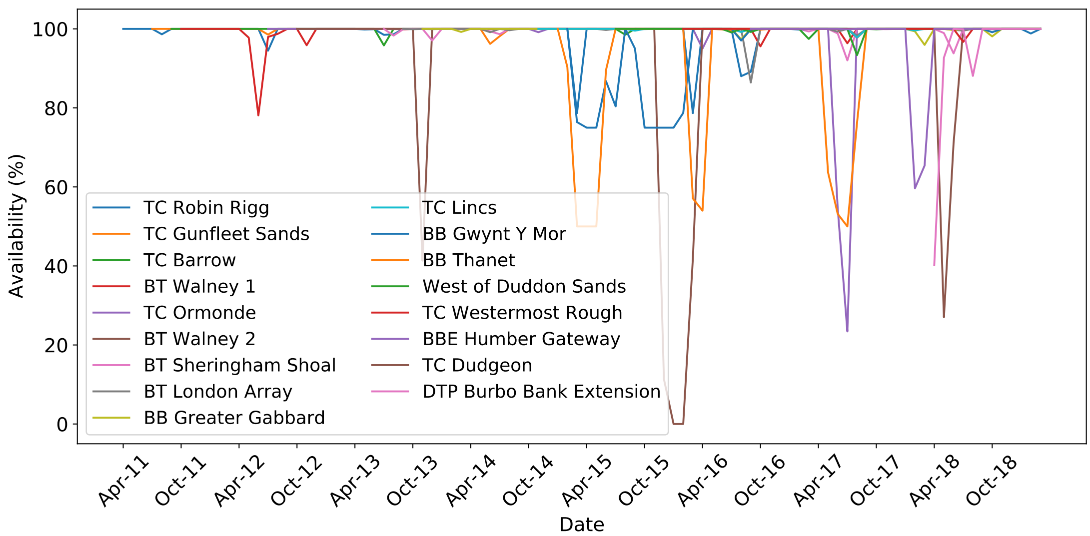


Figure 3.14: Monthly availability for seventeen UK offshore transmission systems (OTSs) between 2011 and 2019.

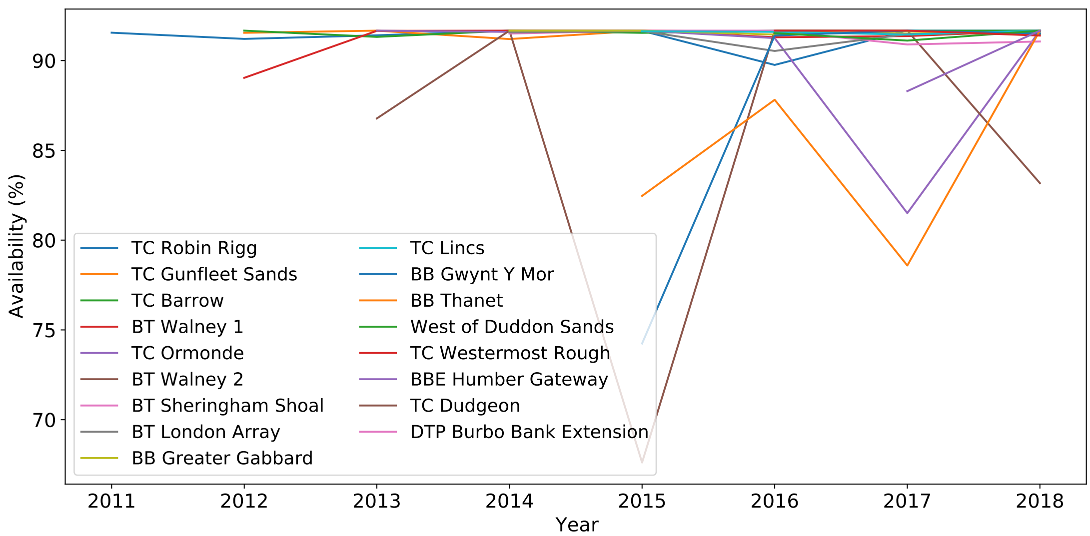


Figure 3.15: Yearly availability for seventeen UK offshore transmission systems (OTSs) between 2011 and 2019.

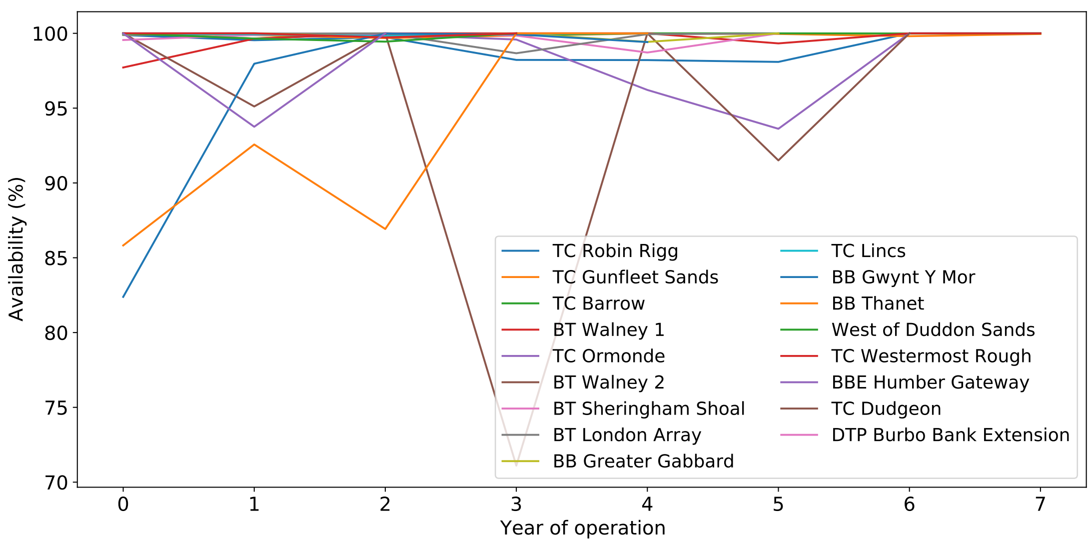


Figure 3.16: Yearly availability for seventeen UK offshore transmission systems (OTSs) between 2011 and 2019 indexed by their year of operation.

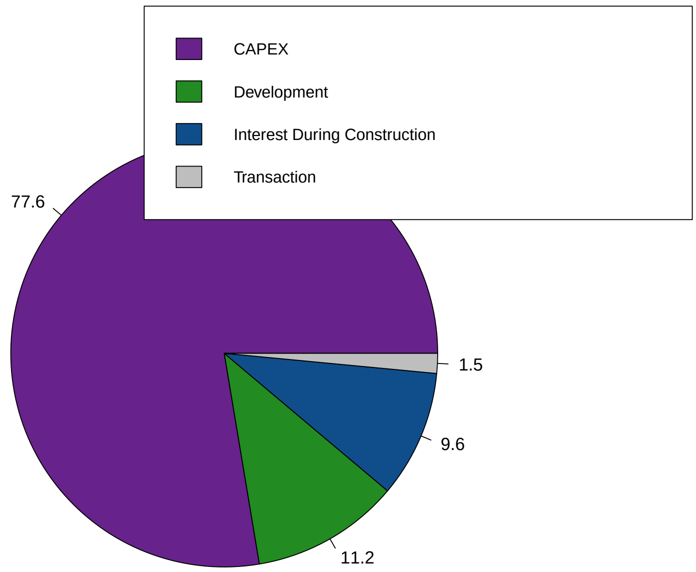


Figure 3.17: Breakdown of the contributions to the final transfer value for the UK projects in Table 3.7. Data from [32].

3.2.5 Costings

The capital cost of an OTS is essential when economically evaluating projects. As discussed in Section 2.4, in the UK, the OFTO pays the developer for the transfer of the offshore transmission assets. The amount the OFTO pays for the assets is called the final transfer value (FTV). During the competitive tender process, a cost assessment is carried out to determine the transfer value of the assets. The developer provides Ofgem with figures and estimates of their costs and Ofgem regulates these [51].

Using data from Ofgem cost assessments [32], Table 3.6 shows the initial transfer value (ITV), final transfer value (FTV) and the difference between these two values for some operational UK projects. The initial transfer value is published in the early stages of project development, and the final transfer value is towards the latter stages. Table 3.7 shows a breakdown of FTV into the sum of CAPEX, development costs, interest during construction (IDC) and transaction costs. Using data from [143, 144, 145], Table 3.7 also shows the base revenue for most of the projects. The base revenue is determined in the OFTO licence [49]. Finally, Fig. 3.17 shows the breakdown of the FTV for all the projects in Table 3.7 combined. From Fig. 3.17 we can deduce that CAPEX is the greatest contribution to the FTV and on average, for the projects considered, it contributes 77.6%.

3.2.6 Offshore Transmission Owner (OFTO) Revenue

For older projects, Ofgem produced OFTO revenue reports [143, 144, 145]. These reports detailed a project's base revenue and each year: the tender revenue stream, the

Wind Farm Name	ITV		FTV		FTV - ITV
	(£million)	Date	(£million)	Date	(£million)
Robin Rigg	58.7	07/2009	65.5	11/2010	6.8
Gunfleet Sands	46.4	07/2009	49.5	11/2010	3.1
Barrow	36.5	07/2009	33.6	07/2011	-2.9
Walney 1	99.4	07/2009	105.4	07/2011	6
Ormonde	87	07/2009	103.9	03/2012	16.9
Walney 2	104.4	07/2009	109.8	07/2012	5.4
Sheringham Shoal	186.7	07/2009	193.1	02/2013	6.4
London Array	475.7	11/2010	458.9	09/2013	-16.8
Greater Gabbard	343.7	07/2009	317.1	04/2013	-26.6
Lincs	310.5	11/2010	307.7	12/2013	-2.8
Thanet	189	07/2009	163.5	10/2013	-25.5
Gwynt Y Mor	305.7	11/2010	351.9	11/2014	46.2
West of Duddon Sands	311	12/2012	268.9	03/2015	-42.1

Table 3.6: Initial transfer value (ITV), final transfer value (FTV) and the difference between the two value for UK projects. The table also shows the dates (in month/year format) for both initial transfer value and final transfer value. Data from [32].

Wind Farm	CAPEX	Development	IDC	Transaction	FTV	B
	(£million)				(£million)	
Robin Rigg	49.5	4.4	10.9	0.7	65.5	6.499
Gunfleet Sands	37.9	6.1	4.2	1.3	49.5	5.983
Barrow	25.7	3.5	3	1.4	33.6	4.819
Walney 1	87.7	7.9	8.1	1.7	105.4	10.966
Ormonde	80.4	13.9	8.6	1	103.9	10.603
Walney 2	87.7	8.3	6.2	1.6	109.8	11.815
Sheringham Shoal	159.3	27.3	4.5	2	193.1	17.948
London Array	343.9	48.8	66.5	2.4	458.9	35.046
Greater Gabbard	241.4	34.3	39.3	2.1	317.1	24.761
Lincs	234.4	35.6	35	2.7	307.7	25.235
Thanet	120.3	26.7	12.7	3.8	163.5	16.548
Gwynt y Mor	252.7	51.5	45.6	2.1	351.9	24.194
West of Duddon Sands	215.1	31	20.7	2.1	268.9	19.778
Humber Gateway	128	14.3	14.8	3.2	160.3	

Table 3.7: Breakdown of final transfer value (FTV) into capital expenditure (CAPEX), development costs, interest during construction (IDC) for UK projects [32, 145]. The table also shows the base revenue (B) for these UK projects. Empty cells in the table are due to missing data in [32, 145].

Capacity (MW)	Cost (£million)	Reference
200	36	[37]
400	50	[37]
400	48	[37]
600	74	[37]
200	36	[36]
400	44	[36]
400	45	[36]
700	81	[36]
700	70	[36]
1000	134	[36]
500	44	[147]
500	46	[147]
1000	127	[148]
1400	156.5	[148]

Table 3.8: Offshore platform capital costs presented in the literature for different platform capabilities.

market rate revenue adjustment, the performance availability and the annual availability.

3.3 Component Costs

In this section, we detail the capital costs associated with the main assets that constitute an OTS. We review several sources for the costs related to the offshore platform. For the rest of the components, we examine cost information presented in [33, 36, 37, 146]. This data will be used throughout the thesis to evaluate the capital expenditure (CAPEX) of offshore transmission systems (OTSs).

We collected data for the costs of an offshore platform from National Grid [36, 37], European Network of Transmission System Operators for Electricity (ENTSO-E) [147], and NorthSeaGrid [148]. This information is shown in Table 3.8.

Next, we seek to answer two questions: How can we use the information in Table 3.8 to inform the costs of future offshore platforms? How can we assign values to larger, perhaps than we have seen in previous projects, offshore platforms? These types of predictions may be required when conducting economic evaluations of future projects. Fig. 3.18 shows the costs of offshore platforms in Table 3.8 against the capacity that the offshore platform is designed to support. Fig. 3.18 indicates that the data could be linear and therefore, we

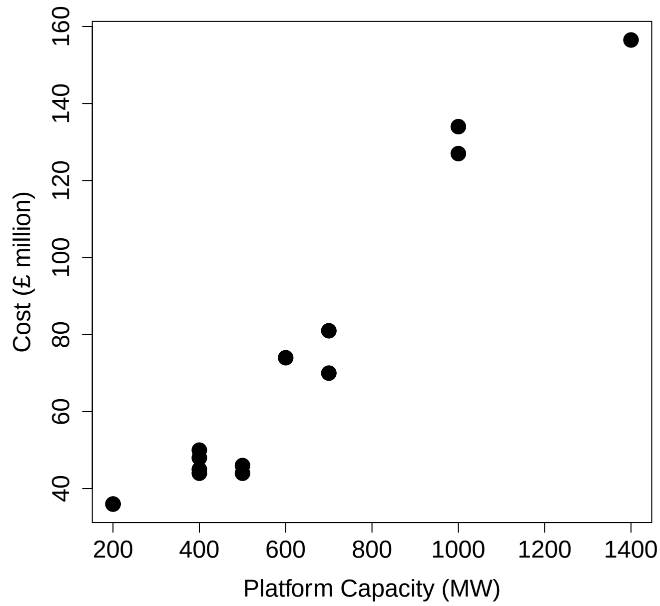


Figure 3.18: Cost of offshore platforms against platform capacity. Data from the literature given in Table 3.8.

fitted a linear model of the form given by Eq. (3.2).

$$\text{offshore platform cost} = \beta_1 \times \text{capacity} + \beta_2 + \epsilon \tag{3.2}$$

Here, $\beta_1 = 0.1$, $\beta_2 = 2$, and ϵ denotes the residual error, which is normally distributed with mean zero and standard deviation 10. The fitted linear model has an R^2 value of 0.9376. Fig. 3.19 and Fig. 3.20 show that the residuals display little pattern and therefore homoscedasticity of the residuals can be assumed. Normality of the residuals can be checked by the quantile-quantile plot shown in Fig. 3.21. Finally, Fig. 3.22 shows Fig. 3.18 with the linear model line added.

For the rest of the components, National Grid presents a comprehensive collection of data related to the costs of components in the OTS. This information was published in the appendix of the National Grid Electricity Ten Year Statement (ETYS) in years 2013, 2014 and 2015 [33, 36, 37]. Each of [33, 36, 37] contain more data than discussed below; however, we only review the data for components we consider in the analysis of this thesis. From the 2013 report [33], we find data for AC platforms (see Table E.23 in [33]) and the installation costs of subsea cables (see Table E.21 in [33]).

From the 2014 edition [36], we find costs of onshore transformers (see Table E.23.3 in [36]), onshore HVAC gas insulated switchgear (GIS) bay (see Table E.23.7 in [36]), onshore shunt reactors (see Table E.23.8 in [36]), onshore shunt capacitor banks (see Table E.23.9 in [36]), onshore static var compensators (see Table E.23.10 in [36]), offshore transformers

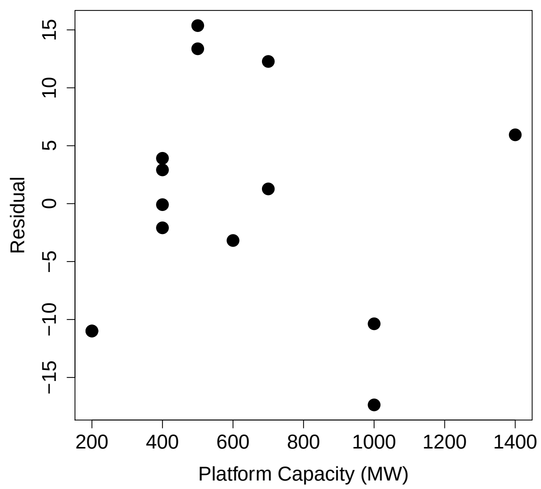


Figure 3.19: Residuals plotted against the capacity of offshore platforms.

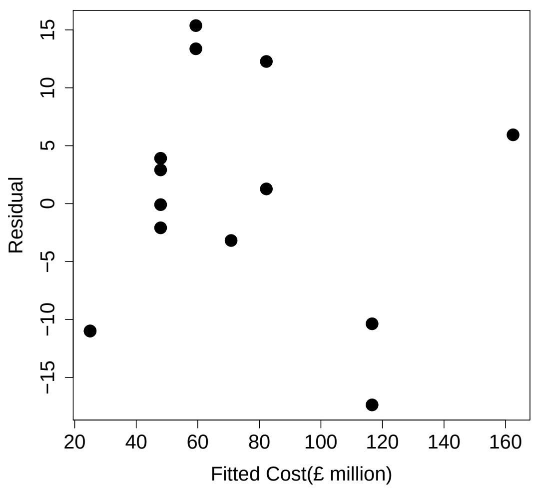


Figure 3.20: Residuals plotted against the fitted cost.

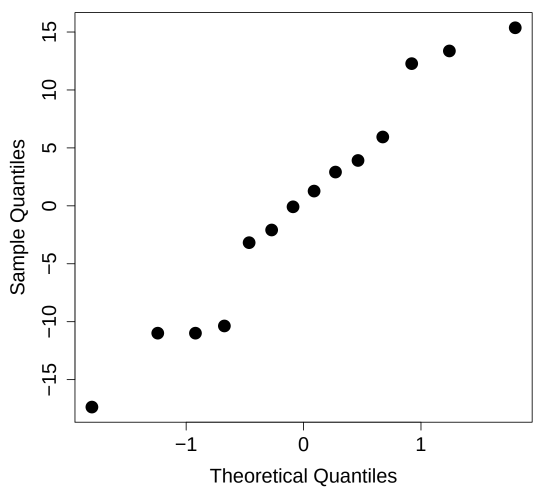


Figure 3.21: Quantile-quantile plot for the residuals.

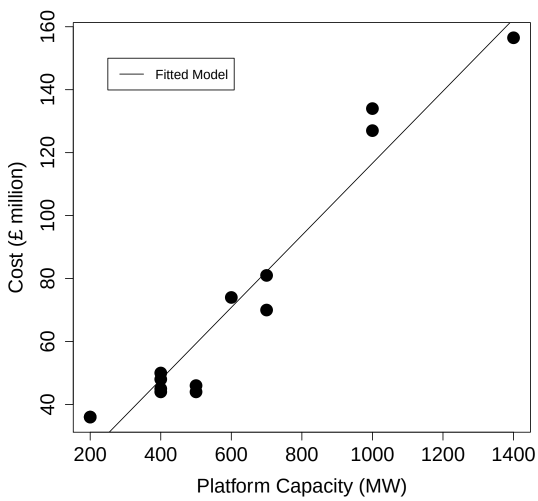


Figure 3.22: Fig. 3.18 with the fitted linear model displayed.

(see Table E.23.14 in [36]), offshore HVAC GISs (see Table E.23.15 in [36]), onshore HVAC cables (see Table E.23.23 in [36]) and installation costs for onshore HVAC cables (see Table E.23.27 in [36]). Finally, [36, 37] gives costs for HVAC offshore cables.

Additionally, the report by [146] carries out a cost assessment, to support Ofgem, of the OTS installed to connect the wind farm at West of Duddon Sands. The work by [146] also verifies whether the system is cost-efficient. The report by [146] includes a summary of the key costs, offshore substation costs, land cable supply costs, onshore substation civil works costs and onshore substation electrical equipment costs.

3.4 Component Failure and Repair Behaviour

In this subsection, we present values from the literature related to the failure and repair of components in the OTS. The main components considered are offshore transformer, onshore transformer, offshore switchgear, onshore switchgear, offshore converter and onshore converter. The work by [99] presents mean time to repair (MTTR) and mean time to fail (MTTF) values for each of these components. Additionally, the work by [20] presents MTTF values for onshore transformers and offshore transformers to be fifty years and forty years, respectively as well as MTTR values for onshore transformers and offshore transformers to be 2232 hours and 3000 hours, respectively.

The report by [142] presents data and analysis collected from a survey of installed underground and submarine cables. In particular, [142] explores the failure rate of land cables, repair rate of land cables and the failure rate of offshore cables. The report by [142] goes on to discuss that the average repair time for reported incidents of submarine cables is sixty days. The work by [142] also details the factors that affect the repair time of submarine cables; they include the availability of spare cable and accessories, the availability of an appropriate vessel and weather conditions. These factors lead to a considerable variation in repair times between incidents.

Several pieces of literature give values for the failure and repair rate of offshore cables. The failure rate of high voltage direct current (HVDC) offshore cables is quoted to be 0.0007 fails/year/km in [149], 0.00001107 fails/year/km in [95], 0.0000213 fails/year/km in [95], and 0.00036889 fails/year/km in [95]. The failure rate of high voltage alternating current (HVAC) offshore cables is quoted to be 0.000705 fails/year/km in [142], 0.00024 fails/year/km in [150], 0.0016 fails/year/km in [82], and 0.003 fails/year/km in [83]. The repair time for offshore cables is quoted to be 60 days in [142], 60 days in [95], and between 30 and 150 days based on operational experience in [141].

The report by [82] gathers data and experience of UK offshore wind farm transmission cables. The report also investigates cable reliability, the cause of cables failures and the cost of cable failures. The report by [82] presents some key summary statistics:

- The average cable repair cost £12.5 million.
- Up to the end of 2016, the UK had installed over $4,400$ km.years of export cables to support offshore wind. Here, 1 km.year represents a one kilometre cable that has been operational for one year.
- Up to the end of 2016, UK offshore export cables had experienced seven major failures.
- Up to the end of 2016, operational data suggests a mean time between failures of 630 km.years.
- The estimated total cost of export cable failures is £160 million. This expense is equivalent to £$170,000$ for every kilometre of high voltage export cable in service.

3.5 Operational Expenditure (OPEX)

Operational expenditure is the cost associated with the repair and maintenance of the assets. Repair and maintenance are carried out to ensure that the assets are in good working conditions. The operational expenditure of the wind farm is estimated in the literature to be €$76,000$ per MW per year in [151], £$79,000$ per MW per year in [152], between €$80,000$ and €$100,000$ per MW per year in [153], and £$72,000$ per MW per year [154].

One significant cost contribution to operational expenditure is the cost of repair vessels. Vessels are required to repair and maintain offshore assets. The following values are costs for vessels given in the literature. The day rate of a heavy lift vessel (HLV) is quoted between £$50,000$ and £$125,000$ in [93]. The study by [92] gives the day rate of a jack-up vessel for major replacements as £$150,000$. [155] presents daily hire rates (in millions of pounds) for jack-up vessels to be 0.102, 0.1473, and 0.1926 for a crane capacity of 800 tonnes, 1000 tonnes and 1200 tonnes, respectively. Additionally, twenty-year charter rates, one-year charter rates and spot market rates are given by [71] for vessels with varying CAPEX.

3.6 Interconnectors

Offshore wind export cables are not the only offshore power transmission systems, and there are some similarities between the interconnectors and offshore wind export cables. Therefore, in this section, we review data for interconnectors. European Network

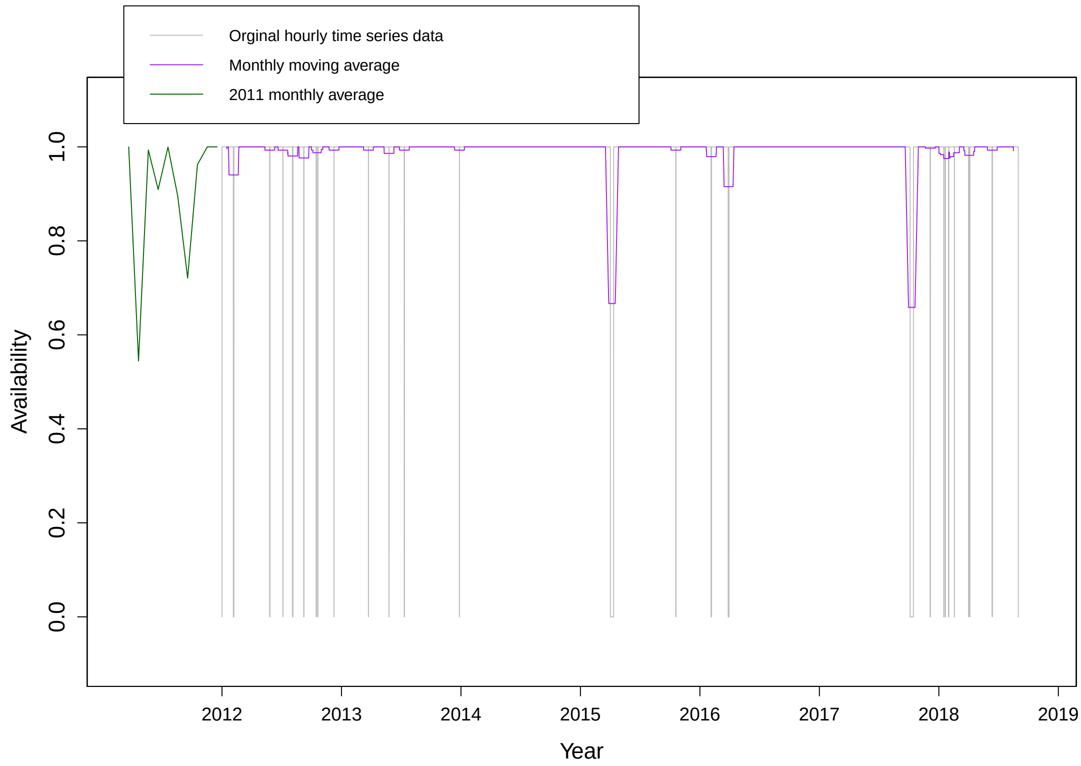


Figure 3.23: BritNed interconnector availability data with monthly moving average added, using data from [156, 159].

of Transmission System Operators for Electricity (ENTSO-E) Transparency Platform [156] contains data relating to electricity generation, transportation and consumption in Europe. The data on this platform that is most relevant to the work of this thesis is around offshore grid outages. In this section, we analyse data related to outages of the interconnector called BritNed. BritNed is an interconnector between England and the Netherlands, specifically a 250 km, 1000 MW, 450 kV, HVDC connection [157]. We note that data related to the BritNed cable should be treated with care as the technology may differ from offshore wind projects. In particular BritNed is a line-commutated converter HVDC (rather than VSC HVDC) and uses mass impregnated cables (rather than XLPE) [158].

BritNed has been operational since March 2011. [156] reports start and end timestamps of the outages, and from this information, hourly time series data can be generated. Outage data for 2011 is missing from ENTSO-E Transparency Platform. 2011 was the first year of operation, and during this year BritNed experienced many outages [159]. Therefore, data from National Grid performance reports [159] has been used to include data for 2011. Fig. 3.23 shows the availability of the interconnector. Using data from both [156] and [159] we obtained time to fail and time to repair data for BritNed interconnector. Histograms of this information are shown in Fig. 3.24 and Fig. 3.25.

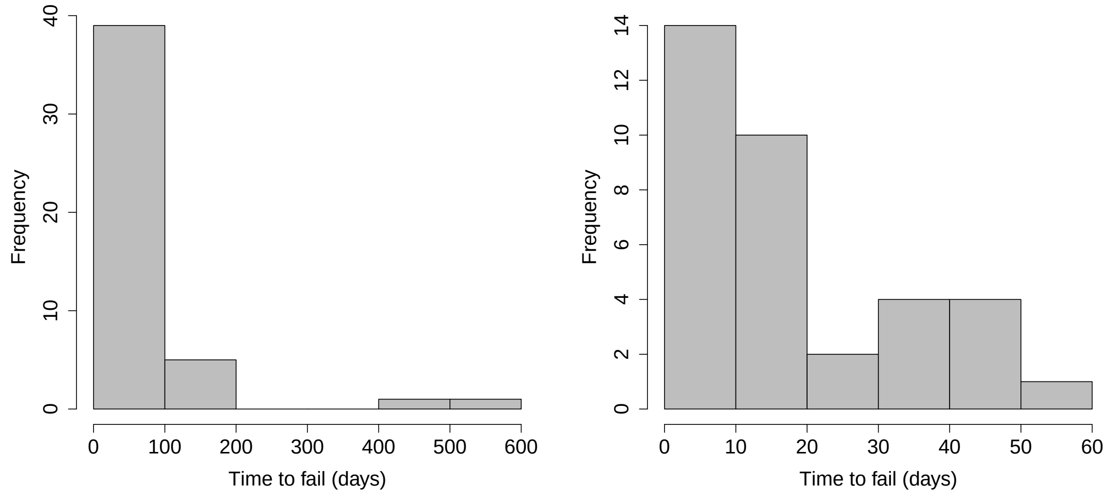


Figure 3.24: Time to fail data for BritNed interconnector using data from [156, 159]. The plot on the left-hand side shows all the time to fail data, and the plot on the right-hand side has removed the highest values to enable a closer look at the peak.

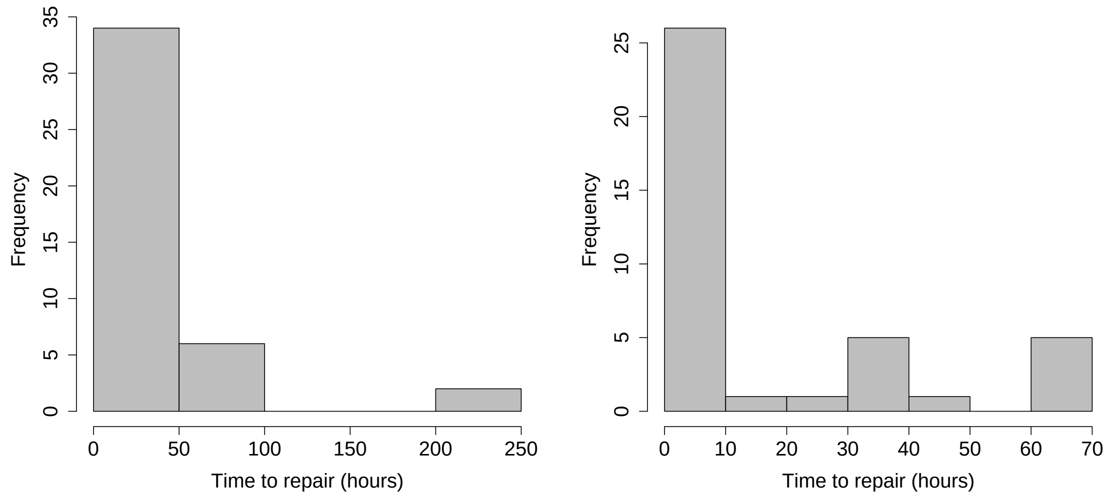


Figure 3.25: Time to repair data for BritNed interconnector using data from [156, 159]. The plot on the left hand-side shows all the time to fail data, and the plot on the right-hand side has removed the highest values to enable a closer look at the peak.

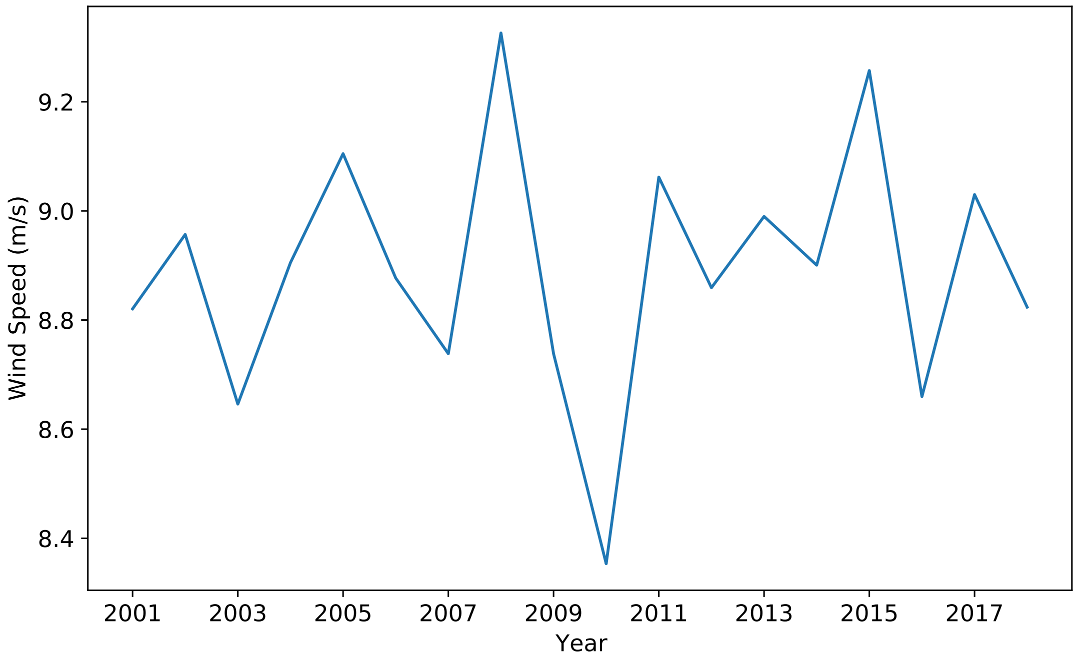


Figure 3.26: Average yearly wind speed data using data from [160, 161] for the location of Race Bank offshore wind farm.

3.7 Wind Speed

Historical time-series wind speed data can be useful for energy systems modelling. The tool called Renewables.ninja [160, 161] provides hourly power outputs (for wind and solar technologies) for any location. The tool also includes hourly wind speed data for any location. It should be noted that Renewables.ninja uses hourly wind speed data from the National Aeronautics and Space Administration (NASA) data set called Modern-Era Retrospective analysis for Research and Applications (MERRA) [162, 163]. It is also important to note that the output of the Renewables.ninja tool is deterministic.

This tool allows the user to select a location, wind farm size and turbine model. For the purpose of presenting an example data set, we chose approximately the site for Race Bank wind farm (latitude of 53.276 and longitude of 0.84), a capacity of 800 MW and the Vestas 164/7000 turbine model. We note that this is an onshore turbine, however as we are interested in the wind speed data (rather than the power output) the turbine model is not relevant. Using the renewables ninja tool [160, 161], we obtain hourly wind speed data for the years 2000 to 2018. Fig. 3.26 shows the mean wind speed each year, and Fig. 3.27 shows the monthly mean wind speed each year. These two figures suggest that 2008 had particularly high wind speeds and 2010 low wind speeds.

Several studies report the capacity factors for offshore wind farms. Capacity factor can be defined as the ratio of actual power output over potential power output. Values

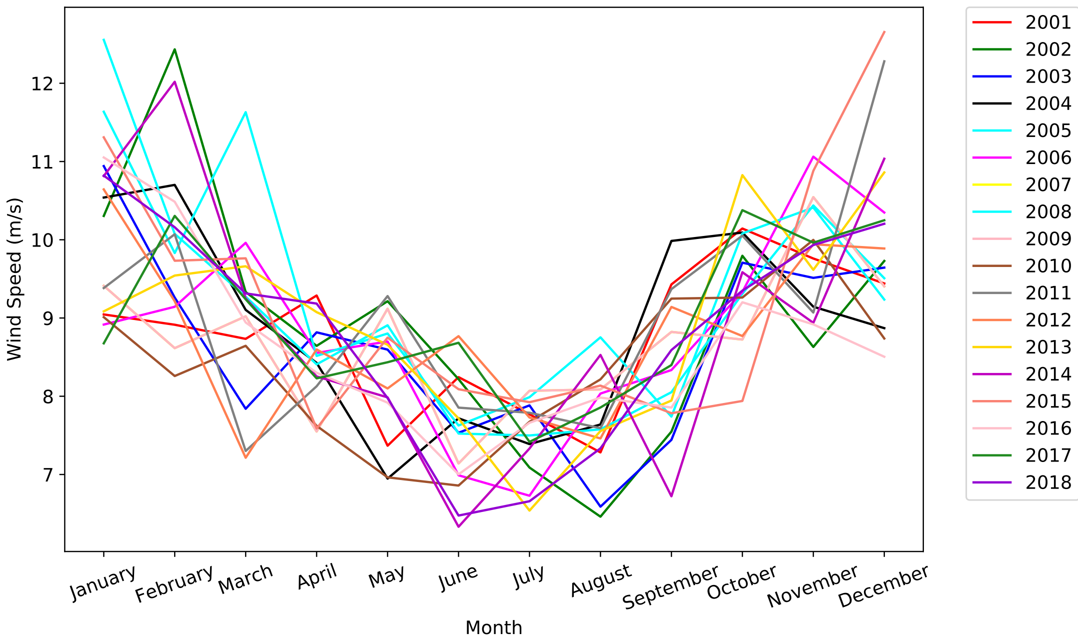


Figure 3.27: Average monthly wind speed data (for years 2000 to 2018) using data from [160, 161] for the location of Race Bank offshore wind farm.

(or ranges of values) for capacity factor reported in the literature include 0.24 to 0.68 in [164], 0.386 in [165], 0.473 in [165], 0.32 to 0.63 in [166], and 0.49 in [166].

3.8 Future Technologies

Most of the data and information so far has been for previous offshore wind projects. As the offshore transmission space is advancing and evolving, it is important to look ahead to new technologies. This enables the analysis of future projects to be more realistic, given the current market conditions. Therefore, in this subsection, we look at recent and future technologies. In Section 3.8.1 characteristics of two recent projects are detailed, and Section 3.8.2 goes on to discuss advancements in HVDC platforms.

3.8.1 Recent Projects

Table 3.9 shows details for two of the more recent offshore transmission projects [167, 11]. These projects are distinctively different from projects previously installed; in particular, they are larger in capacity and located further offshore.

3.8.2 HVDC Converter Platform Optimisation

The offshore wind accelerator, run by the Carbon Trust, aims to reduce the cost of offshore wind through innovation projects [22]. One project has looked at substation

Name	Capacity (MW)	Distance from shore (km)	Number of platforms	Number of cables	Cable Length (km)
East Anglia ONE	714	50	1	2	85
Hornsea One	1218	120	3	3	120

Table 3.9: Offshore transmission system (OTS) details for projects currently in the development stage. Data from [167, 11].

optimisation to reduce the cost of energy transmission. This project explored how the cost of an offshore substation can be reduced by analysing a 1 GW HVDC system. Specifically, the feasibility of combining the two HVAC substations and the HVDC converter platform onto a single jacket substructure. This optimised design has several advantages, including a 20% lower LCoE [34]. The key finding of this study is that a HVAC and HVDC combined topside could be delivered weighing less than $10,000$ tonnes using currently proven HVDC technology [34]. Therefore, there is a potential for cost reduction.

DolWin 5, located in the North Sea, is a HVDC offshore grid connection, 130 km long, with a transmission capacity of 900 MW. This project will implement the innovative concept described above, and is expected to be operational in 2024 [168].

3.9 Conclusions

In this chapter, we have collected and curated data that is relevant to the offshore transmission system (OTS). This study contributes to our understanding of offshore transmission and provides a more in-depth insight into the operational costs and experiences of these projects. As offshore power transmission is an area where data is scarce, presenting a collection of the data that is available can be valuable to the research community.

This chapter provides details of operational projects in the UK, including a breakdown of the assets involved, availability levels, projects costs and revenue streams. The chapter also collected component costing data, failure and repair data, and operational costs from the literature. We presented some data for offshore interconnectors that can further advance our knowledge of offshore power transmission. Furthermore, we discussed a tool to obtain historical wind speed data that can be used for energy modelling. Finally, we detailed future technologies in the offshore transmission space, as it is vital to understand the direction the industry is expected to move when planning future projects.

The insights gained from this chapter may be of assistance to research that requires economic evaluations of OTSs. In particular, we use the findings of this chapter when conducting economic assessments in this thesis.

Chapter 4

An Economic Model for Offshore Transmission Planning Under Severe Uncertainty

The work of this chapter closely follows [1].

4.1 Introduction

In the literature review presented in Chapter 2, we recognised that there had been significant progress in reducing the cost of offshore wind energy, with a strong focus on the overall capital and operational costs of the wind farm. However, we also identified that the offshore transmission system (OTS), which has a significant contribution to the total cost, has not attracted the same attention. As offshore wind projects increase in capacity and move further offshore, the costs associated with the OTS will increase. Furthermore, as well as the investments, the inherent uncertainties related to offshore wind are substantial. Therefore, as the industry looks to become even more competitive in the future, investors are interested in identifying and assessing the risks given the inherent uncertainties.

Accordingly, investors conduct economic evaluations over a project's lifetime as part of the investment decision making process. In this chapter, we present a model to evaluate projects economically from an offshore transmission owner's (OFTO) perspective. There is merit in taking an offshore transmission owner's (OFTO) perspective as they play a vital role in the offshore wind industry. This different perspective requires current, publicly available, economic models to be reshaped to include elements such as revenue streams and loan repayments.

Additionally, to allow a more realistic economic evaluation, data, regulatory information, and expert knowledge are collected, curated and, where necessary, combined with statistical techniques. In the economic assessment presented in this chapter, we consider the repayment structure of the FTV over time rather than CAPEX as an initial investment. Furthermore, the analysis distinguishes random variables from those that are not and applies statistical techniques accordingly. The inclusion of these aspects to the economic model allows a more realistic view as to how investors view future projects. The developed economic framework will be used throughout this thesis to assess offshore transmission projects economically.

Unfortunately, in Chapter 2, we identified that economic evaluations of offshore wind projects are subject to many inherent uncertainties. In particular, Chapter 2 highlights that there exists uncertainty around the failure rates of export cables (a vital asset in the OTS). Significant uncertainties do not necessarily imply a high economic impact on project performance. Therefore, as well as developing an economic framework for OTSs, this chapter identifies uncertain model variables and assesses their impact on project performance. This assessment is valuable for investors who seek high profit and low-risk investments.

In this chapter, we use a generic 1.2 GW project to gain a deeper understanding of the severe uncertainties involved in offshore transmission planning and their impact on a project's expected profit. Understanding their impact, through a sensitivity analysis where individually one factor is varied within an interval, supports decision making with limited information.

The aims of this chapter are:

1. To formulate a model to conduct economic analysis from an offshore transmission owner's (OFTO) perspective. This framework can be used later in this thesis, in particular, in the application chapters.
2. To identify areas of the economic model that contain significant uncertainty and assess their impact on the expected profit of a project.
3. To identify model variables that significantly impact economic performance, and therefore motivate the need to apply advanced statistical techniques here.

This chapter is structured as follows. Section 4.2 presents a range of cost models that are used to economically evaluate projects. Section 4.3 defines how the NPV of the OTS is going to be calculated from an offshore transmission owner's (OFTO) perspective. Section 4.4 formulates the revenue streams and discusses the yearly availability of the system. Section 4.5 formulates the loan repayments and explores CAPEX by proposing and validating a bottom-up evaluation approach. Section 4.6 presents methodology for operational expenditure (OPEX) evaluation. Details of a case study upon which we shall conduct our analysis, input data and results of the expected NPV evaluation are presented in Section 4.7. The impact of uncertain variables on the expected NPV is assessed through interval analysis in Section 4.7. Finally, Section 4.8 outlines the conclusions of this chapter.

4.2 Cost Models

In Chapter 2, we presented several studies that conduct economic assessments of offshore wind projects [104, 89, 17, 87, 169, 170, 171, 113, 172]. In the literature, two metrics are commonly used in economic evaluations of energy-related problems, namely levelised cost of energy (LCoE) [90, 173, 174] and NPV [89, 87, 171, 113]. Other economic metrics exist such as internal rate of return (IRR) and return on investment (ROI). Although there is a range of metrics available, the choice of economic metric should be appropriate for the problem at hand.

In this paragraph, we review two economic models ([173] and [90]) that have been applied to the entire wind farm from the perspective of the developer. The work by [173] breaks down the life cycle costs associated to an offshore wind farm into five main phases: development and consenting, production and acquisition, installation and commissioning, operation and maintenance, and decommissioning and disposal. The economic model presented in [90] aims to advance the deterministic model to account for stochastic inputs by taking a Monte Carlo approach to derive a joint probability distribution for the LCoE for offshore wind. To stochastically model the uncertain variables, CAPEX and OPEX ranges, assumed to follow a normal distribution, are taken from literature. The two economic models reviewed take different approaches: [90] considers the cost components in terms of broad cost areas, and [173] breaks down each of the cost components. When designing and formulating a model, the level of granularity should allow the model to contain the necessary information without over complicating.

One aspect of the economic model is the choice of metric. The metric LCoE can be defined as the lifetime costs of a project per unit of energy generated [29]. Energy sold above this LCoE value yields a greater return on investment [175]. The LCoE, which is based on a discounted cash flow model, is often used when comparing costs across different energy generation technologies. The discounted project costs are divided by the discounted energy output and summed over the lifetime of the project. The LCoE for offshore wind can be evaluated by Eq. (4.1) [175].

$$\text{LCoE} = \frac{\sum_{t=1}^{n} \frac{\text{Investment}_t + \text{Operational costs}_t}{(1+d)^t}}{\sum_{t=1}^{n} \frac{\text{Energy Generation}_t}{(1+d)^t}} \tag{4.1}$$

Here, t denotes the year of operation, d denotes the discount rate and n denotes the lifetime of the project. The numerator contains initial investments and operational costs. The denominator includes the energy generated by the project. Both the numerator and denominator are discounted using the discount rate. The discount rate is discussed in more detail in Section 4.3.2.

The LCoE metric does not consider the revenue stream of an investor, and subsequently, we explore the metric net present value (NPV) [115]. Similar to LCoE, this metric also takes a discounted cash flow approach and this can be seen in Eq. (4.2) [87].

$$\text{NPV} = \sum_{t=1}^{n} \frac{\text{Income}_t - \text{Investment}_t - \text{Operational costs}_t}{(1+d)^t} \tag{4.2}$$

Here, the net cash flow in each year t is calculated in the numerator. The net cash flow considers the income as well as the investment and operational expenditure. The denominator of this sum discounts this cash flow. The NPV is the sum over the lifetime of the project, n, of all the discounted future cash flows. Again, t denotes the year of operation and d is the discount rate.

The economic metrics shown by Eq. (4.1) and Eq. (4.2) both depend on the capital expenditure (CAPEX) and operational expenditure (OPEX) of a project. There has been considerable research into the CAPEX and OPEX of offshore wind projects. In the literature CAPEX is estimated using the following methods: as a function of distance to shore or project capacity [173, 176], by values published in reports [90], or by summing individual component costs [89, 17]. Similarly, in the literature, OPEX is calculated by a variety of methods. The work by [87] estimates turbine maintenance as a price per MWh, whereas the work by [104] and [177] estimates maintenance as a percentage of the CAPEX. The study by [89] considers money lost due to energy not supplied and the work by [17] splits operating costs into maintenance and losses.

Many economic assessments evaluate the cost of an energy generation technology rather than from a particular investor's perspective. Therefore, little research has been done from an offshore transmission owner's (OFTO) perspective. In the following subsections, we present a developed economic framework from the offshore transmission owner's (OFTO) perspective.

4.3 Methodology Outline

In order to assess the impact of severe uncertainties on an offshore transmission owner's (OFTO) expected profit, an economic framework is required. Consequently, a literature review, including academic papers, industrial reports and economic evaluations of the entire offshore wind farm, has been conducted to build an economic model for an OTS. Some studies assess the economic impact of project specifications such as capacity and distance from shore; however, this is not the focus of the work here. A fixed design is taken and used to assess the impact of uncertainty on the expected economic benefit.

4.3.1 Economic Evaluation from Different Stakeholder's Perspectives

The ownership structure of an offshore wind power plant varies between countries as detailed in Chapter 2. The different ownership structures can be broadly classified as third-party ownership, onshore transmission system operator (TSO) ownership and wind farm developer ownership. During a project's planning stage, the ownership structure is usually well defined and therefore, when conducting an economic evaluation, a specific stakeholder's perspective should be taken.

In this work, we focus on the UK perspective who implements a third-party ownership structure called the offshore transmission owner (OFTO) regime [49]. This regime has been discussed in detail in Chapter 2. In summary, this regime involves a separate entity (an OFTO) owning, financing, operating and maintaining the OTS. The developed economic model could be adapted to other markets by changing aspects of the model that are no longer relevant, for example, changing the revenue stream to be in-line with a particular market's practice. Many parts of the model are likely to remain unchanged, such as CAPEX and OPEX.

4.3.2 Net Present Value

This chapter will use the metric termed NPV, to allow potential OFTOs to evaluate the merit of investing in future projects. NPV, chosen as it allows the inclusion of both revenue streams and expenditures, takes a discounted cash flow approach to evaluate the time value of money [115]. A discounted cash flow approach is common practice within the industry.

The metric NPV takes into account the time value of money and how this affects the cash flow. For example, if we have £100 in 10 years, how much is that amount worth today? This concept is incorporated using the discount rate; a rate that discounts future cash flows to the present-day value [178]. The technique of discounting allows costs and benefits that occur at different time periods to be compared. Discounting is a separate concept from inflation, and is based on the principle that consumers prefer to receive goods and services now rather than later [178]. The discount rate in year t is used to bring the cash flow in year t to year $t-1$.

The report by [179] discusses what value is reasonable to use as the discount rate.

The report suggests two values: the social time preference rate (STPR) and the weighted average capital cost (WACC). These two values can be implemented in different ways depending on the systematic risks. We take the Spackman approach [180, 179], which uses the STPR to discount all costs and benefits, including financing costs. A constant discount rate of 3.5%, for projects with a lifetime between zero and thirty years, is recommended by [178]. For long terms project, more than thirty years, the report by [178] recommends variable discount rates. Furthermore, there is some uncertainty in the discount rate that could be explored.

The net cash flow, V_t, in a given year, t, is the difference between the offshore transmission owner's (OFTO) income and expenditure in that year. The cash flow in each year is discounted using the discount factor, d, to retrieve the value a future cash flow would have today. NPV is the sum of these discounted future cash flows as shown by Eq. (4.3).

$$\mathrm{NPV} = \sum_{t=1}^{n} \frac{V_t}{(1+d)^t} \tag{4.3}$$

Here, t represents the year of operation, V_t the uncertain cash flow in that year and n the project lifetime. The analysis presented has been taken from the offshore transmission owner's (OFTO) perspective and thus the NPV model has also been formulated from this perspective.

This chapter aims to use Eq. (4.3) to calculate a project's expected NPV. The model can be used to aid decision making since a NPV greater than zero indicates a worthwhile project. The higher the NPV, the greater the project yield. NPV only indicates if a project is expected to be profitable over its lifetime and not in each year. One would have to look at the cash flow model to observe if there are expected to be financially difficult years, as these individual negative V_t values could have a significant impact for some companies involved.

The main contributions to cash flow are contractual income, loan repayment for capital costs and operational expenditure, as shown by Eq. (4.4).

$$V_t = \text{Contractual Income}_t - \text{Loan Repayment}_t - \text{Operational Expenditure}_t \tag{4.4}$$

Details on how to evaluate contractual income, loan repayment and operational expenditure are given in Section 4.4, Section 4.5 and Section 4.6, respectively. Throughout this chapter, this economic model is referred to as the NPV model.

The described NPV model can be summarised by Fig. 4.1, which gives a graphical representation of the NPV model displaying all the variables required in the model and showing the dependencies between model variables. The model variables with a double circle represent input parameters that are used to evaluate other model variables. The

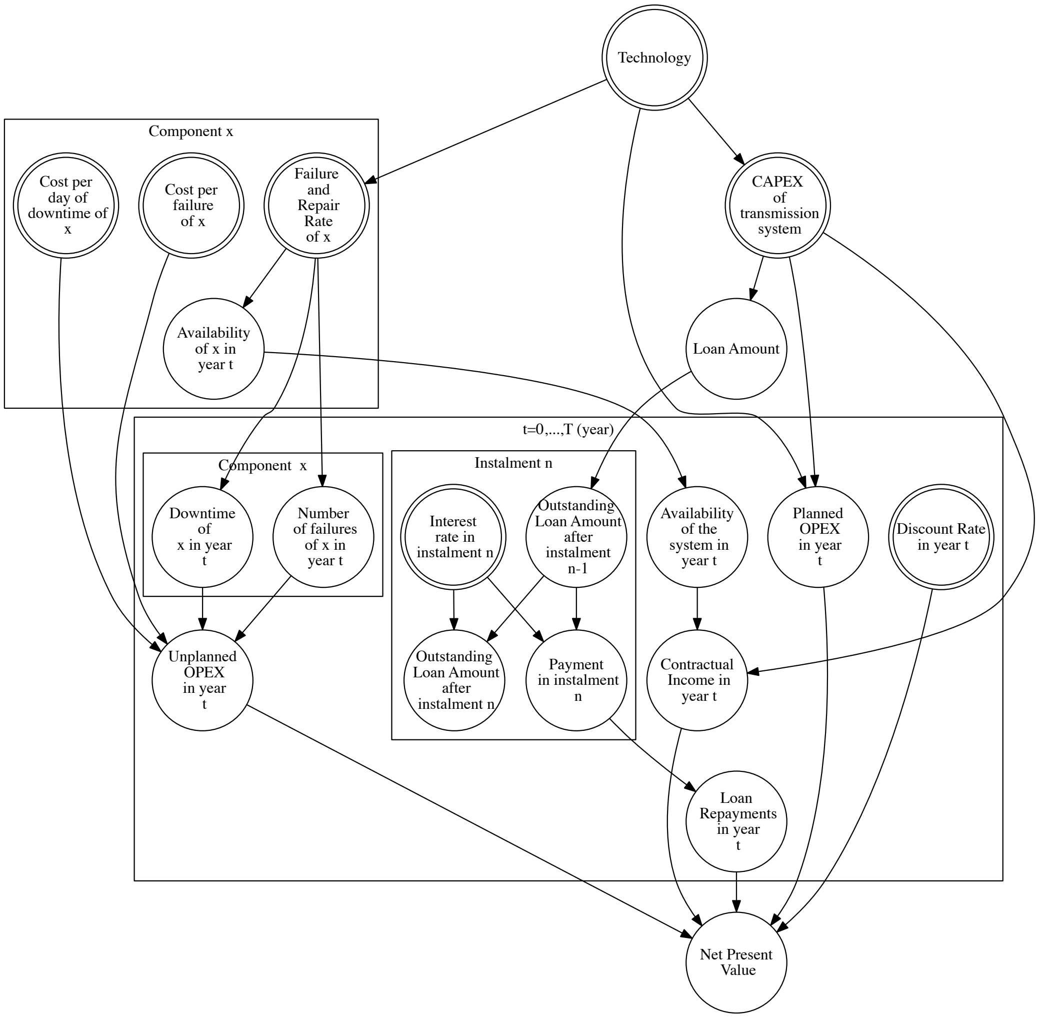


Figure 4.1: Graphical representation of the net present value (NPV) model for a UK offshore transmission system (OTS).

boxes on the graph provide a neat way to represent repeated indices, for example, year of operation. Instead of having a separate node each year for the cash flow in that year, we can represent all of these terms by a node termed cash flow in year t which lies in a box that iterates over t.

Fig. 4.1 shows that contractual income, loan repayments, operational expenditure (planned and unplanned), and discount rate are required to evaluate the NPV. This corresponds to Eq. (4.3) and Eq. (4.4). This NPV evaluation is for a specific topology which is represented in Fig. 4.1 as the input parameter termed technology. Fig. 4.1 is a visual summary of the equations that follow in the rest of the chapter.

4.4 Contractual Income

The OFTO is paid by the National Electricity Transmission System Operator (NETSO) to operate and maintain the offshore transmission assets [53, 181]. The offshore transmission owner's (OFTO) contractual revenue is explained in detail in [182, 145, 50, 53]. Further guidelines presented in [50] state that the allowed OFTO revenue per year is made up of base revenue, pass through items, performance adjustment, and a correction term. Each of these contributions is discussed in this section.

The base revenue provides the most significant contribution to the contractual revenue [143, 144, 145]. Therefore, in the NPV model, we focus on base revenue and availability when evaluating the yearly revenue stream. Base revenue, availability, and their influence on the revenue stream are discussed further in this section.

Wind characteristics are not considered in the revenue stream as they are not directly considered under the OFTO regulatory regime. Uncertain weather conditions do play a role regarding OPEX and are studied in the sensitivity analysis against repair time in Section 4.7.4.

4.4.1 Base Revenue

The base revenue is made up of the tender revenue stream, the market rate revenue adjustment, the post tender revenue adjustment and inflation [182]. The tender revenue stream is established through the tender process and reflects the cost of financing, operating and maintaining the transmission assets [19]. Financing costs are the most significant contribution to the overall tender revenue stream, whereas operational costs only account for around 20% [19]. The market rate revenue adjustment accounts for the difference in financial market rates during the licence consultation process compared to rates at the date of financial close [50]. The post tender revenue adjustment is included if the FTV cannot be calculated on time. The main component of the base revenue is the tender revenue stream. Currently, the base revenue is fixed for the first twenty-five years of operation [49]. After twenty-five years, this value is reviewed, and it is unclear what will happen next as it depends on the demand for the assets.

A project's base revenue is required in the NPV model but unknown in advance of a project licence. Analysis of Office of Gas and Electricity Markets (Ofgem) cost assessments [32], for fully commissioned UK offshore wind projects, identified a relationship between CAPEX and base revenue, as shown by Fig. 4.2. Using linear regression and the method of least squares, we obtained a linear model of the form presented in Eq. (4.5) with an R^2 value of 0.9783. This linear model is shown in Fig. 4.2. R^2 is a goodness-of-fit measure

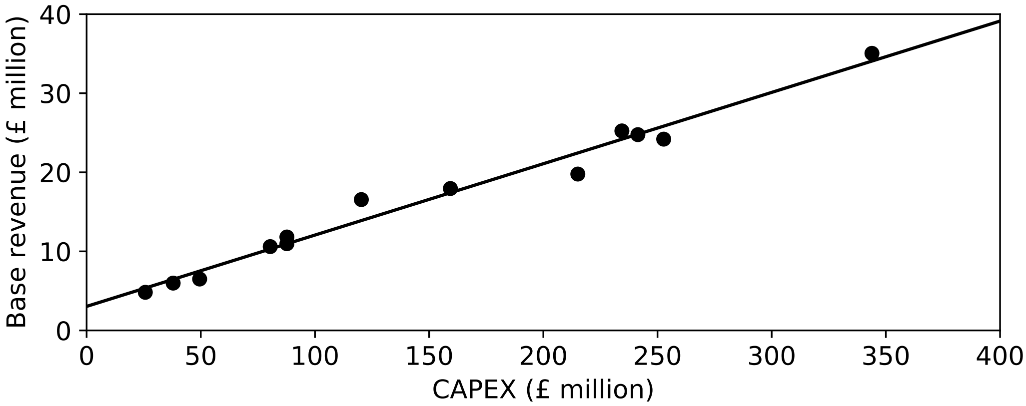


Figure 4.2: Base revenue against capital expenditure (CAPEX) for UK offshore wind projects, with linear model added.

[183]. An R^2 value of one represents models that explain all of the variation in the response variable around its mean, whereas an R^2 value of zero indicates that the model does not explain all of the variation in the response variable around its mean. Eq. (4.5) allows the base revenue, denoted by B, to be approximated from CAPEX.

$$B = \beta_3 \text{CAPEX} + \beta_4 + \varepsilon_1 \tag{4.5}$$

where $\beta_3 = 0.09023$, $\beta_4 = 3.038$ and ε_1 is the residual error.

4.4.2 Pass Through

A detailed explanation of the pass through variable is given in [53]. The OFTO licence adjusts the OFTO's revenue for pass through costs costs that may arise but are difficult to predict during the bidding process. The contributions to the pass through term are licence fee adjustment, network rates adjustment, crown estate lease, tender process costs, decommissioning costs, income adjusting events, temporary physical disconnection payment and additional costs due to the marine and coastal access act [53]. The pass through term allows OFTOs to claim expenditures out of their control back, and as a result, the overall cash flow is zero over the lifetime of the wind farm. Therefore, this term is not included in the NPV model.

4.4.3 Correction Term

The correction term contributes to the OFTO revenue to account for the difference between the allowed OFTO revenue and the regulated OFTO revenue [53]. The allowed OFTO revenue is the amount the OFTO should receive in a year and the regulated OFTO revenue is the OFTO's forecast of the revenue that year which they invoice to the National Electricity Transmission System Operator (NETSO) [53]. These values are likely to be different due to uncertainty when forecasting the revenue [53]. The correction term will have minimal impact on the NPV over the lifetime of the project. As a result, the correction term is not included in the model to calculate the NPV metric.

4.4.4 Performance Availability

Under the regulatory regime, OFTOs are incentivised to maintain high levels of asset availability throughout the revenue period to limit financial losses to generators. This incentivisation is provided through the performance availability term. Dependent on the yearly availability of the OTS, the OFTO receives a reward or penalty based around a target of 98% availability. This structure is described in detail in Chapter 2, and can be described by Eq. (4.6), which has been produced in line with [53].

$$\text{Contractual Income}_t = \begin{cases} 0.9B, & \text{if } Y_t < 0.94 \\ (0.9 + (Y_t - 0.94)2.5)B, & \text{if } Y_t \geq 0.94, \end{cases} \tag{4.6}$$

Here, Y_t represents the availability of the OTS in year t and B denotes the base revenue.

4.4.5 Availability Evaluation

The work by [123, 99] evaluates availability by taking the ratio of uptime to total time. In this work, we take a similar approach but focus on appropriately considering random variables. Fig. 4.3 illustrates a general OTS topology based on the schematics of operational OTSs. Fig. 4.3 will be used to explain the availability evaluation approach for a general OTS. The explanation focuses on HVAC systems, but the approach can be extended to HVDC systems.

Let the OTS contain s identical (with regards to the major equipment) and independent circuits. For example, circuit 1 is illustrated in Fig. 4.3. Let each circuit carry $\frac{1}{s}$ of the load through the system. This approach is a simplification as a real system is likely to include redundancy.

Each node, denoted by three numbers ijk, represents a component (for example, offshore transformer) in the OTS. The first number, i, indicates the circuit a component belongs to, where $i \in I = \{1, \dots, s\}$. As shown by Fig. 4.3, each circuit contains parallel branches, where each branch contains components in series. This represents components on the offshore substation. The second number, j, denotes which branch the component belongs to where $j \in J = \{1, \dots, p\}$ and p is the total number of branches. The set of components in each branch is identical across the branches. The third number, k, denotes

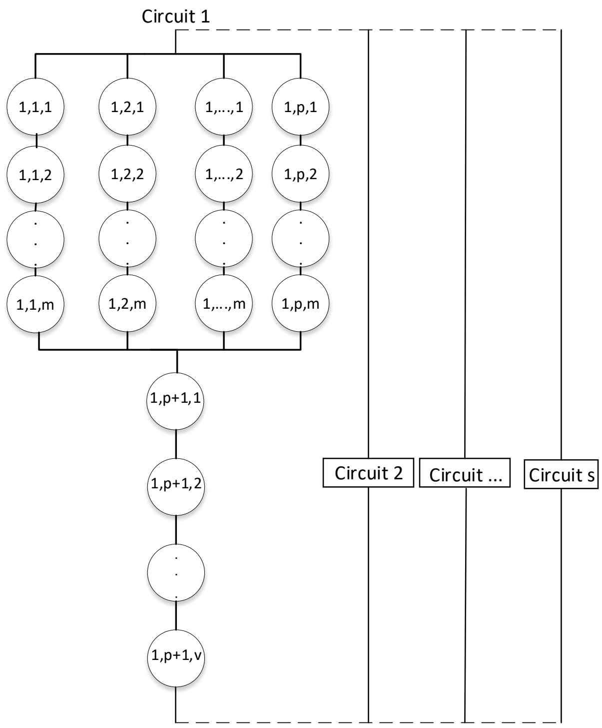


Figure 4.3: A sketch of a general OTS used for availability methodology explanation.

the component in the j^{th} branch where $k \in K_1 = \{1, \ldots, m\}$ and m, is the number of components in each branch. As shown in Fig. 4.3, these parallel circuits are in series with a string of components that represent the assets connecting the offshore substation to the onshore grid. These are indexed by $j = p + 1$ and $k \in K_2 = \{1, \ldots, v\}$ where v is the number of components in this string.

$C_{ijk\tau}$ denotes the availability of the ijk^{th} component at any one given point in time, τ. Each component is either working ($C_{ijk\tau} = 1$) or not working ($C_{ijk\tau} = 0$). The expected availability of each component is evaluated using its failure and repair rates; this is explained later by Eq. (4.21). Components are assumed to fail independently.

Since all circuits are identical, the following analysis focuses on circuit 1. At any one given point in time, the availability of circuit 1, $A_{1\tau}$, is:

$$A_{1\tau} = \frac{\sum_{j \in J} \prod_{k \in K_1} C_{1jk\tau}}{p} \prod_{k \in K_2} C_{1(p+1)k\tau} \tag{4.7}$$

Therefore, by independence and linearity of expectations:

$$E(A_{1\tau}) = \frac{\sum_{j \in J} \prod_{k \in K_1} E(C_{1jk\tau})}{p} \prod_{k \in K_2} E(C_{1(p+1)k\tau}) \tag{4.8}$$

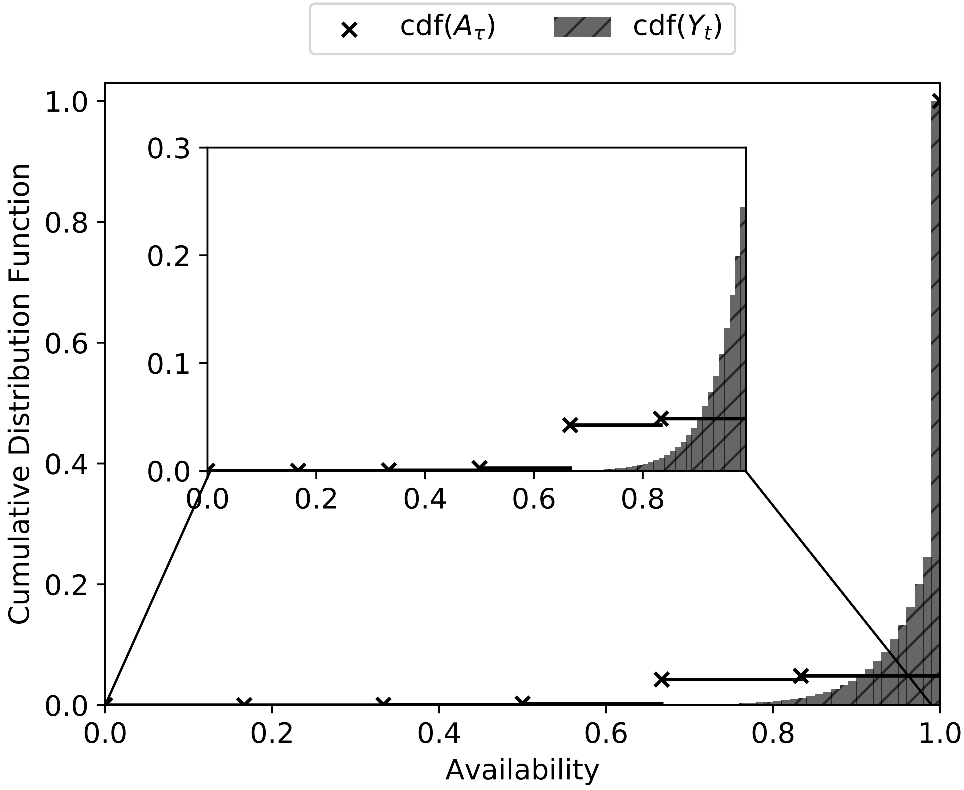


Figure 4.4: Comparison between the cumulative distribution function (cdf) of Y_t (yearly availability) and A_τ (availability at any point in time).

The availability of the entire system, A_τ, is:

$$A_\tau = \frac{1}{s} \sum_{i=1}^{s} A_{\tau i} \tag{4.9}$$

Here, s denotes the number of circuits in the system.

Yearly availability, Y_t, is a continuous random variable required to evaluate the revenue stream. Y_t is defined as the fraction of time the system is capable of transmitting power [141]:

$$Y_t = \frac{1}{1 \text{ year}} \int_0^{1 \text{ year}} A_\tau \, \mathrm{d}\tau \tag{4.10}$$

Yearly availability, Y_t, is a different quantity to availability at one point in time, A_τ as shown in Fig. 4.4.

4.4.6 Non-linearity in Contractual Income

Eq. (4.6) is non-linear in Y_t and therefore, to evaluate the expectation of the contractual income a distribution for Y_t is required. On account of the limited amount of data surrounding availability, a Monte Carlo simulation approach, using hourly discretisation steps to approximate the integral in Eq. (4.10), has been adopted to determine the distribution for Y_t. The simulation results, shown in Fig. 4.4, indicate very little data (9% of the 100,000 samples) below 94% and subsequently, we propose Eq. (4.11) as a simplified expression to estimate the expected contractual income without capping the risk.

Eq. (4.11) is linear in Y_t, unlike Eq. (4.6). This linearity allows the expected yearly system availability to be used, which, under ergodicity, is equal to the expected availability at any given point in time. By ergodicity, we mean that long-run statistical properties are equal to statistical properties at any point in time. The concept of ergodicity has a long history, and for a more in-depth discussion, we refer to [184].

$$\text{Contractual Income}_t = (0.9 + (Y_t - 0.94)2.5)B \tag{4.11}$$

Here, Y_t denotes the average yearly availability and B denotes the base revenue. Taking the expectation of Eq. (4.11) requires the expected yearly system availability:

$$E(Y_t) = E(A_\tau) = \frac{1}{s}\sum_{i=1}^{s} E(A_{i\tau}) = \frac{sE(A_{1\tau})}{s} = E(A_{1\tau}) \tag{4.12}$$

where $A_{i\tau}$ is the availability of circuit i at any one given point in time.

In the scenario considered, the percentage error for using Eq. (4.11) instead of Eq. (4.6) is 2.2%. This simplification is only appropriate when the majority of the mass lies above 94% availability. As the availability falls below 94%, Eq. (4.11) underestimates the availability with greater error for lower values of availability. However, in this situation, Eq. (4.11) consistently gives a conservative estimate to the contractual income. Underestimating a project's NPV is suitable for investment decisions as this will not lead to a risky over-optimistic scenario. This justifies using the simplified Eq. (4.11) for contractual income.

4.5 Loan Repayment

Most economic assessments, not taken from an investor's perspective, consider CAPEX as an upfront cost [89, 87]. The NPV model presented here considers the repayment structure over a repayment period rather than an upfront cost. Under the OFTO regime, the OFTO is required to pay the developer for the assets. The payment amount is called the final transfer value (FTV). We recall from Chapter 2 that the FTV is the sum of capital (CAPEX), development, contingency, interest during construction and transaction costs.

The NPV model requires the project's FTV, which is unknown until after the competitive tender process. Accordingly, CAPEX is used to estimate the FTV. CAPEX is chosen for three reasons: it can be estimated with acceptable accuracy (see Section 4.5.1), it contributes the largest proportion to the FTV, and this proportion can be estimated.

Using data from Ofgem cost assessments [32], CAPEX has an average contribution of 77.8% for projects up to date.

4.5.1 Capital Expenditure

Capital expenditure (CAPEX) refers to the cost to develop, construct, install and commission the OTS [145]. As this value is unknown for future projects, a methodology to evaluate CAPEX is required. This work, similar to [89, 17], proposes a bottom-up approach by summing component costs found in literature [33, 36, 37]. This process requires the knowledge of the topology of the transmission system.

A high-level breakdown of the OTS into offshore substation(s), offshore cable(s), onshore cable(s) and onshore substation(s) is considered. The CAPEX evaluation also includes costs regarding the electrical equipment, platform structures and installation [33, 36, 37]. The costs used in the analysis are presented in Chapter 3. Usually, the cost of a component is presented in literature as an interval of costs and in this situation the middle value of the interval has been taken. However, when required, judgement was used to take a particular value within the range.

To validate the modelling strategy and input data used in this bottom-up approach, the CAPEX of six operational OTSs are assessed. The six projects chosen are London Array, Thanet, Gwynt Y Mor, West of Duddon Sands, Westermost Rough and Burbo Bank Extension. Their topologies, found in the Preliminary Information Memorandum for each project [185], combined with data contained in Office of Gas and Electricity Markets's (Ofgem) Cost Assessment for each project [32] are used to validate and calibrate this approach. Table 4.1 and Table 4.2 shows the results of the CAPEX evaluation.

Our evaluation estimates the CAPEX of London Array, Thanet, Gwynt Y Mor, West of Duddon Sands, Westermost Rough and Burbo Bank Extension to be £357 million, £140 million, £282 million, £194 million, £113 million and £137 million respectively. Table 4.2 shows approximately a ±10% difference between the CAPEX values stated by Ofgem and the CAPEX values estimated via the bottom-up approach. This approach seems to overestimate the CAPEX for systems with a nominal voltage of 132 kV and 220 kV and underestimate systems with a nominal voltage of 150 kV; however, due to a small sample size, this pattern cannot be validated. Unfortunately, detailed project cost breakdowns are, usually unavailable for those not directly involved.

The NPV model requires CAPEX values in advance of them being published by Ofgem. To use our CAPEX evaluation ($\mathrm{CAPEX_{Own}}$) to predict actual CAPEX values ($\mathrm{CAPEX_{Ofgem}}$), a linear model is fitted. Due to limited data available, a simple log-log linear model of the form given in Eq. (4.13) has been chosen. Logarithms are used to

	CAPEX From Own Evaluation (£million)				
Wind Farm	Offshore Substation	Onshore Substation	Offshore Cables	Onshore Cables	Total
	132 kV Export Cable				
London Array	107.6	53.6	193.3	2.8	357.3
Thanet	55.2	28.9	49.6	6.1	139.8
Gwynt Y Mor	107.2	29.9	89.0	55.9	282.0
	150 kV Export Cable				
West of Duddon Sands	57.5	27.8	96.1	12.3	193.8
Westermost Rough	57.4	21.1	14.0	20.0	112.5
	220 kV Export Cable				
Burbo Bank Extension	57.7	34.4	29.8	14.7	136.5

Table 4.1: Breakdown of capital expenditure (CAPEX) values for five operational offshore transmission systems (OTSs) based on our own evaluation. The breakdown considers the costs of offshore substation, onshore substation, offshore cables and onshore cables.

	CAPEX		
Project	Our Evaluation (£million)	Ofgem (£million)	Difference (%)
London Array	357.3	343.9	+3.8
Thanet	139.8	120.3	+14.0
Gwynt Y Mor	282.0	252.7	+10.4
West of Duddon Sands	193.8	215.1	-11.0
Westermost Rough	129.7	122.3	+6.1
Burbo Bank Extension	153.6	152.6	-0.6

Table 4.2: Comparison of estimated and actual capital expenditure (CAPEX) values for operational offshore transmission systems (OTSs).

reflect a multiplicative error (the error scales with magnitude). The intercept and slope are given fixed values of one and zero, respectively, since analysis showed them not to differ from these values significantly.

$$\log(\text{CAPEX}_{\text{Ofgem}}) = \log(\text{CAPEX}_{\text{Own}}) + \varepsilon_2 \tag{4.13}$$

Here, ε_2, the residual error, is normally distributed with mean zero and standard deviation of σ_1. In R, we obtained $\sigma_1 = 0.09$. On the original (non-log) scale this translates as a 95% probability of the multiplicative error being between 0.84 and 1.19.

4.5.2 Loan Repayment Structure

As mentioned in Chapter 2, the UK has an OFTO regulatory regime which is different to other markets. The OFTO licence specifies the FTV (the amount the OFTO pays the developer for the assets). The NPV model presented here takes into account the economic structure for the payment of the FTV to the developer. Specifically, in the NPV model, the OFTO pays for the transmission assets using a loan as detailed below.

A term loan (often used in the European offshore wind market) is defined as a facility being provided by a lender for a fixed repayment period [186]. Correspondingly, in this chapter, the NPV model assumes that the OFTO takes a loan to pay for the transmission assets and pays it back over a repayment period in regular instalments affected by an interest rate. The economic structure is detailed below.

- The loan period is usually between 10 and 15 years [186].
- n_1 denotes the total number of repayment instalments.
- η_ℓ denotes the interest rate in the ℓ^{th} instalment period.
- Two sequences of numbers are generated to feed into the NPV model: the repayment amount in each instalment and the outstanding loan amount after each repayment denoted by P and O, respectively: $P_1, \ldots, P_n$ and $O_0, O_1, \ldots, O_n$.
- It is not the purpose of this chapter to analyse OFTO debt financing strategies specifically, and therefore the initial loan amount is taken to be the FTV.
- The payment in each instalment, P_ℓ, is calculated using Eq. (4.15).
- The repayment structure must ensure that the initial loan amount, O_0, is repaid after n_1 instalments and that repayments are constant for a fixed interest rate. A mathematical proof is presented in Appendix B to show that Eq. (4.15) along with Eq. (4.16) satisfies these two constraints.
- Eq. (4.15) calculates the repayment amount for the ℓ^{th} instalment, P_ℓ. Eq. (4.16) calculates the outstanding loan after the ℓ^{th} repayment, O_ℓ.

The repayment amount in each instalment, P_ℓ, feeds into the NPV model through the node termed loan repayment in year t. This is shown by Eq. (4.14).

$$\text{Loan Repayment}_t = \sum_{\ell \,\in\, \text{All instalments in year t}} P_\ell \tag{4.14}$$

$$P_\ell = \frac{O_{\ell-1}\eta_\ell}{1-(1+\eta_\ell)^{-(n_1+1-\ell)}} \tag{4.15}$$

$$O_\ell = O_{\ell-1}(1+\eta_\ell) - P_\ell \tag{4.16}$$

4.6 Operational Expenditure

The NPV model splits operational expenditure (OPEX) into planned and unplanned OPEX, as shown by Eq. (4.17). Expenditure due to energy not supplied is not considered under the OFTO regulatory regime.

$$\text{OPEX}_t = \text{Planned OPEX}_t + \text{Unplanned OPEX}_t \tag{4.17}$$

4.6.1 Planned Operational Expenditure

OFTOs conduct planned maintenance to ensure good system conditions, prevent future failures and therefore, avoid costly unplanned maintenance. When detailed data is unavailable, a common approach to estimate the yearly planned OPEX is to evaluate it as a percentage of the CAPEX of the OTS [104, 177]. The value assigned to this percentage is determined by expert knowledge and denoted by α in this work. This leads to Eq. (4.18).

$$\text{Planned OPEX}_t = \alpha\text{CAPEX} \tag{4.18}$$

4.6.2 Unplanned Operational Expenditure

Unplanned OPEX accounts for the costs incurred by the OFTO due to unplanned maintenance of the OTS. When components fail, OFTOs perform unplanned corrective maintenance to maintain high availability levels. The following assumptions have been made when estimating the unplanned OPEX of a project.

- Specific asset management strategies are beyond the scope of the chapter and, therefore, we assume component replacement upon failure. This approach is a worst-case scenario since, usually, the component will be in a condition where a more economical repair, rather than a complete replacement, is satisfactory. Cable repairs are an exception, since generally only a small section, typically 200 metres, of the cable is replaced [177].

- We only consider the unplanned maintenance of six major pieces of equipment: offshore transformer, offshore switchgear, offshore cable, onshore cable, onshore switchgear and onshore transformer. There are many other pieces of equipment; however, this assumption seems reasonable since these six pieces of equipment make up the main body of the system and are the most costly.
- A constant failure rate has been assumed throughout the lifetime of the assets. This assumption may not be the case and should be explored further if regarded to be important. Concerns about this assumption will be revisited and addressed in the rest of the thesis.
- Due to limited data, we assume that each component has the same failure rate regardless of their power rating. The cables are an exception as there is slightly more data available.
- We assume that for both onshore and offshore cables, the length of cable replaced due to a failure is 200 metres. The method to repair a cable is outlined in [187] and summarised in the rest of this bullet point. First, the cable fault is located, and the cable is cut on one side of the damage. Then, the damaged end is pulled onto the vessel. Next, the cable is cut on the other side of the damage, and this end is also lifted onto the vessel. Now the cable fault section has been removed. The spare cable is joined to both of the retrieved cable ends. Finally, the cable is then laid back onto the seabed and protected if needed.

Eq. (4.19) presents the formulation to estimate unplanned OPEX and has been developed from the literature [173, 93, 82].

$$\begin{aligned}\text{Unplanned OPEX}_t = \sum_{\{x\}} \Big(&\text{Cost per failure}_x \times \text{Number of failures}_{x,t} \\ &+ \text{Cost per day of downtime}_x \times \text{Downtime in days}_{x,t} \Big)\end{aligned} \tag{4.19}$$

Here, $\{x\}$ is the set of components in the OTS.

Eq. (4.19) contains two random variables: the number of failures and downtime in a year for each component. We find expectations of these variables by modelling each component as a two-state (not working and working) continuous-time Markov chain. r and f represent the component's repair and failure rate, respectively. For each component, we obtain the expectation of the random variables required for Eq. (4.19):

$$E(\text{Number of fails}_t) = \frac{fr}{f+r} \tag{4.20}$$

$$E(\text{Downtime}_t) = \frac{f}{f+r} \tag{4.21}$$

Eq. (4.19) contains the variable termed cost per failure. For components located offshore, this is the component replacement cost. However, for components located onshore, it is the replacement and one-off repair cost associated with that component. The variable in Eq. (4.19) termed cost per day of downtime is zero for onshore components and equal to the daily vessel hire rate for offshore components. Due to high vessel hire rates, the unplanned OPEX for components located offshore is generally much greater than those onshore. Additionally, Eq. (4.21) can be used to find the expected availability of a component which we recall is required to evaluate the contractual income in Section 4.4.

4.7 Case Study, Results and Uncertainty Impact Assessment

4.7.1 Case Study

For the purpose of the analysis in this chapter, a case study has been created. The design is based on current project trends [188] and recent project topologies [185]. The methodology described throughout the chapter will be applied to the HVAC offshore transmission system (OTS) shown in Fig. 4.5. Each project deployed is growing in capacity and distance from the shore. Therefore, the case study is located 140 km offshore with a capacity of 1.2 GW. A reactive compensation unit and three circuits are considered necessary for this transmission length when approaching with HVAC technologies. Each circuit contains two sets of offshore transformers and offshore switchgear in parallel and then in series with offshore switchgear, offshore cable (220 kV, 140 km), onshore cable (40 km), onshore switchgear and onshore transformer.

4.7.2 Input Data

The following input data is used to evaluate the NPV of the case study: 3.5% discount factor [178], 25 year project lifetime, £1228.8 million CAPEX evaluated using the bottom-up approach (a breakdown is shown in Table 4.3), a twelve year loan period and four repayment instalments per year [186]. Inputs for availability, α, interest rate and unplanned OPEX are discussed below.

The expected yearly availability of the case study, evaluated using methodology detailed in Section 4.4.5, is 0.9772649. The expected availability of each component, calculated using component failure and repair rates [99, 142], is shown in Table 4.4.

Literature estimates the operational expenditure of cables to be 0.4% of capital costs [177]. Similarly, the study by [104] uses a yearly maintenance cost of the substation to be

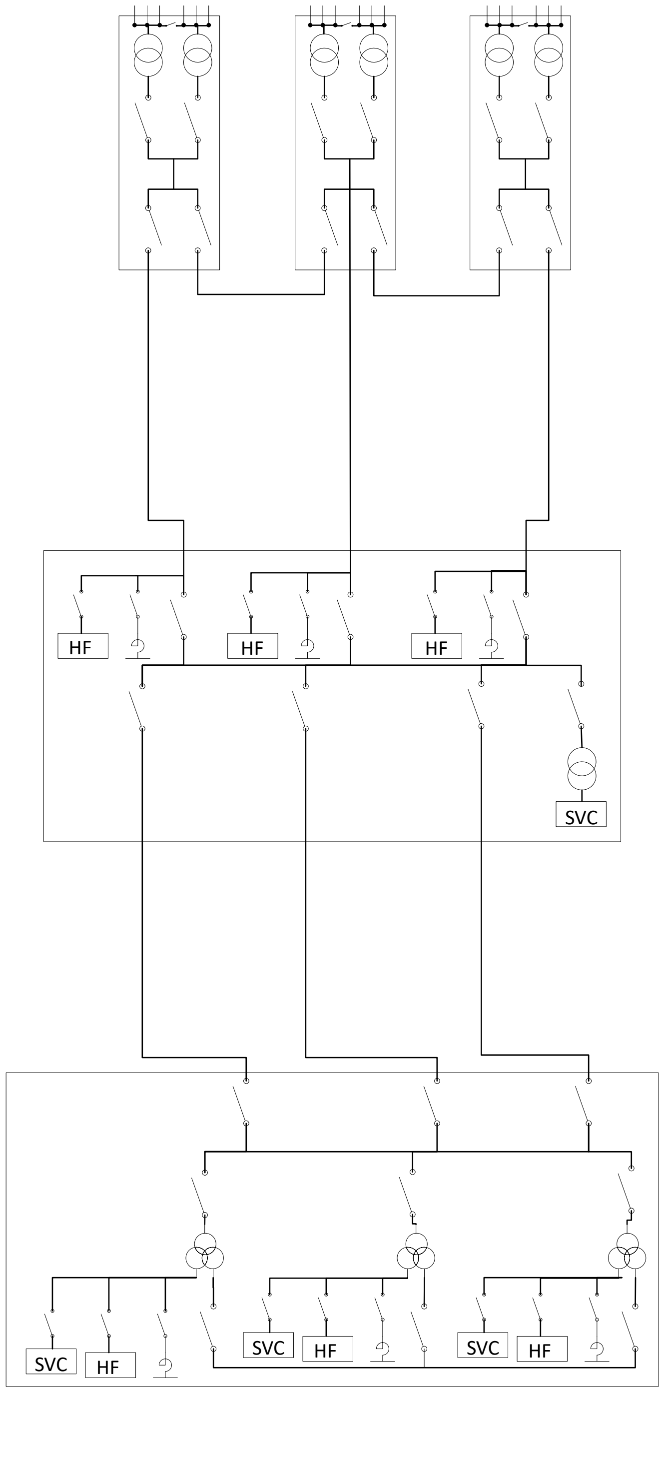


Figure 4.5: Schematic drawing of the high voltage alternating current (HVAC) offshore transmission system (OTS) used in the case study.

Component	Cost (£million)	Component	Cost (£million)
Offshore		Onshore	
Substation	220.9	Substation	85.6
Cable	640.1	Cable	151.3
Reactive compensation unit	130.9		

Table 4.3: Estimated capital expenditure (CAPEX) for the case study.

Component	Availability	Component	Availability
Onshore		Offshore	
Transformer	0.99819	Transformer	0.99879
Switchgear	0.99992	Switchgear	0.99995
Cable	0.99655	Cable	0.98381

Table 4.4: Component availability for the case study.

0.4% of the capital costs of the transmission link. Furthermore, the work by [17] takes the lifetime maintenance costs of HVAC connection to be 15%. Accordingly, α is assumed to be 0.5% for the OTS.

Margin rates (interest on top of the base cost of lending) are set by the lender to reflect the expected risk of a project [186]. Between 2010 and 2019, the base cost of lending varied between 0.25% and 0.75% [189]. Margin rates, during the operational phase of an offshore wind project, are between 2.5% and 4% [186]. Therefore, considering this data, and taking a conservative approach, an interest rate of 3% is implemented.

Estimation of unplanned OPEX requires component failure and repair rates presented in [99] and [142], component costs given in [33, 36, 37], one off repair costs interpreted from [146] and vessel hire rates per day taken from [93, 155].

4.7.3 Results

For the described input data, the model estimates the expected NPV for the case study to be £195 million. Breaking this down into the cash flow contributions: the expected yearly contractual income is £113 million during the project's lifetime, and the expected loan repayments are £157 million for the first twelve years of the project. The remaining contributions are the expected planned and unplanned OPEX for each year of operation, evaluated to be £6 million and £2 million, respectively. These results are shown in Fig. 4.6. For the chosen input data, the project is unprofitable in the first twelve years due to the

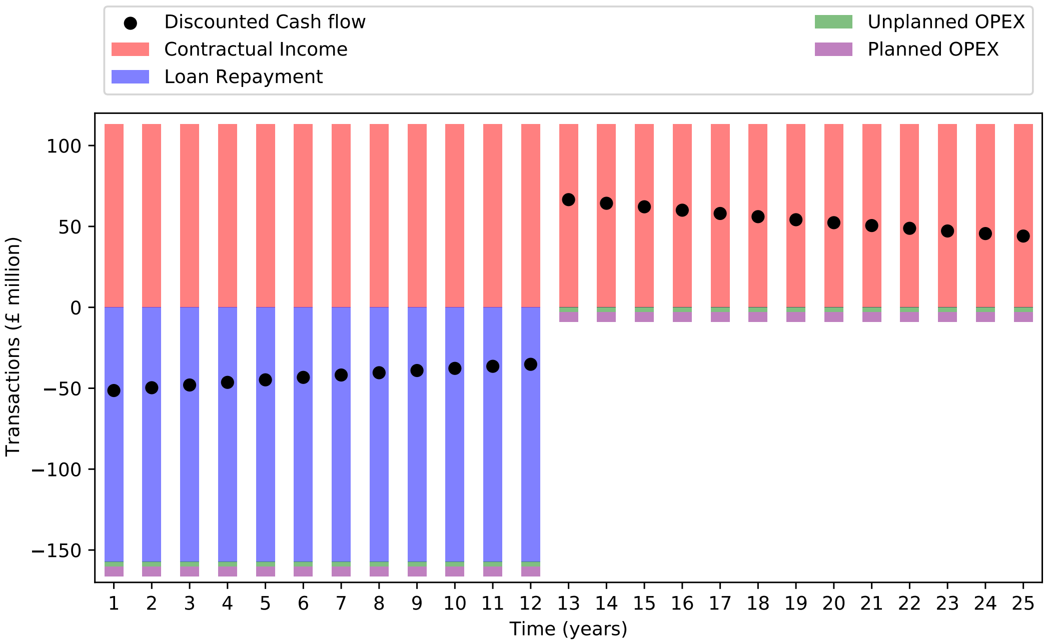


Figure 4.6: Results of the cash flow throughout the lifetime of the case study showing a breakdown of the cash flow into revenue, loan repayment, unplanned operational expenditure and planned operational expenditure.

considerable loan repayments; this could be critical to some OFTOs. Overall the project is profitable; however, many assumptions are required for the analysis, and some input values have severe uncertainty associated with them.

4.7.4 Uncertainty and Sensitivity Analysis

The quantification of the case study requires the input parameters discussed in Section 4.7.2. It may not always be possible to know these input parameters with certainty, and thus the model will contain uncertainty. The following section aims to, through sensitivity analysis, identify the variables that, due to their uncertainty, could have a significant impact on the project's expected NPV. As it is challenging to put realistic distributions on these parameters, we will consider reasonable ranges for these parameters instead, and see how values in these ranges affect the NPV. By doing so, we assess the economic impact of real-world variations on key and uncertain aspects of the project.

The sensitivity analysis considers the following parameters: α, vessel hire rate for cable repairs, interest rate, offshore cable failure rate, offshore cable repair time and ε_2. The choice of values for each parameter is discussed below and presented in Table 4.5.

α is determined by expert knowledge and therefore contains uncertainty. As suggested by literature [104, 17, 177], α values between 0.15% and 1.5% are considered.

Based on the following literature, we consider vessel hire rates between £0.05 million

Symbol	⋆	▲	× **Initial input**	•	●	■	Worst Case Scenario
α (%)	-	0.15	**0.50**	0.75	1.0	1.5	1.5
Vessel Hire (£million)	0.05	0.085	**0.1**	0.125	0.14	-	0.14
Interest Rate (%)	-	1.5	**3.0**	6.25	-	-	6.25
Failure Rate (fails/year/km)	-	-	**0.000705**	0.0016	0.00705	-	0.00705
Repair Time (days)	-	-	**60**	90	120	150	150
ε_2	-	0.09	**0**	-0.09	-	-	-0.09

Table 4.5: Summary of input parameters and the values considered in the interval analysis. The column denoted by a cross details the initial input scenario. Individually, for each input parameter, the initial input is varied to values shown in this table. The table shows the symbol assigned to each input change that corresponds to Fig. 4.7. The last column corresponds to the worst-case scenario inputs discussed in the chapter.

and £0.14 million. The day rate of a heavy lift vessel is quoted between £50,000 and £125,000 in [93]. Vessel daily rates are quoted to be £102,000, £147,300, and £192,600 for a 800, 1000, 1200 tonne jack up crane capacity, respectively [155]. Daily rates for the spot market are quoted between £95,300 and £287,400 in [71]. In a recent export cable repair, the rate for vessel and crew hire per day in UK waters was approximately £100,000 [190].

Due to the uncertain nature of interest rates, three reasonable interest rates of 1.5%, 3% and 6.25% are considered [189].

Industry experience points out that the failure rate used in this chapter, 0.000705 fails/year/km [142], could be too small [82]. Therefore, the sensitivity analysis considers two failure rates: ten times the value used in this chapter to observe the impact of a larger failure rate (and in-line with values presented in [83]), and a failure rate of 0.0015873 fails/year/km based on recent experience [82].

Repair times are quoted in the literature between two and five months [142, 82], and therefore the the sensitivity analysis considers repair times in this interval.

Since the CAPEX linear model is only based on six data points, the model parameters contain uncertainty. Based on the residuals of individual data points, the impact of varying ε_2 in Eq. (4.13) between -20 and 30 is assessed.

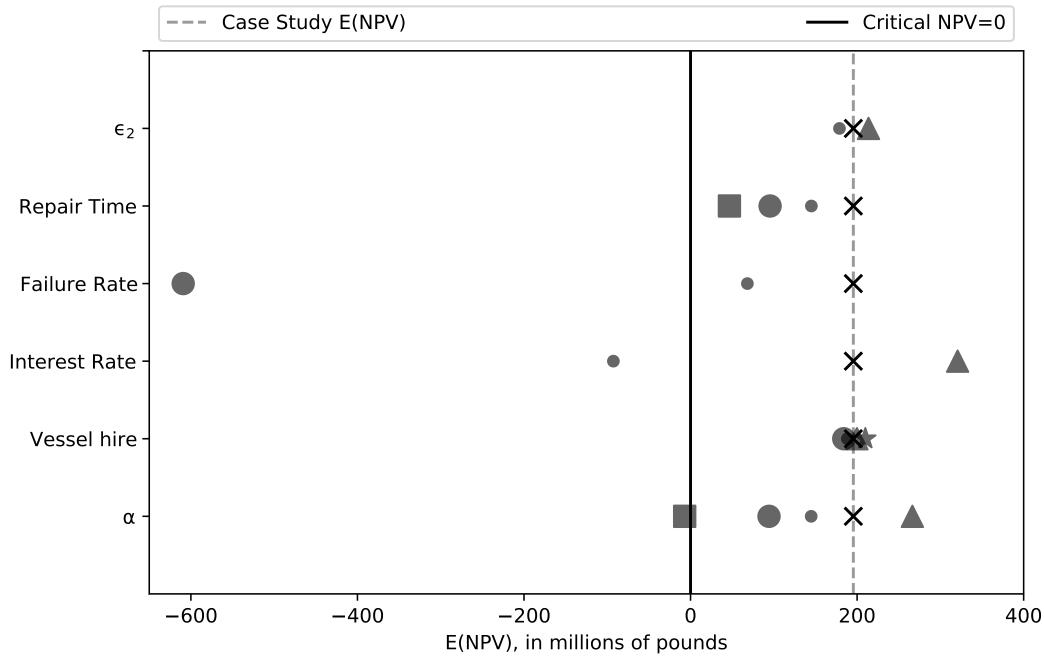


Figure 4.7: Interval analysis of uncertain input parameters. The symbols and their corresponding numerical inputs are presented in Table 4.5.

The sensitivity analysis varies the variables, singly, as discussed above. The resulting expected NPV for each scenario is plotted in Fig. 4.7. Table 4.5 shows the values of each variable analysed and the corresponding symbol on Fig. 4.7.

With the input variables considered in Table 4.5, Fig. 4.7 shows that daily vessel hire rates have a small impact on the project's expected NPV. Cable failure rate, interest rate and planned OPEX appear to have a critical impact, with the sensitivity analysis indicating a negative expected NPV for some input values. The sensitivity analysis also shows that increasing the repair time of an offshore cable (a variable influenced by the inherent uncertainties associated with offshore wind) also significantly impacts the expected NPV.

As shown in Fig. 4.7, increasing cable failure rate by a factor of ten results in the expected NPV falling to $-£609$ million. This decrease is a combination of increased unplanned OPEX and the effect of Eq. (4.11). As stated in Section 4.4.5, Eq. (4.11) underestimates the expected contractual income for availability values less than 94%. This underestimation is applicable here since a failure rate of 0.00705 fails/year/km results in 85% availability. Under the OFTO regulatory regime, the contractual income is capped at 90% of the base revenue, and thus the expected NPV is estimated to be $-£208$ million. This negative NPV still suggests a very unfavourable project and highlights the large impact of cable failure rate on expected NPV. This example also highlights the safety provided to the OFTO through the regulatory regime.

Fig. 4.7 indicates that both an increased failure rate and longer repair time result in a lower expected NPV. These two variables influence system availability and therefore, a lower availability results in a smaller expected NPV. The OFTO regulatory regime provides some protection; however, a 94% availability results in a significantly lower expected profit compared to 100% availability. Therefore, further work into increasing the availability of an OTS should be investigated, especially when aiming to maximise profit.

A worst-case scenario, with regards to input data, resulted in an expected NPV of $-£1889$ million, a very unfavourable project. The last line of Table 4.5 shows the input data for the worst-case scenario. This scenario has 71% availability, and consequently, Eq. (4.11) underestimates the contractual income as previously described. Under the OFTO regulatory regime, the expected NPV is estimated to be $-£885$ million, still an unfavourable project.

This investigation provides a deeper understanding of the uncertainties associated with offshore transmission and highlights the importance of assessing their impact on economic performance. The findings of this work indicate that some of the uncertain input parameters have a significant impact on the economic evaluation. As project planning and investment decisions may be based on these economic assessments, the conclusions of this work have significant implications for decision makers in offshore wind transmission. The insights gained from this work suggest that care should be taken when economically evaluating projects under severe uncertainty. In particular, the results indicate that the offshore cable failure rate has a notable impact on NPV, and therefore the input value for this parameter should be carefully considered. Furthermore, techniques to handle these uncertainties should be explored and implemented.

4.7.5 Comparison to Operational Projects

Due to a limited amount of publicly available data, comparing a full economic evaluation to real-life projects is beyond the scope of this chapter. However, access to some data allows a comparison between individual parts of the economic model. In Section 4.5.1, we compared our CAPEX evaluation to real project CAPEX values. In this subsection, we compare two more parts of the proposed model with real-life data: the operational expenditure of offshore cables and the availability of the OTS.

The operational expenditure of offshore cables for some operational projects is reported to be on average £12.5 million per repair [82]. For the case study considered, an offshore cable failure lasting 60 days has an expected repair cost of £6.1 million and an offshore cable failure lasting 150 days has an expected repair cost of £15.1 million. These figures are in good agreement with the average repair cost of £12.5 million.

In the UK, the availability of OTSs is reported in [141]. Between 2011 and 2019, yearly availability values have ranged between 82.47% and 100%, with an average yearly availability of 98.7% [141]. It is important to note that these values are for a range of different projects that each have their design specification, located at varying distances from shore, and importantly have a smaller capacity than the offshore wind project considered here. For the case study considered, using the initial input data, results in a yearly availability of 97.7%. During the sensitivity analysis shown in Fig. 4.7, the availability of the OTS ranged between 85.5% and 97.7%. These results suggest that the availability values obtained in this work are in good agreement with the data presented in [141].

4.8 Conclusion

This chapter presents model formulation and analysis from the offshore transmission owner's (OFTO) perspective in the UK. A net present value (NPV) model, formulated using the literature available, considers revenue stream, loan repayments and operational expenditure (OPEX), among other details that enables it to be applied in many offshore transmission system (OTS) planning scenarios. The novelty of this economic assessment is based on incorporating an offshore transmission regulatory regime and including the final transfer value (FTV) repayment structure. The methodology is implemented on a 1.2 GW project. This application required the collection and curation of useful data regarding capital expenditure (CAPEX), availability, and OPEX from a variety of sources.

During the quantification process, many areas were highlighted to contain severe uncertainty with regards to the input data. This study investigates six input parameters that are uncertain to a degree where it is difficult to assign them a distribution. Interval analysis is conducted to quantify the economic impact of these uncertainties on project performance. This work shows that interest rates, planned operational expenditure and, particularly, cable failure rates are unknowns in offshore power transmission that are critical to the offshore transmission owner's (OFTO). For the case study considered, comparing cable failure rates based on operational experience to inputs based on literature, resulted in a 64.2% lower NPV.

The results of this study indicate that cable failures have a significant impact on the economic evaluation of an offshore wind transmission project, and strengthens the idea that further research into offshore cable reliability could be beneficial to the industry. Additionally, further work could explore advanced statistical techniques that handle these severe uncertainties. This advancement, in particular, incorporating these techniques into economic evaluations, could have useful implications for decision makers in offshore transmission.

In Chapter 2 we identified from the literature that there is a need to develop suitable techniques to handle severe uncertainties when making decisions in offshore power transmission. In this chapter, we have developed and set up an economic framework to base offshore transmission investment decisions. In addition, we used this framework to assess the impact of uncertain model variables on the expected NPV. We found that some variables, in particular, export cable failure rate, have a significant impact on the economic benefit. Since these economic assessments are used in part of the decision making process, we identify a need for advanced statistical techniques when planning future power transmission systems. Therefore, this motivates the research aims of this thesis, and in particular, necessitates the need for advanced statistical methods for decision making in offshore power transmission under severe uncertainty. The next chapter will explore these advanced statistical techniques.

Chapter 5

Advanced Statistical Techniques

5.1 Introduction

The main focus of this research is the application of statistical methods for long-term decision making (such as investment planning) under the presence of severe uncertainty due to limited information. Specifically, we are dealing with uncertainty in the input parameters (required to evaluate projects economically) due to a limited amount of data available, and therefore there is a limit to our knowledge when it comes to making long-term decisions. In this chapter, we revisit statistical techniques currently implemented, discuss their limitations when applied to problems that involve uncertainty and therefore explore more robust techniques under severe uncertainty. These advanced statistical techniques will be implemented in the application chapters of this thesis.

Chapter 2 identified uncertainties in offshore power transmission and the challenges they bring to project planning. Furthermore, Chapter 4 highlighted the economic impact of these uncertainties. The combination of these two chapters strengthens the case to research and implement more suitable techniques when making decisions in offshore power transmission under severe uncertainty.

Furthermore, statistical techniques based on the classical theory of probability provide suitable tools to make statistical inferences when there is abundant data, for example, from a repeated experiment. Unfortunately, in many applications, including offshore power transmission, there is often an insufficient amount of data to justify these techniques. Therefore, in these scenarios, using techniques based on classical probability theory may lead to misleading inferences. Given the substantial stakes at risk, it is justified to seek and apply other methods that enable conclusions to be made under weaker assumptions.

The aims of this chapter are:

- To define and explain what we mean by severe uncertainty.

- To discuss statistical techniques currently implemented when taking decisions in offshore power transmission and explain the limitations of these techniques.
- To present and explain techniques that advance current practice and address some of the limitations of currently used methods when implemented under severe uncertainty.
- To present small example applications of these advanced statistical techniques to demonstrate the benefits and limitations of the proposed approach.

This chapter begins by defining and discussing uncertainty in Section 5.2. Next, in Section 5.3 we detail statistical techniques currently used in practical applications and show the limitations of these methods. Many statistical methods have been implemented in the work of Chapter 4. However, these techniques are reliant on assumptions that may not always be valid. In Section 5.3, the validity of these assumptions is assessed and where appropriate, more suitable approaches are proposed, mainly, based on imprecise probability. Then, in Section 5.4, we go on to present an overview of imprecise probability theory before focusing on the more relevant topics within the theory (lower and upper previsions, imprecise Markov chains and decision making techniques). Finally, we discuss the advantages and limitations of these advanced statistical techniques through small applications in Section 5.5.

5.2 Uncertainty

The focus of this chapter is to explore techniques that could be implemented when there is severe uncertainty. We first define uncertainty which is a word commonly used in everyday language. Uncertainty is defined in the English dictionary [191] as a situation in which something is not known, or something is not certain; the feeling of not being sure what will happen in the future; something one cannot be sure about; or a state of being uncertain. For a more scientific definition of uncertainty, we refer to [192] who discusses uncertainty and its link to risk. To ensure that there is no ambiguity about what we mean by severe uncertainty, in the rest of this section, we discuss our definition.

Many practical applications require predictions and forecasts about events that will, or perhaps will not, happen in the future. One approach to achieve this is to use historical data about previous events to say something about a future event. In the absence of enough relevant data, an alternative approach is to construct a model that describes the underlying processes of the real system, that can be used to replicate the real system and say something about future events. This model may be analytical, numerical, or a combination of both.

The modelling approach introduces uncertainty as we are creating a model that resembles the real-life events, but of course, is not the real-life event. For example, we may not be able to capture all of the real-life processes involved in a complex system. Furthermore, we may only be interested in predicting a single event, and therefore there may be uncertainty around any given realisation of the model. The quality of a model could be judged against its ability to imitate the real-life processes accurately, and, perhaps even more critical, that any inferences made are in good agreement with real-life outcomes. The model will require input values or distributions that propagate through the analysis and influence the output. These inputs can also introduce a level of uncertainty.

The level of uncertainty about the model inputs determines the approach we take. Many statistical techniques based on the classical theory of probability require enough data or expert information to assign values or distributions to inputs accurately. If we do not feel that we have enough data or expert information to assign these inputs confidently, then we classify this as severe uncertainty. We identified in Chapter 2 and Chapter 4 that this is often the case in offshore power transmission. A combination of short operational history, each project is an advancement of previous projects resulting in a lack of standardisation, and confidentiality within the industry means that there is insufficient data or information when planning future projects. Although these severe uncertainties exist, decision makers must make investment decisions about the design of future offshore transmission systems (OTSs). Consequently, there is a need for decision making techniques that are robust under severe uncertainty.

When using a model to conduct analysis, we might ask ourselves whether we have enough information to assign values or distributions to the inputs accurately. If we do have this information, we could proceed with using the classical theory of probability, which we briefly discuss later in this chapter. However, if we do not have this information, we should seek an alternative approach, and in Section 5.4, we discuss how imprecise probability could be a solution.

Thinking back to Chapter 4 and the net present value (NPV) model formulated there, several of the inputs were identified to be challenging to assign inputs values. These inputs included α (planned operational expenditure (OPEX) factor), vessel hire rate for cable repairs, interest rate (for the loan repayment of the capital costs), offshore cable failure rate, offshore cable repair time and ε_2 (capital expenditure (CAPEX) evaluation parameter). Therefore, we say that we have severe uncertainty about these inputs. In Chapter 4, we also identified that uncertainty in interest rates, planned operational expenditure and, particularly, cable failure rates have a significant impact on the NPV, and therefore further motivates the need for an alternative approach.

Several modelling parameters contain uncertainty, and the type of uncertainty can be described by two broad categories: aleatory uncertainty and epistemic uncertainty. Aleatory uncertainty comes from variability, and epistemic uncertainty arises due to a lack of completeness in our knowledge. These definitions are further explained in the coin toss example below. Additionally, the terms aleatory uncertainty and epistemic uncertainty are used throughout the thesis.

Coin toss example

Say we have a coin that we can toss and when it lands, it can either land on heads or tails. Lets first assume that we know the coin is fair, and therefore the probability of getting heads is equal to the probability of getting tails. Therefore, in this scenario, we would say that the probability of observing heads is 0.5. If we were to flip the coin and predict whether the outcome is heads or tails, there is uncertainty here called aleatory uncertainty. For example, we could not say for sure that the next toss will land on heads. This uncertainty is because we are observing a random process, and therefore there is variability in possible realisations of an event.

Now let us assume we have another coin that we do not know whether it is biased and therefore, we do not know the probability of this coin landing on heads. This uncertainty is our epistemic uncertainty: we do not have enough information or knowledge to accurately assign a value to the probability that the coin lands on heads. In this case, we still have aleatory uncertainty about the outcome of the next coin flip as it is a random process, but we also have epistemic uncertainty as we do not know the probability of observing heads. As the number of coin flips increases, our epistemic uncertainty reduces as we learn more about the bias of the coin, and eventually, we will have enough information about the probability of observing heads. However, our aleatory uncertainty about the outcome of the next coin toss will remain as we are still observing a random process.

5.3 Statistical Techniques Currently Implemented

In many applications, we use methods to express and reason with our knowledge about an event. If we are certain about our knowledge, we could use logic, and if we are uncertain, we could use probability theory. Within probability, there exist many interpretations, for example, the classical interpretation, the frequency interpretation and the subjective interpretation. These probability interpretations are briefly introduced below; however, for a more in-depth discussion, we refer to [193, 194].

5.3.1 Interpretations of Probability

Using the classical interpretation of probability, each outcome is treated as though it is as equally likely to occur as all the other outcomes [195]. To put this into context, as an example, let us consider the failure behaviour of a cable we plan to install. To conduct this analysis, we might wish to work with the probability of a cable failure occurring. In this cable failure example, there are two outcomes (working or not working). Therefore, based on the classical interpretation of probability, we assign a probability of 0.5 to each option. This classical interpretation of probability is likely to be inappropriate for many applications, including the cable failure example presented here. For examples where there is clear physical symmetry, such as dice or card games, assigning equal probability may be more suitable. In summary, if there are n possible outcomes of an experiment, then under the classical interpretation of probability each outcome is equally likely, and so we assign each outcome the same probability of $\frac{1}{n}$.

An alternative interpretation is called the frequency interpretation of probability [196, 197]. This interpretation is based on the long-term relative frequency of occurrences of a particular outcome. This relative frequency is used as the probability that we observe a particular outcome if the process is repeated under similar conditions for a large enough number of repetitions [194]. Unfortunately, many problems are not repeatable in this sense. Furthermore, the requirement that the process is repeatable under similar conditions brings additional challenges. Firstly, the definition of similar condition may not be well defined; secondly, similar conditions may be unrealistic to achieve if we consider repeating an experiment in the same place at the same time; and thirdly, it may not be feasible (usually due to time, space or cost), to repeat experiments [194]. For example, a project developer will only build one wind farm in any given location, at any given point in time. Again, let us consider the cable failure example. Based on the frequency interpretation of probability, we could use previous cable failure data, specifically the number of times the cables have previously failed, to arrive at the probability of a future cable failing. However, we may question whether the conditions surrounding each cable are similar enough, and therefore whether this event can be repeated.

Another interpretation is called the subjective interpretation of probability. Under the subjective interpretation, probabilities are degrees of belief of a subject and are assigned based on a subject's judgement about the likelihood that a given outcome will be obtained [194]. The work by de Finetti [198, 199] details one way to measure a subject's judgement, and this is through betting rates; a subject can express their degree of belief about an event occurring by a betting rate. This betting rate is the price a subject is willing to buy or sell a bet that returns one if the event occurs and zero if it does not. Naturally, one subject's beliefs (and therefore betting rates) may differ from another subject's as the probability assignments are likely to be based on the information a subject has about an event. Returning to the cable failure example, a subject may assign the probability of a specific cable failing based on the information they have about previous cables, as well as information that may be unique to this situation. Ultimately, a subject will assign probabilities based on all the evidence they have available.

5.3.2 Probability Theory

At this point, it is necessary to note that the theory of probability does not depend on the chosen interpretation of probability. The theory of probability has evolved since the 17^{th} century, where it is generally thought that the mathematical theory of probability was introduced by Pascal and Fermat [194]. For a more in-depth discussion of the history of probability we refer to [194]. Today, probability theory is a widely used tool across many fields of study. A fundamental contribution to probability theory was made by Kolomogorov who introduced the axioms of probability [200]. The three axioms of probability are [200]:

1. The probability of every event, A, is non-negative. This can be expressed as for all $A, P(A) \geq 0$.
2. If an event A is certain to occur then $P(A) = 1$.
3. For an infinite sequence of disjoint events $A_1, A_2, \ldots,$ we have that:

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i). \tag{5.1}$$

A probability can be defined mathematically as, on a sample space, the specification of numbers $P(A)$ for all A that satisfy the three axioms of probability [200]. From these axioms, other fundamental properties of probability can be derived. Probability is used to quantify how likely an event is to occur, and probability theory contains numerous techniques that can be implemented in a range of applications. In practice, we are often interested in discussing the expectation of an event occurring.

Let X be a random variable. The distribution of X contains all the probabilistic information about X [194]. However, sometimes summary information is preferred to describing the full distribution, for example, to communicate results concisely. One way to achieve this is to consider the expected value, $E(X)$, of X. If X is a discrete random variable, the expected value is defined by:

$$E(X) = \sum_{x} xp(x). \tag{5.2}$$

Here, $p(x) = P(X = x)$, where $X = x$ is the event that the random variable X equals the value of x. If X is a continuous random variable, the expected value is defined by:

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx. \tag{5.3}$$

Here, X has the probability density function $f(x) = \frac{d}{dx} P(X \leq x)$, where $X \leq x$ is the event that the random variable X is less than or equal to the value of x. For clarity, we point out that we are using standard notation by denoting the probability density function by $f(x)$. The use of f in this way is limited to Eq. (5.3), since elsewhere in this work (unless stated) f denotes the failure rate. We also note that X is continuous if it has a density (this means that the derivative exists for all x), and discrete if X only takes a finite number of values. The expected value of X is sometimes referred to as the mean of X and is commonly used in decision making. The expectation is used throughout the application chapters of this thesis.

We may also be interested in other probability concepts and techniques to quantify uncertainty such as probability distributions, variances and quantiles. For more information, we refer to [194].

5.3.3 Statistical Inference

The concepts of probability are used in problems, and this is called statistical inference [194]. One characteristic of a statistical inference problem is a statistical model, which is a family of probability distributions and is discussed in detail in [201]. Statistical inferences then make probabilistic statements (using concepts in probability) about parts of the statistical model. When conducting statistical inference, there are different philosophies about the treatment of parameters, namely frequentist statistics and Bayesian statistics. In the frequentist approach unknown but fixed parameters are not treated as random variables, whereas in the Bayesian approach, they are [194].

As previously described, when modelling a system, there may be aspects we are unsure about. When inferences and decisions are being made under severe uncertainty, it is essential to quantify this uncertainty. Uncertainty quantification is usually conducted using techniques based on probability theory. By this, we mean for a given event, say that an export cable will fail in the next year, we assign a probability to this event occurring. This probability is then used for inferences and decision making. In the case of the export cable, this may be predicting the expected number of failures a cable experiences, evaluating the expected availability of the cable, the availability of the system it belongs to, or predicting the expected cost of export cable failures.

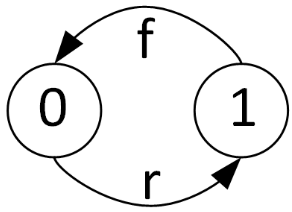


Figure 5.1: Two-state Markov chain. Here, state zero is the not working state and state one is the working state, f denotes the failure rate and r denotes the repair rate.

This approach is widely used, especially in practical applications; however, the approach has some limitations. When there only exists a small amount of information (that may be qualitative, irrelevant, or conflicting), we may not be able to specify a probability distribution since this requires a substantial amount of information. Unfortunately, there are situations where it is challenging to determine the probability of an event occurring, for example, and in the case of offshore power transmission, when there is a limited amount of useful data. Frequentist statistics and Bayesian statistics are often debated and compared. However, in the case where the problem at hand contains severe uncertainty, both options based on the classical theory of probability, may not be adequate. This shortcoming motivates a need for more robust techniques under severe uncertainty.

5.3.4 Limitations

In Chapter 4, we used many classical probability techniques, including modelling the component's failure and repair behaviour as a Markov process [123]. A component is either in the not working state (state 0) or the working state (state 1), and moves between the two states according to the component's failure and repair rate. Consequently, component behaviour is often modelled using Markov chains, as shown by Fig. 5.1. A Markov chain can be interpreted as a mathematical system that transitions between states according to specific probabilistic rules. Modelling a component in this way allows the expected downtime and number of failures to be calculated using Eq. (5.4) and Eq. (5.5). These equations are simple to use and are popular in engineering applications.

$$E(\text{Downtime}) = \frac{f}{f+r} \tag{5.4}$$

$$E(\text{Number of failures}) = \frac{fr}{f+r} \tag{5.5}$$

Here, f and r are the failure and repair rate of a component, respectively.

Unfortunately, precise Markov chains require assumptions to be made that may be unrealistic. Modelling a process using a Markov chain makes three assumptions [202]:

1. Time stationarity.
2. The Markovian property, that the process is memory-less: the transition rate to any other state only depends on the current state.
3. The transition rates (in the component behaviour case this is the failure and repair rates) are known precisely.

One consequence of these assumptions is that the transition times between states should be exponentially distributed.

Unfortunately, these assumptions may not be justified in the offshore wind setting. The first assumption may not be justified as the transition rates may vary in time. With regards to the second assumption, let us consider an offshore cable; the next state of the cable will likely depend on the entire history of the cable and not just its current state. Additionally, if we consider the repair rate of a component, as we see from the example below and Table 5.1, repairs typically fall into two categories: shorter repair time and longer repair time. A short repair time (perhaps less than one day) will be the case if a remote repair is possible; however, a longer repair time will be the case if the fault needs to be located and repaired by sending a vessel and crew offshore. Therefore, assuming a constant repair rate may be unrealistic. Many components do not satisfy this Markovian property (the second assumption) and subsequently, assuming that they do could be an oversimplification.

Finally, in practice, due to a limited amount of useful data, it may be challenging to specify the values of the transition rates. Therefore, the third assumption may not be reasonable. Usually, the most likely estimate is taken to be the value of the parameter, and as a result, any inferences made may not reflect the uncertainty of the input values. The validity of these assumptions is also discussed in the work of [140], who demonstrates the use of Markov chains and interval analysis techniques to study the availability of multi-state systems.

Let us look at a small example. Gwynt Y Mor is an offshore wind farm that became operational in February 2015. Between 2015 and 2017, two of the cable have experienced three failures each [141]. Data for these failures is given in Table 5.1. As there have not been many failures, there is minimal data and therefore checking that the time to fail and time to repair values are exponentially distributed is very challenging. Consequently, we do not have enough information to justify the Markovian property required to model the system using a Markov chain. Furthermore, we do not have enough data to reasonably assign a value to the failure and repair rates. Usually, the mean time to fail (MTTF) and mean time to repair (MTTR) would be evaluated to achieve this. However, given that we only have three data points for each cable and the values are quite varied, taking a mean would not be appropriate. Moreover, the export cables at Gwynt Y Mor have a nominal voltage of 132 kV, and as we have seen, the industry is moving towards 220 kV export cables. This advancement leads to the question of whether this data is relevant for future projects.

	Time to fail (days)	Time to repair (days)
Cable 1	13, 454, 0.23	106.08, 0.053, 0.0375
Cable 2	218, 294, 0.0014	153.64, 0.057, 0.053

Table 5.1: Time to fail and time to repairs in days for the export cables in Gwynt Y Mor offshore transmission system (OTS). Data interpreted from [141].

This subsection has highlighted that precise Markov chains are not suitable modelling techniques to model the failure and repair of components under severe uncertainty. We do not have enough information to confirm whether the modelling assumptions are realistic, and therefore any inferences and decisions made from this analysis should be treated with care. Although we have only demonstrated the limitations for Markov chain modelling, we can see how this extends to other techniques based on the classical theory of probability. In the next section, we suggest that techniques based on imprecise probability are a more robust approach under severe uncertainty than methods based on classical probability theory.

5.4 Imprecise Probability

5.4.1 Overview

The study of imprecise probability has a long history, including the work by [203]. More recently, [25] developed the theory further and coined the term imprecise probability. The techniques in this field have been advanced and applied by the research community several pieces of literature detail the theory, including [25, 204, 205]. In the next sections, we present an overview of imprecise probability theory following the work of [25, 204]. In summary, imprecise probability can be thought of as sets of probability models.

The techniques within the theory of imprecise probability are an extension of traditional probability concepts that allow for the more appropriate handling of severe uncertainties, and, importantly, as we will see for investment planning, indecision. By severe uncertainty we mean, for example, due to insufficient data (perhaps, very little data or even no data just expert intuition), and therefore, we cannot accurately specify a probability distribution. In contrast, if we have sufficient data, we have enough information to accurately specify a probability distribution. The methods provide an elegant framework for more accurately representing our knowledge and, enable inferences and decisions to be made under severe uncertainty [206]. Consequently, applying imprecise probability could have invaluable consequences for offshore power transmission.

A single probability measure is limited in the way that it can appropriately represent our knowledge of an event. For example, we may wish to model the failure behaviour of an export cable during the planning stage of a future project. In practice, we may not have enough data for the following reasons: the technology has a short operational history; previously installed cables may be in different conditions resulting in data that is likely to be site-specific; as technology advances, previous cables may not be representative of future cables; and finally, much of the data that exists is not publicly available. Therefore, representing our knowledge by a probability distribution may not be suitable under this level of uncertainty.

Let us say that we do not have enough information or data to assign a value or distribution to the probability of event A occurring, $P(A)$. However, we may be willing to make a weaker commitment. One approach, using a behavioural interpretation is to introduce a gap and specify supremum buying, $\underline{P}(A)$, and infimum selling, $\overline{P}(A)$, prices for, in this case, the indicator function I_A. Supremum is the greatest lower bound (often shortened to sup) and infimum is the smallest upper bound (often shortened to inf). In the literature, this described approach is called the theory of lower and upper previsions [207, 208, 25]. In a broader sense, the term imprecise probability is used to cover theories related to generalised uncertainty quantification, including lower and upper previsions [25].

The study of subjective probability as betting behaviours has a long history and was introduced by de Finetti [198, 199]. Building on this work, Williams studied imprecise subjective probabilities [209], and more recently Walley detailed this further [25]. By introducing the gap described above, imprecise probabilities can better represent our knowledge by assigning different values to the prices we are willing to sell and buy the occurrence of event A. Introducing this gap allows for indecision since we are willing to buy for any price less than $\underline{P}(A)$ and sell for any price greater than $\overline{P}(A)$. However, we note that between $\underline{P}(A)$ and $\overline{P}(A)$ we are undecided. Imprecise probabilities allow uncertainties about events to be quantified by intervals instead of a single value or distribution. Instead of representing the probability of event A occurring by $P(A)$, an interval $[\underline{P}(A), \overline{P}(A)]$ is assigned [204]. Here, $0 \leq \underline{P}(A) \leq \overline{P}(A) \leq 1$, and $\underline{P}(A)$ and $\overline{P}(A)$ are the upper and lower probabilities, respectively.

The theory of imprecise probabilities contains a range of techniques that are usually an extension of techniques found in the classical theory of probability. The selection of which techniques are most appropriate for a given problem should be chosen and applied based on the problem at hand. Accordingly, we reviewed the NPV model from Chapter 4 and identified that the foundations of imprecise probability (including lower and upper previsions), imprecise Markov chains and decision making techniques are required. Each of these topics will be discussed in the next sections.

5.4.2 Foundations of Imprecise Probability

Imprecise probability theory centres on the behavioural interpretation of subjective probabilities. By behavioural, we mean a subject's willingness to take certain actions. In the explanation, we use the word subject to represent the person taking actions. The knowledge that we have can be interpreted as a belief; an inclination to act. Imprecise probabilities consider a specific action called accepting a gamble. The definition below of a gamble follows [204].

Let $\mathcal{X}$ be a finite state space: the set of all possible states of the system. Any possible state of the system is denoted by x. A gamble, g, is defined as an uncertain pay off as the subject will obtain a different reward depending on the observed state [204]. g is a real-valued function on $\mathcal{X}$ such that $g\colon \mathcal{X} \to \mathbb{R}$. This can be interpreted as, if we take gamble g and observe the state x then the reward, as a result of gamble g, is $g(x) \in \mathbb{R}$. The reward is measured in units of utility. The utility received as a result of observing x is a measure of how x is valued and can be used to compare to the value of observing other $x \in \mathcal{X}$. $\mathcal{L}(\mathcal{X})$ denotes the set of all gambles on $\mathcal{X}$.

The reward of a gamble falls onto a linear utility scale, by that we mean that receiving two lots of the same reward is double the value compared to receiving one reward [204]. This is the case when the reward is money. We also consider a simple utility scale, by that we mean small scale money as large amounts may affect the way a subject gambles. Therefore, we assume a subject is risk-neutral for small amounts. It should also be noted that by these definitions, a reward can be negative. In this case, taking gamble g and observing state x results in the subject losing money, and therefore $g(x)$ is negative.

To put this into context, let us study a small example. We ask the question, what will the state of the export cable be tomorrow? To this question, we consider two options: working (a) and not working (b). In this case, $\mathcal{X} = \{a, b\}$. Let us say that if the cable is working, we receive five, but if the cable is not working, we owe ten that is $g(a) = 5$ and $g(b) = -10$.

A subject can accept a gamble; this means that they agree to the conditions of the gamble (which describes a subject's reward or loss for different possible outcomes) despite the outcome being uncertain. A subject's willingness to accept a gamble is likely to depend on their knowledge about an event. In the cable failure example, the reward if the cable is working is smaller than the penalty if the cable is not working. However, if the subject strongly believes that the cable is in an excellent working condition, they may be willing to accept the proposed gamble. A collection of gambles that a subject accepts forms a set of gambles termed desirable gambles [204]. We denote a set of desirable gambles by $\mathcal{D}$, where $\mathcal{D} \subseteq \mathcal{L}(\mathcal{X})$.

To extend the set of desirable gambles, we consider the following rationality requirements for desirability [204]:

1. A transaction that results in a loss should not be acceptable.
2. If a transaction is acceptable, then any transaction that gives a greater reward should also be acceptable.
3. A combination of acceptable gambles should also be acceptable.
4. Scaling an acceptable gamble by a positive constant should also be acceptable.

Specifically, axioms two to four can be used to extend the set of desirable gambles, and if axiom one is violated, then the initial selection was bad.

These rationality requirements motivate the following rationality axioms for desirability [204]. Let $g, g_1, g_2 \in \mathcal{L}(\mathcal{X})$ and $\zeta_1 \in \mathbb{R}_{>0}$, then we have:

1. If $g(x) \leq 0 \ \forall x \in \mathcal{X}$ and $g(x) < 0$ for at least one $x \in \mathcal{X}$ then $g \notin \mathcal{D}$.
2. If $g(x) \geq 0 \ \forall x \in \mathcal{X}$ then $g \in \mathcal{D}$.
3. If $g_1, g_2 \in \mathcal{D}$ then $g_1 + g_2 \in \mathcal{D}$
4. If $g \in \mathcal{D}$ then $\zeta_1 g \in \mathcal{D}$

A set of desirable gambles $\mathcal{D}$ is coherent if the axioms above are satisfied [204]. Coherence will be discussed later in this section.

Returning to the cable failure example, we present several gambles, g_i, and discuss whether they are desirable gambles. The gamble $g_1(a) = 0$ and $g_1(b) = 0$ is always desirable as whatever the outcome the subject will not lose a reward. The gamble $g_2(a) = -1$ and $g_2(b) = -10$ is never desirable since whatever the outcome the subject will be at a loss. If the subject thinks the gamble $g_3(a) = 5$ and $g_3(b) = -10$ is desirable, then $g_4(a) = 15$ and $g_4(b) = -30$ is also desirable to the same subject due to the positive scaling axiom. Similarly, if $g_5(a) = 7$ and $g_5(b) = -12$ is desirable then $g_6(a) = 12$ and $g_6(b) = -22$ is also desirable, due to the addition axiom ($g_3 + g_5 = g_6$). Additionally, the gamble $g_7(a) = 6$ and $g_7(b) = -9$ is also desirable since it offers a greater reward than g_3 which we assumed to be desirable.

The concepts of desirability provide the foundations upon on which the general theory of imprecise probability is built [204]. Unfortunately, desirability uses an unfamiliar language, especially in comparison to terms more commonly used in classical probability theory such as events, probability and expectations [204]. To connect the concepts of desirability and the more traditional theory of probability, lower and upper previsions are used [204].

5.4.3 Lower and Upper Previsions

Upper and lower previsions are direct generalisations of the probabilities and expectations we see in classical theory [204]. This theory was largely developed by Peter Williams [207, 208] and Peter Walley [25]. The theory considers two types of transactions:

1. A subject accepts to buy the gamble g for a price ϕ, which is equivalent to accepting the gamble $g - \phi$.
2. A subject accepts to sell the gamble g for a price of ψ, which is equivalent to accepting the gamble $\psi - g$.

A lower prevision $\underline{P}(g)$ for gamble g is the supremum acceptable buying price for g and the upper prevision $\overline{P}(g)$ for gamble g is the infimum acceptable selling price for g. Mathematically, the definitions for lower and upper previsions are expressed by Eqs. (5.6) and (5.7) [204]. Here, $\mathcal{D}$ denotes a set of desirable gambles.

$$\underline{P}(g) \coloneqq \sup\{\phi \in \mathbb{R} \colon g - \phi \in \mathcal{D}\} \tag{5.6}$$

$$\overline{P}(g) := \inf\{\psi \in \mathbb{R} : \psi - g \in \mathcal{D}\} \tag{5.7}$$

To put this into context, we return to the cable failure example. Again, let gamble g be defined by $g(a) = 5$ and $g(b) = -10$. If the subject were to buy gamble g for a price of ϕ then if the cable is working, they would receive $5 - \phi$, and if the cable is not working, they will receive $-10 - \phi$. We recall that the lower prevision is the supremum amount that the subject is willing to pay for the gamble. If the subject knew for certain that the cable would be working, they might be willing to pay up to five for the gamble. Similarly, if the subject were to sell the gamble g for a price of ψ, then they would receive $\psi - 5$ if the cable is working and $\psi + 10$ if the cable is not working. The upper prevision is the infimum amount the subject is willing to pay for the gamble. In this case, the subject will make money if they sell the gamble for any price higher than five.

At this point, it is important to note that selling the gamble g for ϕ is the same as buying the gamble $-g$ for $-\phi$. This can be shown, as in [204], to lead to $\overline{P}(g) = -\underline{P}(-g)$.

Also, we note that if the lower prevision is equal to the upper prevision, then we have a precise prevision.

In the theory of lower previsions, we are not directly working with a subject's set of desirable gambles. Instead, we model their beliefs by lower and upper previsions [204]. Let a subject indicate a lower prevision, $\underline{P}$, this is a real-valued function such that $\underline{P}\colon \mathcal{K} \to \mathbb{R}$, where $\mathcal{K}$ is the domain of $\underline{P}$. We can define a subject's lower prevision, $\underline{P}(g)$, as their supremum buying price for g. This definition means that a subject is willing to pay any price up to $\underline{P}(g)$ for g. Specifying a lower prevision, $\underline{P}$, is equivalent to the subject accepting $g - \underline{P}(g) + \epsilon$ for all $\epsilon > 0$. Likewise, a subject's upper prevision $\overline{P}(g)$ is defined as a subject's infimum acceptable selling price for g [204].

Lower and upper previsions are subject to specific requirements that are based on the rationality of a subject's behaviour. Previously, we outlined the rationality requirements for desirability. Similarly, here, we discuss two notions of irrational behaviour that lead to requirements for the lower prevision. Firstly, the subject should not lose for all outcomes. This condition is called avoiding sure loss, and we require that a lower prevision $\underline{P}$ avoids sure loss. Mathematically, this is expressed by Eq. (5.8) [204]. $\underline{P}$ avoids sure loss if, $\forall n \in \mathbb{N}$ and $\forall g_i \in \mathcal{K}$, we have:

$$\sup_{x\in\mathcal{X}} \left(\sum_{i=1}^{n} (g_i(x) - \underline{P}(g_i)) \right) \geq 0. \tag{5.8}$$

Here, $\mathbb{N}$ denotes the natural numbers including zero: $\mathbb{N} = \{0, 1, 2, \dots\}$.

Returning to the cable failure example, we consider the gamble $g_8(a) = 2$ and $g_8(b) = -5$, and the subject specifies a lower prevision $\underline{P}(g_8) = 4$. In this scenario, the subject loses regardless of the cable's status since $g_8 - \underline{P}(g_8)$ is -2 if the cable is working and -9 if the cable is not working. Similarly, let's take the gamble $g_9(a) = 10$ and $g_9(b) = 2$, and the subject specifies a lower prevision $\underline{P}(g_9) = 9$. Let's also consider the gamble $g_{10}(a) =1$ and $g_{10}(b) = 5$, and say the subject specifies a lower prevision of $\underline{P}(g_{10}) = 4$. In this scenario, the subject buys both of the gambles for thirteen, but only makes eleven if the cable is working and seven if the cable is not working. Therefore, this case does not avoid sure loss. This example to illustrate avoiding sure loss follows an example given in [204] for a different context.

Secondly, we require that the subject is consistent with the gambles they accept. Therefore, we require that the lower prevision for a gamble cannot be increased by considering a positive linear combination of a finite number of other acceptable gambles [25]. This condition is called coherence and can be mathematically expressed by Eq. (5.9). $\underline{P}$ is coherent if, $\forall n \in \mathbb{N}, m \in \mathbb{N}$, and $\forall g_0, g_1, \dots, g_n \in \mathcal{K}$, we have that:

$$\sup_{x\in\mathcal{X}} \left(\sum_{i=1}^{n} (g_i(x) - \underline{P}(g_i)) - m(g_0(x) - \underline{P}(g_0)) \right) \geq 0. \tag{5.9}$$

Again, we recall the cable failure example. This example to illustrate coherence also follows an example given in [204] for a different context. Let $g_{11}(a) = 0$ and $g_{11}(b) = 5$, and the subject specifies a lower prevision $\underline{P}(g_{11}) = 4$. Also let $g_{12}(a) = 7$ and $g_{12}(b) = 2$, and the subject specifies a lower prevision $\underline{P}(g_{12}) = 3$ and an upper prevision $\overline{P}(g_{12}) = 5$. We see that buying gamble g_{11} for 4 results in a reward of -4 if the cable is working and a reward of 1 if the cable is not working. However, if the subject sells gamble g_{12} for 4, they receive -3 if the cable is working and 2 if the cable is not working. This reward is higher than buying g_{11} for 4. Therefore, selling g_{12} for 4 should be desirable. However, the subject specified the upper prevision $\overline{P}(g_{12}) = 5$, which means that the subjects sells g_{12} for any price her than 5. Therefore, the accepted gambles are inconsistent.

So far, in this section, we have detailed lower previsions. Next, we need to consider how to apply these concepts to an investment planning decision problem. Coherent lower previsions satisfy several properties; these are detailed in full in [25, 204]. In this section, we present the properties that are most relevant to our applications. These properties allow us to reason with lower and upper previsions. Eq. (5.10) relates the lower prevision of a sum to the sum of its lower previsions. Eq. (5.11) relates the prevision of a product of a constant and a gamble with the previsions of the gamble. Eq. (5.12) shows that the lower prevision of a constant, upper prevision of a constant, and the constant itself are all equal. Eqs. (5.13) and (5.14) shows how to relate a prevision of a gamble plus a constant to the prevision of a gamble. Let g_1 and g_2 be gambles, $\underline{P}$ a coherent lower prevision and $\overline{P}$ its conjugate upper prevision. Let $\zeta_2 \in \mathbb{R}_{\geq 0}$ and $\zeta_3 \in \mathbb{R}$. Then we have Eqs. (5.10) to (5.14) [25, 204].

$$\underline{P}(g_1) + \underline{P}(g_2) \leq \underline{P}(g_1 + g_2) \leq \underline{P}(g_1) + \overline{P}(g_2) \leq \overline{P}(g_1 + g_2) \leq \overline{P}(g_1) + \overline{P}(g_2) \tag{5.10}$$

$$\underline{P}(\zeta_2 g_1) = \zeta_2 \underline{P}(g_1) \tag{5.11}$$

$$\underline{P}(\zeta_3) = \overline{P}(\zeta_3) = \zeta_3 \tag{5.12}$$

$$\underline{P}(g_1 + \zeta_3) = \underline{P}(g_1) + \zeta_3 \tag{5.13}$$

$$\overline{P}(g_1 + \zeta_3) = \overline{P}(g_1) + \zeta_3 \tag{5.14}$$

Throughout this work, upper and lower quantities will be denoted by the symbol having an underline and overline, respectively. For example, if Q denotes the rate operator, then $\underline{Q}$ denotes the lower rate operator.

5.4.4 Imprecise Markov Chains

In this section, we explain continuous-time imprecise Markov chains which have been developed and applied by [210, 211, 212, 213, 214, 215, 216]. From a practical point, we usually formulate a probabilistic model and assign input parameters for the purpose of making inferences and decisions. These inferences will typically consider the expectation of an event of interest. Therefore, the discussion in this section will focus on the methodology required to make these inferences. We also focus on a two-state system as this is the case for our application. For further details on the history, methodology developments and a more general case of an imprecise continuous-time Markov chain, we refer to [212, 214].

Markov chains are mathematical models used to describe the evolution of a system under stochastic uncertainty. Unfortunately, as previously identified, precise Markov chains require assumptions to be made that may not always be realistic. One assumption is the Markovian property which in the offshore power transmission setting may not be justified. Furthermore, precise Markov chains require point estimates for the transition rates. Unfortunately, due to a limited amount of useful data, this may not be possible in the offshore wind setting. These assumptions allow continuous-time Markov chains to be described by simple analytical expressions and thus are widely used. In contrast, imprecise continuous-time Markov chains provide more robust generalisations that relax these described assumptions [214]. For a two-state system, these assumptions can be relaxed, and the equations are still relatively simple to work with.

An imprecise continuous-time Markov chain is a set of stochastic processes where conditions are specified on the bounds of these processes; however, in the set, the processes may not be Markovian. When making inferences, rather than computing expected values of a function, we compute lower and upper expectations. The lower and upper expectations can be thought of as providing worst- and best-case scenarios when all of the stochastic processes in the set are considered. An imprecise continuous-time Markov chain is similar to a Markov chain and therefore can be used to model similar types of systems. The development of imprecise Markov chains ([210, 211, 212, 213, 214, 215, 216]) provides a framework to model stochastic processes under severe uncertainty.

Definitions and Notation for Imprecise Continuous-Time Markov Chains

Previously, in this chapter, we introduced a precise continuous-time Markov chain, which describes a stochastic process whose transition rate to any other state only depends on the current state. For a continuous-time Markov chain there exists a transition matrix, T_t, which describes the probability of the system moving between states at any fixed time t. Mathematically, this can be expressed as:

$$(T_t)_{ij} \coloneqq P(X_{s+t} = j | X_s = i) \tag{5.15}$$

where i and j are states in $\mathcal{C}$ and X_s is the state of the system at time s. Importantly, modelling a system using a precise continuous-time Markov chain assumes that the probability of transitioning to the next state is conditional on X_s, but is independent of all previous states of the system. Therefore, since T_t does not depend on the time s, the process is stationary. Later in this chapter, when using imprecise continuous-time Markov chains, we introduce upper and lower transition matrices denoted by $\overline{T}_t$ and $\underline{T}_t$.

The transition matrix, T_t, satisfies Kolmogorov's forward and backward equations given by Eq. (5.16) and Eq. (5.17), with the initial condition $T_0 = I$. Here, I is the identity matrix. Let Q denote the transition rate matrix that describes how a Markov chain moves between states. If Q is constant in time, then it can be shown that $T_t = \exp(tQ)$ is the solution to Eq. (5.16) and Eq. (5.17).

$$\frac{\mathrm{d}}{\mathrm{d}t}T_t = T_tQ \tag{5.16}$$

$$\frac{\mathrm{d}}{\mathrm{d}t}T_t = QT_t \tag{5.17}$$

If $Q = \begin{pmatrix} -r & r \\ f & -f \end{pmatrix}$, then $Q_{01} = r$ describes a system moving from state 0 to state 1 at a rate of r. In this two-state case, the transition matrix can be expressed by:

$$T_t \coloneqq I + \tfrac{1-e^{-(r+f)t}}{r+f}Q. \tag{5.18}$$

Again, in the imprecise case, we have upper and lower rate matrices denoted by $\overline{Q}$ and $\underline{Q}$. At this point, it is important to discuss what is meant by $\overline{Q}$ and $\underline{Q}$. Here, we provide an explanation that is sufficient for our applications. For more in-depth definitions and descriptions, we refer to [213, 212, 214, 217]. Moving from a precise continuous-time Markov chain to an imprecise continuous-time Markov chain, we relax the stationarity assumption and the Markovian assumption. Consequently, using imprecise continuous-time Markov chains, we now consider a set of transition rate matrices $\mathcal{Q}$. Following the definition given by [212], an imprecise continuous-time Markov chain is a random process whose transition rate matrix is a function $Q \in \mathcal{Q}$. Furthermore, all that is known about Q is that it takes some values in $\mathcal{Q}$; beyond this, we do not make any further assumptions. Since Q is allowed to be time-dependent and history-dependent (and following the notation given by [213]), $Q_{ij}(t, t_n, x_n, \dots, t_0, x_0)$ can be a function that depends on the full history of the system. Here, $t_0 > t_1 > \cdots > t_n > t$.

A methodology that does not assume time and history dependence is convenient for offshore transmission applications since we previously discussed that, due to limited data, we could not validate these assumptions. We are especially interested in making inferences about the system, and in the imprecise case, this is possible by performing a sensitivity analysis over all the continuous-time processes in $\mathcal{Q}$. As we see later in this chapter, to make inferences about an imprecise continuous-time Markov chain, we require $\underline{T}_t$ and $\underline{Q}$. Following [213], the lower rate operator $\underline{Q}$ is defined by:

$$[\underline{Q}g]_i \coloneqq \min_{Q \in \mathcal{Q}} [Qg]_i = \min_{Q_{i*} \in \mathcal{Q}_{i*}} [Q_{i*}g]_i \tag{5.19}$$

for any real function g on the state space of the Markov chain. Here, Q_{i*} denotes the i^{th} row of Q. For further details, we refer to [213].

Based on the example given in [215], we present an example of a lower rate operator for a two-state system:

$$\begin{aligned}
\underline{Q}g &= \min \left\{ \begin{pmatrix} -r & r \\ f & -f \end{pmatrix} \begin{pmatrix} g(0) \\ g(1) \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}] \right\} && (5.20) \\
&= \min \left\{ \begin{pmatrix} r(g(1) - g(0)) \\ f(g(0) - g(1)) \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}] \right\} && (5.21) \\
&= \begin{cases} \begin{pmatrix} \underline{r}(g(1) - g(0)) \\ \overline{f}(g(0) - g(1)) \end{pmatrix}, & \text{if } g(1) > g(0) \\ \begin{pmatrix} \overline{r}(g(1) - g(0)) \\ \underline{f}(g(0) - g(1)) \end{pmatrix}, & \text{if } g(1) < g(0) \end{cases} && (5.22)
\end{aligned}$$

Using precise Markov chains, the transition rates are specified by single values. However, using imprecise Markov chains we can to relax this constraint since, as shown in Eq. (5.20), transition rates are specified by a set of values (for example, $r \in [\underline{r}, \overline{r}]$). Relaxing this requirement also relaxes the time stationarity assumption, as the rate parameters can vary in time provided they stay within the bounds. Therefore, the imprecise Markov chain allows us to relax the Markovian property since we only require the Markov assumptions to be satisfied on the bounds.

The indicator function, which will be used later on, is defined by Eq. (5.23).

$$I_j(i) = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases} \tag{5.23}$$

Imprecise Continuous-Time Markov Chain: Analytical Solution to the Differential Equation

Making inferences about an imprecise continuous-time Markov chain requires the solution of the non-linear differential equation given by Eq. (5.24). Usually, analytical expressions for solutions to this differential equation are not available, and consequently, numerical approximation methods have been developed [212, 214, 215]. Fortunately, for the simple two-state case that we are considering, the work by [215] shows and proves that an analytical solution exists. A generic version of this solution is presented here as well as a shorter proof that it does indeed satisfy Eq. (5.24). This proof is also presented in [218].

$$\frac{\mathrm{d}}{\mathrm{d}t}[\underline{T}_t g] = \underline{Q}[\underline{T}_t g] \qquad\qquad \text{with initial condition } \underline{T}_0 = g \tag{5.24}$$

Once we have a solution to the differential equation, we can make inferences such as the expected time spent in each state and the expected number of visits to each state. These quantities are usually of interest when modelling a process using a Markov chain. In the rest of this section, we first give a solution to the differential equation in the two-state case and present a proof that the solution does satisfy Eq. (5.24). Then, we explain how to use this imprecise Markov chain to make inferences.

Proposed Solution to the Differential Equation

Eq. (5.25) proposes a general solution to Eq. (5.24).

$$\underline{T}_t g \coloneqq g + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g} Q_g g, \tag{5.25}$$

Here,

$$Q_g \coloneqq \begin{pmatrix} -r_g & r_g \\ f_g & -f_g \end{pmatrix} \tag{5.26}$$

and

$$(r_g, f_g) \coloneqq \begin{cases} (\underline{r}, \overline{f}) & \text{if } g(0) \leq g(1) \\ (\overline{r}, \underline{f}) & \text{if } g(0) > g(1) \end{cases} \tag{5.27}$$

where $0 \leq \underline{f} \leq \overline{f}$ bound the transition from state 1 to state 0, and $0 \leq \underline{r} \leq \overline{r}$ bound the transition from state 0 to state 1.

At this point, we note that the solution proposed in Eq. (5.24) is quite unusual; usually, the lower operator is not corresponding to the precise operators. This feature makes the two-state case special. Furthermore, in practice, two-state imprecise Markov chains may be more convenient than n-state Markov chains, where $n > 2$, to make inferences. This simplicity arises as we have closed analytical expressions for typical quantities of interest, such as expected time spent in each state and the expected number of transitions to each state. Conveniently, many of the processes we model can be reasonably modelled by a two-state imprecise Markov chain.

Next, we aim to show that $\underline{T}_t$ given by Eq. (5.25) is the lower transition operator and does satisfy Eq. (5.24). This proof is given in [218] and is presented below for completeness. First, we prove Theorem 5.4.1 (which is required in the rest of the proof) by induction.

Next, we prove that Eq. (5.25) is the lower transition operator. We then prove Lemma 5.4.2 and Lemma 5.4.3, and use these to prove Theorem 5.4.4: that Eq. (5.25) does satisfy Eq. (5.24).

Throughout, we use the fact that for any matrix A:

$$\exp(A) = \sum_{n=0}^{\infty} \frac{1}{n!} A^n. \tag{5.28}$$

Theorem 5.4.1. *For every a and $b \in \mathbb{R}$ such that $a + b \neq 0$, and for every $n \in \mathbb{N}$, $n \geq 1$, we have that*

$$\begin{pmatrix} -a & a \\ b & -b \end{pmatrix}^n = c_n \begin{pmatrix} -a & a \\ b & -b \end{pmatrix} \tag{5.29}$$

where $c_n := \frac{-(-a-b)^n}{a+b}$.

Proof. We proceed to prove Eq. (5.29) by induction. Clearly Eq. (5.29) holds for $n = 1$. We assume Eq. (5.29) holds for a particular fixed value of $n \geq 1$. Then,

$$\begin{pmatrix} -a & a \\ b & -b \end{pmatrix}^{n+1} = \begin{pmatrix} -a & a \\ b & -b \end{pmatrix}^n \begin{pmatrix} -a & a \\ b & -b \end{pmatrix} \tag{5.30}$$

$$= c_n \begin{pmatrix} -a & a \\ b & -b \end{pmatrix} \begin{pmatrix} -a & a \\ b & -b \end{pmatrix} \tag{5.31}$$

$$= c_n \begin{pmatrix} a^2 + ab & -a^2 - ab \\ -ab - b^2 & ab + b^2 \end{pmatrix} \tag{5.32}$$

$$= c_n \begin{pmatrix} -a(-a-b) & a(-a-b) \\ b(-a-b) & -b(-a-b) \end{pmatrix} \tag{5.33}$$

$$= c_{n+1} \begin{pmatrix} -a & a \\ b & -b \end{pmatrix} \tag{5.34}$$

So, by induction, Eq. (5.29) must hold for all $n \in \mathbb{N}$, $n \geq 1$. $\square$

Next, we want to prove that the expression for $\underline{T}_t$, repeated here for convenience, corresponds to the lower transition operator.

$$\underline{T}_t g := g + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g} Q_g g, \tag{5.35}$$

We prove that this operator, $\underline{T}_t$, solves the specific differential equation given in Eq. (5.24). It follows then from [212] that the solution to this differential equation is the lower transition operator.

Lemma 5.4.2. *For every $g \in \mathbb{R}^2$, we have that*

$$[\underline{T}_t g](0) - [\underline{T}_t g](1) = (g(0) - g(1))e^{-(f_g+r_g)t}. \tag{5.36}$$

Proof.

$$
\begin{aligned}
&[\underline{T}_t g](0) - [\underline{T}_t g](1) && (5.37)\\
&= \left(g(0) + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g}[Q_g g](0)\right) - \left(g(1) + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g}[Q_g g](1)\right) && (5.38)\\
&= \left(g(0) + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g} r_g(g(1)-g(0))\right) - \left(g(1) + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g} f_g(g(0)-g(1))\right) && (5.39)\\
&= g(0) - g(1) + (g(0)-g(1))(-r_g - f_g)\tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g} && (5.40)\\
&= (g(0)-g(1))e^{-(f_g+r_g)t} && (5.41)
\end{aligned}
$$

□

Lemma 5.4.3. *$f_{\underline{T}_t g} = f_g$ and $r_{\underline{T}_t g} = r_g$.*

Proof. f_g and r_g are determined solely by the sign of $g(0) - g(1)$. Since, by Lemma 5.4.2, the sign of $[\underline{T}_t g](0) - [\underline{T}_t g](1)$ is the same as the sign of $g(0) - g(1)$, we have that $(f_g, r_g) = (f_{\underline{T}_t g}, r_{\underline{T}_t g})$. □

Theorem 5.4.4. *The operator $\underline{T}_t$, as defined in Eq.* (5.35)*, solves*

$$\frac{\mathrm{d}}{\mathrm{d}t}[\underline{T}_t g] = \underline{Q}[\underline{T}_t g] \tag{5.42}$$

with initial condition $\underline{T}_0 g = g$.

Proof. We see that the initial condition $\underline{T}_0 g = g$ is satisfied. Evaluating the left-hand side of Eq. (5.42) we have:

$$\frac{\mathrm{d}}{\mathrm{d}t}[\underline{T}_t g] = e^{-(f_g+r_g)t} Q_g g \tag{5.43}$$

Evaluating the right-hand side of Eq. (5.42) and using Lemma 5.4.3 we have:

$$
\begin{aligned}
\underline{Q}[\underline{T}_t g] &= Q_{\underline{T}_t g}[\underline{T}_t g] && (5.44)\\
&= Q_g[\underline{T}_t g] && (5.45)\\
&= \left(Q_g + \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g} Q_g^2\right) g && (5.46)
\end{aligned}
$$

By Eq. (5.29), $Q_g^2 = -(f_g + r_g)Q_g$. Therefore,

$$
\begin{aligned}
\underline{Q}[\underline{T}_t g] &= \left(Q_g - \tfrac{1-e^{-(f_g+r_g)t}}{f_g+r_g}(f_g + r_g)Q_g\right) g && (5.47)\\
&= e^{-(f_g+r_g)t} Q_g g && (5.48)
\end{aligned}
$$

□

This work proves that the general solution given by Eq. (5.25) satisfies the initial condition and the differential equation. Subsequently, this verifies that Eq. (5.25) is a solution of the differential equation and can be used to make inferences about the imprecise continuous-time Markov chain.

Solutions to the Differential Equation for Specific Scenarios

Below are the solutions for cases where $g(0) > g(1)$ and $g(0) < g(1)$. These will be used later in the work and thus are here for future reference.

For $g(0) > g(1)$:

$$[\underline{T}_t g](0) = g(0) - \frac{\overline{r}}{\overline{r} + \underline{f}}(g(1) - g(0))(1 - e^{-t(\overline{r}+\underline{f})}), \tag{5.49}$$

$$[\underline{T}_t g](1) = g(1) + \frac{\underline{f}}{\overline{r} + \underline{f}}(g(1) - g(0))(1 - e^{-t(\overline{r}+\underline{f})}), \tag{5.50}$$

and similarly,

$$[\overline{T}_t g](0) = g(0) - \frac{\underline{r}}{\underline{r} + \overline{f}}(g(1) - g(0))(1 - e^{-t(\underline{r}+\overline{f})}), \tag{5.51}$$

$$[\overline{T}_t g](1) = g(1) + \frac{\overline{f}}{\underline{r} + \overline{f}}(g(1) - g(0))(1 - e^{-t(\underline{r}+\overline{f})}). \tag{5.52}$$

For $g(1) > g(0)$:

$$[\underline{T}_t g](0) = g(0) + \frac{\underline{r}}{\underline{r} + \overline{f}}(g(1) - g(0))(1 - e^{-t(\underline{r}+\overline{f})}), \tag{5.53}$$

$$[\underline{T}_t g](1) = g(1) - \frac{\overline{f}}{\underline{r} + \overline{f}}(g(1) - g(0))(1 - e^{-t(\underline{r}+\overline{f})}), \tag{5.54}$$

and similarly,

$$[\overline{T}_t g](0) = g(0) + \frac{\overline{r}}{\overline{r} + \underline{f}}(g(1) - g(0))(1 - e^{-t(\overline{r}+\underline{f})}), \tag{5.55}$$

$$[\overline{T}_t g](1) = g(1) - \frac{\underline{f}}{\overline{r} + \underline{f}}(g(1) - g(0))(1 - e^{-t(\overline{r}+\underline{f})}). \tag{5.56}$$

Using an imprecise Markov chain to make inferences

Now that we have a solution to the differential equation, we can use the model to make inferences. In the rest of this section, we show how to use an imprecise continuous-time Markov chain to make inferences. We begin by considering how to evaluate bounds on the expected time spent in each state (the stationary distribution). The lower stationary distribution is defined by [213]:

$$\underline{\pi}_i = \lim_{t\to\infty} [\underline{T}_t I_i]_j. \tag{5.57}$$

And similarly, the upper stationary distribution is defined by:

$$\overline{\pi}_i = \lim_{t\to\infty} [\overline{T}_t I_i]_j. \tag{5.58}$$

Following on from Eqs. (5.57) and (5.58), expressions for the upper and lower stationary distribution are given by:

a) The lower expected proportion of time spent in state 0: $\underline{\pi}_0 = \lim_{t\to\infty}[\underline{T}_t I_0]_1$

b) The lower expected proportion of time spent in state 1: $\underline{\pi}_1 = \lim_{t\to\infty}[\underline{T}_t I_1]_0$

c) The upper expected proportion of time spent in state 0: $\overline{\pi}_0 = \lim_{t\to\infty}[\overline{T}_t I_0]_1$

d) The upper expected proportion of time spent in state 1: $\overline{\pi}_1 = \lim_{t\to\infty}[\overline{T}_t I_1]_0$

In order to evaluate the expressions above, we need to use the analytical solutions given in Eqs. (5.49) to (5.56). Using these analytical solutions, we obtain the expressions given in Eqs. (5.59) to (5.62).

a)

$$\lim_{t\to\infty}[\underline{T}_t I_0] = \lim_{t\to\infty}\left[\begin{pmatrix} I_0(0) - \frac{\overline{r}}{\underline{f}+\overline{r}}(1-e^{-t(\underline{f}+\overline{r})}) \\ I_0(1) + \frac{\underline{f}}{\underline{f}+\overline{r}}(1-e^{-t(\underline{f}+\overline{r})}) \end{pmatrix}\right] = \begin{pmatrix} 1 - \frac{\overline{r}}{\underline{f}+\overline{r}} \\ \frac{\underline{f}}{\underline{f}+\overline{r}} \end{pmatrix} \tag{5.59}$$

b)

$$\lim_{t\to\infty}[\underline{T}_t I_1] = \lim_{t\to\infty}\left[\begin{pmatrix} I_1(0) + \frac{\underline{r}}{\underline{r}+\overline{f}}(1-e^{-t(\underline{r}+\overline{f})}) \\ I_1(1) - \frac{\overline{f}}{\underline{r}+\overline{f}}(1-e^{-t(\underline{r}+\overline{f})}) \end{pmatrix}\right] = \begin{pmatrix} \frac{\underline{r}}{\underline{r}+\overline{f}} \\ 1 - \frac{\overline{f}}{\underline{r}+\overline{f}} \end{pmatrix} \tag{5.60}$$

c)

$$\lim_{t\to\infty}[\overline{T}_t I_0] = \lim_{t\to\infty}\left[\begin{pmatrix} I_0(0) - \frac{\underline{r}}{\overline{f}+\underline{r}}(1-e^{-t(\overline{f}+\underline{r})}) \\ I_0(1) + \frac{\overline{f}}{\overline{f}+\underline{r}}(1-e^{-t(\overline{f}+\underline{r})}) \end{pmatrix}\right] = \begin{pmatrix} 1 - \frac{\underline{r}}{\overline{f}+\underline{r}} \\ \frac{\overline{f}}{\overline{f}+\underline{r}} \end{pmatrix} \tag{5.61}$$

d)

$$\lim_{t\to\infty}[\overline{T}_t I_1] = \lim_{t\to\infty}\left[\begin{pmatrix} I_1(0) + \frac{\overline{r}}{\overline{r}+\underline{f}}(1-e^{-t(\overline{r}+\underline{f})}) \\ I_1(1) - \frac{\underline{f}}{\overline{r}+\underline{f}}(1-e^{-t(\overline{r}+\underline{f})}) \end{pmatrix}\right] = \begin{pmatrix} \frac{\overline{r}}{\overline{r}+\underline{f}} \\ 1 - \frac{\underline{f}}{\overline{r}+\underline{f}} \end{pmatrix} \tag{5.62}$$

Using these equation, we obtain the upper and lower stationary distributions given by:

$$\underline{\pi} = \left(\frac{\underline{f}}{\underline{f}+\overline{r}}, \frac{\underline{r}}{\underline{r}+\overline{f}}\right), \tag{5.63}$$

$$\overline{\pi} = \left(\frac{\overline{f}}{\overline{f}+\underline{r}}, \frac{\overline{r}}{\overline{r}+\underline{f}}\right). \tag{5.64}$$

Note that we see the following:

$$\underline{\pi}_1 = 1 - \overline{\pi}_0, \tag{5.65}$$

$$\overline{\pi}_1 = 1 - \underline{\pi}_0. \tag{5.66}$$

Next, we consider the lower and upper expectation of the number of visits to a given state in a given period. This metric is usually of interest when making inferences about a system modelled using a Markov chain. γ_i denotes the expected number of visits to state i in a given time period of length κ. The lower and upper values of γ_i are given in Eq. (5.68) and Eq. (5.68), respectively [213].

$$\underline{\gamma}_i = \kappa \sum_{j\neq i} \underline{\pi}_j [\underline{Q} I_i]_j \tag{5.67}$$

$$\overline{\gamma}_i = \kappa \sum_{j\neq i} \overline{\pi}_j [\overline{Q} I_i]_j \tag{5.68}$$

Using Eqs. (5.67) and (5.68), we can formulate the upper and lower expected number of transitions in one year from any state to each of the other possible states. The resulting formula is given below. Note that $\kappa = 1$ since we are analysing one year.

e) The lower expected number of transitions to state 0: $\underline{\gamma}_0 = \underline{\pi}_1[\underline{Q}I_0]_1$

f) The lower expected number of transitions to state 1: $\underline{\gamma}_1 = \underline{\pi}_0[\underline{Q}I_1]_0$

g) The upper expected number of transitions to state 0: $\overline{\gamma}_0 = \overline{\pi}_1[\overline{Q}I_0]_1$

h) The upper expected number of transitions to state 1: $\overline{\gamma}_1 = \overline{\pi}_0[\overline{Q}I_1]_0$

In order to evaluate the upper and lower number of transitions to each state, we evaluate the upper and lower stationary distributions ($\underline{\pi}$ and $\overline{\pi}$), and the result of the transition rate operator operating on the indicator function (for example, $[\underline{Q}I_1]$). We have already evaluated the upper and lower stationary distributions. The next step is to evaluate the transition rate operator operating on the indicator function. Eqs. (5.69), (5.72), (5.74) and (5.76) show the results of this evaluation, and will be used to evaluate the expected number of visits to each state.

e)

$$[\underline{Q}I_1] = \min\left\{\begin{pmatrix} r(I_1(1) - I_1(0)) \\ f(I_1(0) - I_1(1)) \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}]\right\} \tag{5.69}$$

$$= \min\left\{\begin{pmatrix} r \\ -f \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}]\right\} \tag{5.70}$$

$$= \begin{pmatrix} \underline{r} \\ -\overline{f} \end{pmatrix} \tag{5.71}$$

f)

$$[\underline{Q}I_0] = \min\left\{\begin{pmatrix} r(I_0(1) - I_0(0)) \\ f(I_0(0) - I_0(1)) \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}]\right\} \tag{5.72}$$

$$= \begin{pmatrix} -\overline{r} \\ \underline{f} \end{pmatrix} \tag{5.73}$$

g)

$$[\overline{Q}I_1] = -\min\left\{\begin{pmatrix} r(I_1(0) - I_1(1)) \\ f(I_1(1) - I_1(0)) \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}]\right\} \tag{5.74}$$

$$= \begin{pmatrix} \overline{r} \\ -\underline{f} \end{pmatrix} \tag{5.75}$$

h)

$$[\overline{Q}I_0] = -\min\left\{\begin{pmatrix} r(I_0(0)-I_0(1)) \\ f(I_0(1)-I_0(0)) \end{pmatrix} : r \in [\underline{r}, \overline{r}], f \in [\underline{f}, \overline{f}]\right\} \tag{5.76}$$

$$= \begin{pmatrix} -\underline{r} \\ \overline{f} \end{pmatrix} \tag{5.77}$$

Therefore, the upper and lower expected number of transitions in one year from any state to each of the other possible states are given by:

$$\underline{\gamma} = \left(\frac{\underline{r}\underline{f}}{\underline{r}+\overline{f}}, \frac{\underline{r}\underline{f}}{\underline{f}+\overline{r}}\right), \tag{5.78}$$

$$\overline{\gamma} = \left(\frac{\overline{r}\overline{f}}{\overline{r}+\underline{f}}, \frac{\overline{r}\overline{f}}{\overline{f}+\underline{r}}\right). \tag{5.79}$$

In this section, we have introduced imprecise continuous-time Markov chains, discussed how they allow potentially unjustified assumptions to be relaxed, focused on a two-state process and shown how to make inferences for this case. Importantly, going forward, we have the methods required to evaluate bounds on the expected time spent in a given state and the expected number of visits to each state. These quantities will prove useful when modelling the failure and repair behaviour of an offshore transmission system (OTS) later in this work.

5.4.5 Decision Making using Imprecise Probabilities

In this thesis, the application is focused on investment planning which requires a range of decisions to be made. There will usually be a set of options from which an optimal option or many optimal options can be selected. To put this into context, we may aim to select a topology for an OTS, and let us say that we have two viable options to select from; for example, to be connected using HVAC technologies or HVDC technologies. We need some way to select which option we prefer. In this section, we present decision making techniques using imprecise probability. These techniques are presented in more detail in [204, 219].

A common approach is to measure and compare each option against some metric such as expected cost. For example, let a HVAC approach cost £150 million, and a HVDC cost £200 million. From these options, if we aim to minimise cost, we would select the HVAC technology. However, if there are uncertainties about some of the inputs required to evaluate the expected cost of each option, we may choose to use the theory of imprecise probability to formulate the decision problem. In this case, we may no longer have point estimates for the expected cost of each approach but instead bounds on the expected cost. For example, we may have that the HVAC expected cost is bounded by £140 million and £240 million, whereas the HVDC expected cost is bounded by £180 million and £210 million. Since these bounds overlap, selecting the optimal option is no longer trivial.

There exist several decision criteria to approach the problem of decision making using imprecise probability [204, 219]. These criteria include interval dominance, maximality, E-admissible, Γ-maximin and Γ-maximax. Each criterion has advantages and disadvantages, and therefore the suitability of a criterion may depend on the specifics of the decision problem and also the decision maker's risk aversion. As previously discussed, we also note that using imprecise probabilities allows for indecision, which is in contrast to using classical probability theory. This point means that if there is insufficient information to make a decision, the inferences reflect this. As a simple example, let the expected cost of a HVAC project be bounded by £140 million and £240 million, and the expected cost of a HVDC project be bounded by £150 million and £230 million. In this case, the analysis, for example, using the interval dominance decision criterion (which will be introduced shortly), may suggest that neither option is preferred over the other.

In many practical applications, like the case studies considered in this thesis, we encounter act-state dependence. Act-state dependence is discussed in [204, 219, 220, 221], and means that the distribution of the state of nature depends on the decision taken. The presence of act-state dependence dictates the approach taken and the decision criterion implemented. Importantly, the presence of act-state dependence prevents the use of maximality as a decision criterion and requires careful handling of variables. Consequently, we use two decision criteria: interval dominance [222, 223] and Γ-maximin [224, 225, 226]. In the rest of this section, we introduce and discuss each of these criteria.

Γ-maximin is a more conservative decision criterion, and selects the option with the greatest lower bound. This decision criterion could be used if the decision maker is risk-averse as the criterion selects the decision (or decisions) that maximise the worst expected gain [224, 225, 226, 219, 204]. Let $\mathcal{J}$ be the sets of all options, j be a single option and g be a function used to evaluate the metric that we are basing our selection on. We define:

$$E^* := \max_{j \in \mathcal{J}} \underline{E}(g_j). \tag{5.80}$$

Any option j such that $\underline{E}(g_j) = E^*$ is identified as optimal using the Γ-maximin criterion. This criterion can be thought of analogous to a decision criterion that selects the option that maximises the pointwise expected value. This is a common approach if lower and upper previsions are not used. However, using Γ-maximin, the pointwise expected value is replaced with the expected lower bound. In other words, we have:

$$\mathrm{opt}(\mathcal{J}) \coloneqq \arg\max_{j\in\mathcal{J}} \underline{E}(g_j). \tag{5.81}$$

Here, $\mathrm{opt}(\mathcal{J})$ contains all the optimal options j that are selected using the Γ-maximin decision criterion. Alternatively, if the decision maker is risk tolerant, then they may use the decision criterion called Γ-maximax, which selects the highest upper bound. Usually, Γ-maximin and Γ-maximax selects only one option each, and they can be thought to select the most pessimistic or optimistic option, respectively.

Another decision criterion that could be used is called interval dominance and may be chosen if the decision maker is risk tolerant. Interval dominance decision criterion selects any option which is not interval dominated by another option. Here, an option is interval dominant if its interval is completely to the right-hand side of an interval for another option. Let $j_1, j_2 \in \mathcal{J}$ be two options. j_1 interval dominates j_2 if [222, 223, 219, 204]:

$$\underline{E}(g_{j_1}) > \overline{E}(g_{j_2}). \tag{5.82}$$

Using the interval dominance criterion, we select j_k if:

$$\overline{E}(g_{j_k}) \geq \max_{j_i\in\mathcal{J}} \underline{E}(g_{j_i}). \tag{5.83}$$

This decision criterion usually selects a larger set of optimal options.

To demonstrate the different decision criteria, we use the example presented in Fig. 5.2. Here, we have four options (A, B, C and D), and we wish to select the option that maximises the net present value (NPV). If we are risk-averse, we may use Γ-maximin which selects option C (since option C has the greatest lower bound with a profit of £6 million). If we are risk tolerant, we might use Γ-maximax which also selects option C. However, using interval dominance, we would select options B, C and D, as only option A lies entirely to the left of another option.

5.5 Technique Comparison

So far, in this chapter, we have described statistical techniques (based on the classical theory of probability) currently implemented for decision making in offshore power transmission. We put forward the case that these techniques may not be adequate in the offshore transmission setting, as many evaluations are taken under severe uncertainty due to a limited amount of useful information and data. Motivated by this shortcoming of currently used techniques, we introduced a behavioural interpretation of probability and a framework that more accurately reflects our knowledge; particularly, when we do not have enough information to assign a single probability distribution. This approach is called

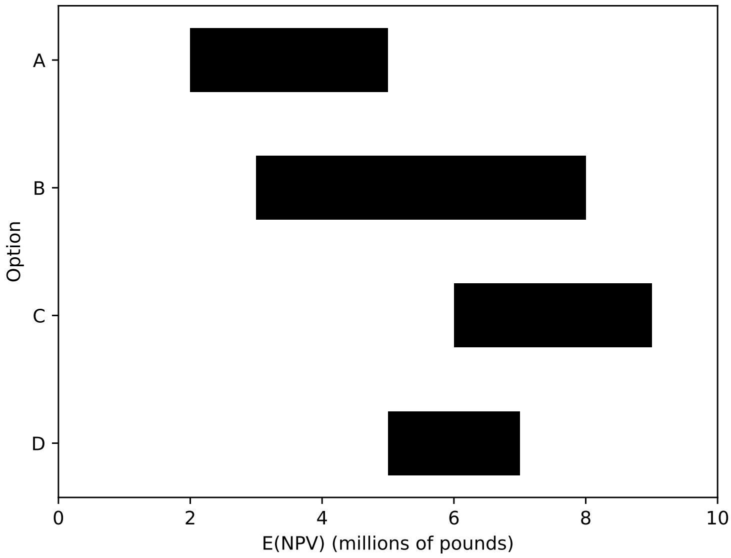


Figure 5.2: Example of four options (A, B, C and D) and their bounds on the expected NPV which is used to explain different decision criteria.

imprecise probability and can broadly be thought of as working with sets of probability distributions.

At this point in the chapter, we have introduced the theory of imprecise probability and some of the more relevant topics for our applications, namely imprecise continuous-time Markov chains and decision making criteria. The next step is to apply these techniques to offshore transmission applications and assess the benefits of doing this. These applications are presented in Chapters 6 to 8. There are some advantages and disadvantages that are specific to the decision problem at hand; these individual points will be discussed in the relevant applications chapters. However, before moving on to these applications, we present two small examples to demonstrate the advantages and disadvantages of the proposed techniques on a smaller scale.

5.5.1 Example 1: Theoretical Problem

Objective

Let X be a random variable that is normally distributed with unknown mean μ and known variance σ^2: $X \mid \mu \sim \mathcal{N}(\mu, \sigma^2)$. The expectation of X^2 (conditional on μ) is given by Eq. (5.84).

$$E(X^2|\mu) = \theta(\mu) = \int x^2 \frac{1}{\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2}} dx \tag{5.84}$$

We aim to find the lower and upper expectation of X^2. Let $\mu \in U = [\underline{\mu}, \overline{\mu}]$, where $\underline{\mu} \geq 0$. Assume $\theta(\mu)$ has a minimum:

$$\underline{E}(X^2) = \theta_* = \min_{\mu \in U} \theta(\mu). \tag{5.85}$$

Also assume that $\theta(\mu)$ has a maximum:

$$\overline{E}(X^2) = \theta^* = \max_{\mu \in U} \theta(\mu). \tag{5.86}$$

Here, $\underline{E}(X^2)$ and $\overline{E}(X^2)$ represent the lower and upper expectation of X^2.

Assumptions

Here, we present a very simplistic example where μ is uncertain, but σ^2 is known. If we have enough data, we could use this data to assign a value or specify a distribution to the input parameter μ. If we do not have enough information to specify a distribution, we can instead bound μ. For example, perhaps we do not have data (or enough data) to approximate μ, but instead, we have an expert who believes that the mean is in a specified range. Allowing expert judgement then opens up the question of how to use this expert information to bound μ. However, we do not focus on this problem here. In this example, we assume we have a limited amount of information, and therefore, we have epistemic uncertainty about μ. In this scenario, we consider μ in a set: $\mu \in U = [\underline{\mu}, \overline{\mu}]$, where $\underline{\mu} \geq 0$. This set represents a set of distributions. In this example, we assume σ is known and has a fixed value of 1: $X \mid \mu \sim \mathcal{N}(\mu,\, 1)$.

Approach

For the purpose of this example, let us assume that we cannot compute the integral in Eq. (5.84). Therefore, we aim to find an estimate to the expectation of X^2 conditional on μ. As we cannot compute $\theta(\mu)$, we estimate $\theta(\mu)$ using $\hat{\theta}$, where $\hat{\theta}$ is the standard Monte Carlo estimator: $E(\hat{\theta}(Z, \mu)) = \theta$. $\hat{\theta}$ can be formulated using the process below.

Let Z be a random vector of m random variables, Z_i, that are independently and identically distributed: $Z_i \sim \mathcal{N}(0, 1)$. As we are interested in $X \mid \mu \sim \mathcal{N}(\mu, 1)$, we consider the transformation $X_i = Z_i + \mu$. Therefore, the estimator for the expectation of X^2 is given by:

$$\hat{\theta}(Z, \mu) = \frac{1}{m} \sum_{i=1}^{m} (Z_i + \mu)^2. \tag{5.87}$$

In this simple example, we have assumed that we know where the extremes occur. If we did not know this, we would first need to find the extremes, and this can be difficult. [227] provides more information about how to achieve this. As we know where the minimum and maximum occur, we proceed as follows.

As $\theta(\mu)$, in this simple example, is an increasing function of μ (since $\underline{\mu} \geq 0$), the minimum value of $\theta(\mu)$ occurs at the minimum value of μ which is $\underline{\mu}$. If $\underline{\mu} < 0$ then the minimum value of $\theta(\mu)$ would occur at $\mu = 0$. Similarly, if $\overline{\mu} < 0$ the maximum value of $\theta(\mu)$ would occur at $\mu = \underline{\mu}$. In this example we assume $\underline{\mu} > 0$, and therefore we have:

$$\theta_* = \min_{\mu \in U} \theta(\mu) = \theta(\mu)|_{\mu=\underline{\mu}}. \tag{5.88}$$

Similarly, the maximum value of $\theta(\mu)$ occurs at the maximum value of μ which is $\overline{\mu}$. Therefore,

$$\theta^* = \max_{\mu \in U} \theta(\mu) = \theta(\mu)|_{\mu=\overline{\mu}}. \tag{5.89}$$

$\theta(\mu) \in [\theta_*, \theta^*]$ by definition. As previously stated:

$$E(\hat{\theta}(Z, \mu)) = \theta(\mu). \tag{5.90}$$

Using the minimum and maximum points:

$$E(\hat{\theta}(Z, \underline{\mu})) = \theta_* \tag{5.91}$$

and

$$E(\hat{\theta}(Z, \overline{\mu})) = \theta^*. \tag{5.92}$$

We can then evaluate:

$$\hat{\theta}(Z, \underline{\mu}) = \frac{1}{m} \sum_{i=1}^{m} (Z_i + \underline{\mu})^2 \tag{5.93}$$

and

$$\hat{\theta}(Z, \overline{\mu}) = \frac{1}{m} \sum_{i=1}^{m} (Z_i + \overline{\mu})^2. \tag{5.94}$$

Here, it should be noted that Z_i (in Eq. (5.93) for the lower estimate and Eq. (5.94) for the upper estimate) are the same sample. Using the same sample ensures that the estimates are coherent; specifically, the lower estimate is less than the upper estimate. For scenarios where $\underline{\mu}$ and $\overline{\mu}$ are equal (or sufficiently close together), and the sample error is large, the upper estimate may be less than the lower estimate if the same sample is not used for both bounds. In this case, the estimates would no longer be coherent, and this could cause issues.

To demonstrate the need to use the same sample, we use the following example. Let $\underline{\mu} = 0$ and $\overline{\mu} = 1$. If we consider a sample size of one ($m = 1$), and let Z and Z' be separate samples for the lower and upper estimates. If $Z = 0.823309$ and $Z' = -1.129038$ then $\hat{\theta}(Z, \underline{\mu}) = 0.67784$ and $\hat{\theta}(Z, \overline{\mu}) = 0.01665$. We see that $\hat{\theta}(Z, \underline{\mu})$ is greater than $\hat{\theta}(Z, \overline{\mu})$: that is the lower estimate of the expectation of X^2 is greater than the upper estimate. Therefore, it is good practice to use the same sample for both estimates to avoid this (by fixing the seed in the simulation).

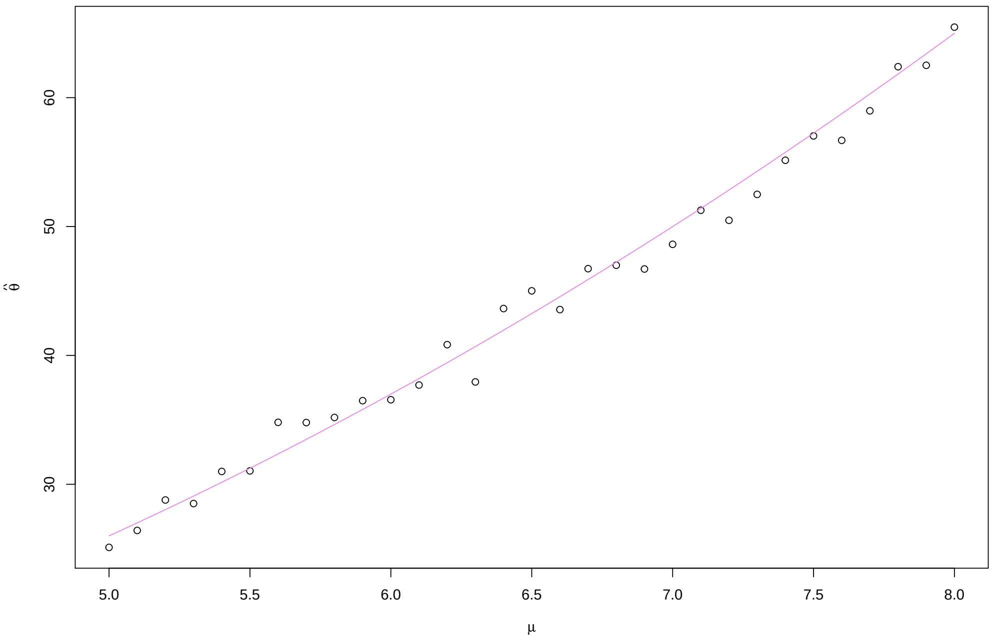


Figure 5.3: $\hat{\theta}$ against μ, for values of μ between five and eight in steps of 0.1. For each value of μ, one hundred samples (m=100) are used. The pink line shows the real value, that is the $E(X^2) = \mu^2 + \sigma^2$.

An approximate 95% confidence interval for $\hat{\theta}(Z, \mu)$ can be given by:

$$\hat{\theta}(Z, \mu) \pm 1.96 \frac{\sigma(Z, \mu)}{\sqrt{n}} \tag{5.95}$$

where

$$\sigma^2(Z, \mu) = \frac{1}{m-1} \sum_{i=1}^{m} ((Z_i + \mu)^2 - \hat{\theta}(Z, \mu))^2. \tag{5.96}$$

Numerical example

Let $\underline{\mu} = 5$, $\overline{\mu} = 8$ and $\sigma^2 = 1$. Fig. 5.3 shows the value of $\hat{\theta}$ for values of μ between five and eight and in steps of 0.1. For sample sizes ten, fifty and one hundred we estimate bounds on the lower and upper expectation of X^2, as well as confidence bounds on these estimates. These results are presented below and visualised in Figs. 5.4 to 5.6.

- For a sample size of ten ($m = 10$):
  - $\hat{\theta}(Z, \underline{\mu}) = 28.051957$
  - Approximate 95% confidence interval for θ_* : $[24.047451, 32.056462]$
  - $\hat{\theta}(Z, \overline{\mu}) = 70.96344$
  - Approximate 95% confidence interval for θ^* : $[59.73324, 82.19365]$
- For a sample size of fifty ($m = 50$):

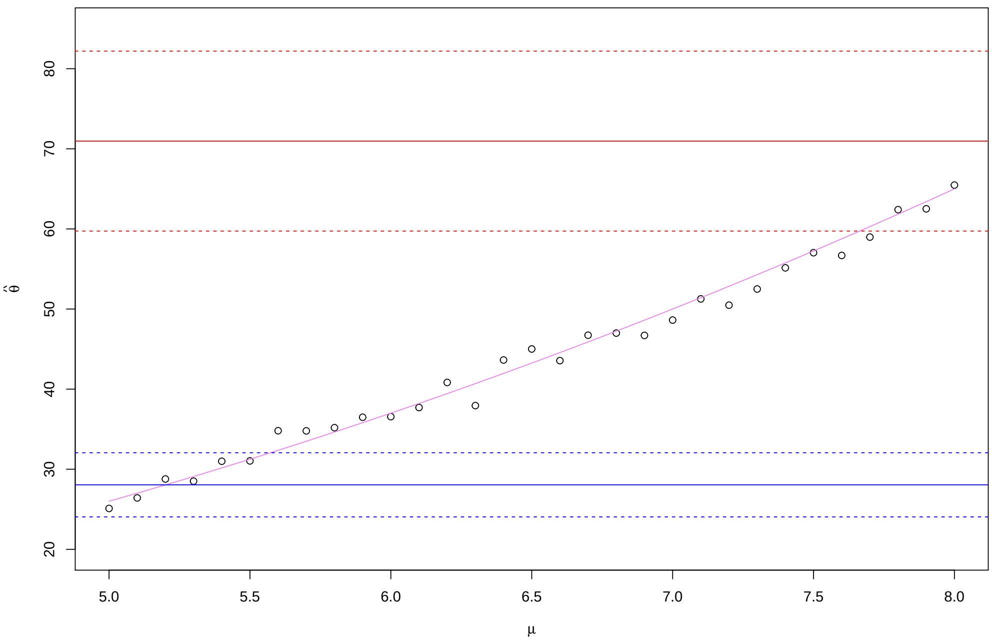


Figure 5.4: Fig. 5.3 with confidence bounds added. $\hat{\theta}(Z, \underline{\mu})$ and $\hat{\theta}(Z, \overline{\mu})$, for $m = 10$, are shown in solid blue and red lines respectively. 95% confidence bounds are shown for θ_* and θ^* by dashed blue and red lines respectively.

- $\hat{\theta}(Z, \underline{\mu}) = 26.624366$
- Approximate 95% confidence interval for θ_* : $[24.129142, 29.119591]$
- $\hat{\theta}(Z, \overline{\mu}) = 63.68158$
- Approximate 95% confidence interval for θ^* : $[59.72543, 67.63774]$

• For a sample size of one hundred ($m = 100$):

- $\hat{\theta}(Z, \underline{\mu}) = 24.982932$
- Approximate 95% confidence interval for θ_* : $[23.232308, 26.733556]$
- $\hat{\theta}(Z, \overline{\mu}) = 67.43350$
- Approximate 95% confidence interval for θ^* : $[64.38156, 70.48543]$

Summary

As we did not have enough knowledge about μ, we have epistemic uncertainty. To handle this uncertainty we bounded the input parameter μ by considering $\mu \in U = [\underline{\mu}, \overline{\mu}]$. This epistemic uncertainty leads to bounds on the $E(X^2)$: $\underline{E}(X^2)$ and $\overline{E}(X^2)$. In this work, the bounds on $E(X^2)$ are denoted by θ_* and θ^*. In this analysis, the aleatory uncertainty is modelled by sampling from the normal distribution. However, this is not communicated by the mean. To consider the aleatory uncertainty, we looked at confidence

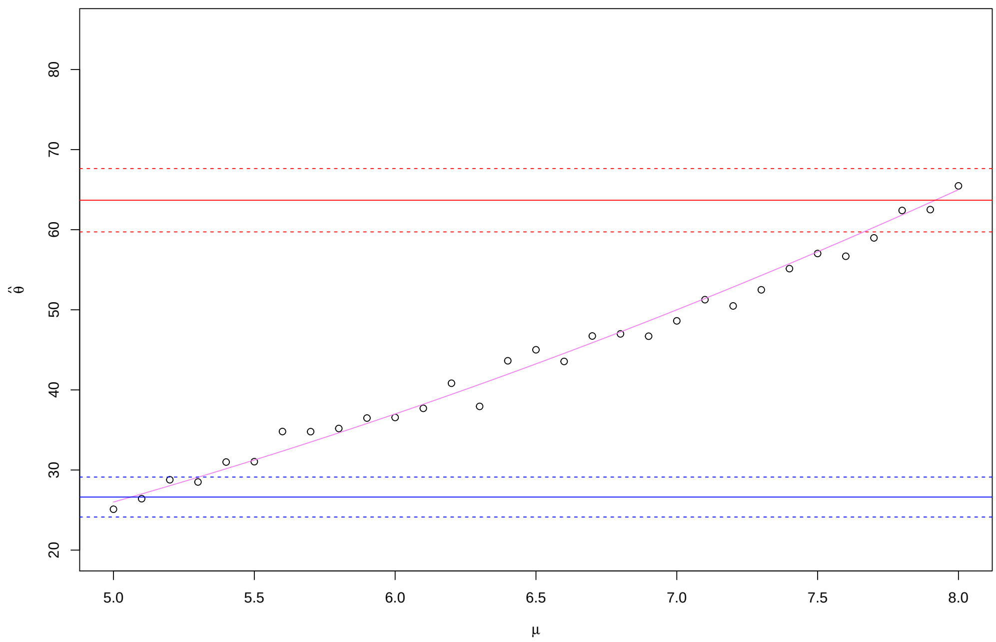


Figure 5.5: Fig. 5.3 with confidence bounds added. $\hat{\theta}(Z, \underline{\mu})$ and $\hat{\theta}(Z, \overline{\mu})$, for $m = 50$, are shown in solid blue and red lines respectively. 95% confidence bounds are shown for θ_* and θ^* by dashed blue and red lines respectively.

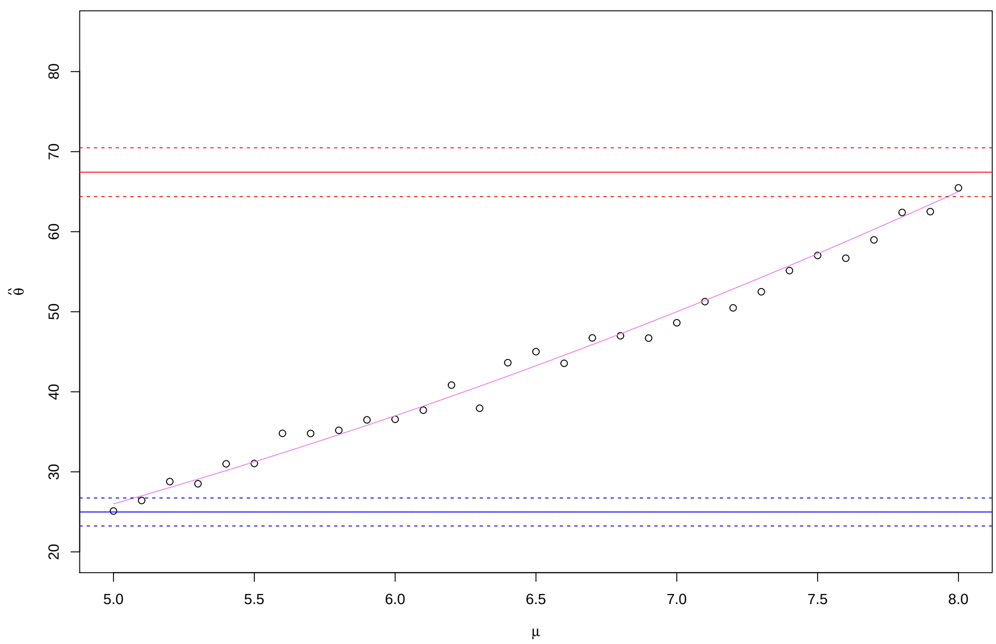


Figure 5.6: Fig. 5.3 with confidence bounds added. $\hat{\theta}(Z, \underline{\mu})$ and $\hat{\theta}(Z, \overline{\mu})$, for $m = 100$, are shown in solid blue and red lines respectively. 95% confidence bounds are shown for θ_* and θ^* by dashed blue and red lines respectively.

intervals around θ_* and θ^*.

To conclude this example, we discuss how techniques used here based on imprecise probability compare to techniques based on classical probability theory. In this example, we see that, through lower and upper previsions, there exists a framework to model the epistemic uncertainty in the modelling parameter μ. Techniques based on the classical theory of probability do not as easily accommodate this. However, we note that the example presented here is simple. More complex problems could be more computationally expensive; in particular, where the extremes need to be located.

5.5.2 Example 2: Component Failures

In this section, we focus on a more practical application. For this small example, we are interested in evaluating the yearly availability of a single component. Additionally, we aim to compare the proposed approach to techniques used in the literature and practice. The bullet points below give a summary of the main differences between the techniques.

- In classical probability theory, we usually assign a single distribution to the probability of an event occurring; however, this may require strong modelling assumptions. In the case of evaluating the yearly availability of a component, conventional techniques used in the literature assume that the failure and repair times of components are exponentially distributed. In Chapter 2, we discussed that these techniques are based on the work by Billinton [125]. When these standard techniques are applied to practical applications, the approach is usually not questioned and therefore, the modelling assumptions are often not verified. As we saw earlier in this chapter, the assumption that the failure and repair times of components are exponentially distributed may be too strong in offshore transmission, and therefore we suggest techniques that allow this assumption to be relaxed.
- Many techniques used are based on classical probability theory that requires input parameters to be specified by a precise value or distribution. When there is a limited amount of useful data, we may not be able to assign a probability distribution accurately. Instead, we model epistemic uncertainty by considering bounds on these inputs.
- Using imprecise probabilities allows for indecision, and this is beneficial in cases where there is not enough information to select one option over another.

To further demonstrate these points, we evaluate the yearly availability of a single component using two approaches, which, for convenience, we call approach A and approach

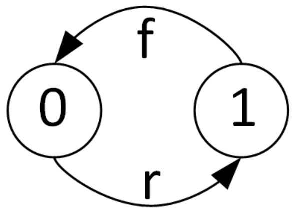


Figure 5.7: Two state Markov chain. State 0 represents a component not working and state 1 represents a working component.

B. Approach A models the component as a precise Markov chain, whereas approach B models the component as an imprecise Markov chain.

Approach A

Using approach A, we model the component as a precise two-state Markov chain, as shown in Fig. 5.7. Here, state 0 represents a component not working, state 1 represents a working component, and f and r are the failure and repair rates, respectively. As we have seen before, the rate matrix, given by Eq. (5.97), describes the rate a Markov chain moves between states.

$$Q = \begin{pmatrix} -r & r \\ f & -f \end{pmatrix} \tag{5.97}$$

We recall that the yearly availability of a component is a continuous random variable that can take any value between zero and one, and is affected by the duration a component spends in the failed and working states. The yearly availability of the component can be defined by Eq. (5.98) (as seen in Chapter 4).

$$Y_t = \frac{1}{1 \text{ year}} \int_0^{1 \text{ year}} A_\tau \, \mathrm{d}\tau \simeq \frac{1}{8760} \sum_{h=0}^{8760} A_h \tag{5.98}$$

Here, Y_t denotes the average yearly availability of the component, A_τ denotes the availability of the component at any one given point in time, and A_h denotes the hourly availability of the component. On account of the limited amount of data surrounding availability, a Monte Carlo simulation approach, using hourly discretisation steps to approximate the integral in Eq. (5.98), can be used to determine the distribution for Y_t. The simulation generates N realisations, $y_1, \ldots, y_N$, of Y_t. From these realisations, we can examine the distribution of availability.

Approach A models aleatory uncertainty, but not epistemic uncertainty. Consequently, this approach relies on the Markovian assumptions being satisfied and requires enough data to assign a value to f and r. Unfortunately, we may not have enough information to be confident that these assumptions are satisfied in the offshore transmission setting.

Based on approach A, a long-term average of the yearly availability is often considered which, under ergodicity (in other words, the long-term expected yearly availability is equal to the expected availability at any given point in time), can be evaluated by Eq. (5.99) (or equivalently Eq. (5.100)). This approach is frequently used in the literature, for example, by [99], to evaluate availability.

$$\text{Availability} = \frac{r}{r+f} \tag{5.99}$$
$$= \frac{\text{mean time to fail}}{\text{mean time to fail} + \text{mean time to repair}} \tag{5.100}$$

Eq. (5.100) requires enough data to assign values to the mean time to fail (MTTF) and the mean time to repair (MTTR) that accurately represents the information available about a component. Using Eq. (5.100) directly does not model aleatory or epistemic uncertainty; furthermore, we only obtain a single availability value, unlike in the simulation above.

Approach B

In the second approach, which for convenience we call approach B, we model the components using imprecise continuous-time Markov chains. Imprecise continuous-time Markov chains and the corresponding theory were introduced and explained earlier in this chapter in Section 5.4.4. In the example at hand, we adopt this modelling approach and bound the transition rate from the working state to the failed state by $\underline{f}$ and $\overline{f}$. Similarly, we bound the transition rate from the failed state to the working state by $\underline{r}$ and $\overline{r}$. Here, $0 < \underline{f} < \overline{f}$ and $0 < \underline{r} < \overline{r}$.

In this approach, we work with a set of processes and therefore, the modelling assumptions of a Markov process are relaxed. Importantly, we no longer require that the transition rates are independent of the history of the system. Instead, we consider a set of transition matrices that may depend on the full time and history of the system. Furthermore, approach B no longer requires us to specify transition rates as precise values. When making inferences, rather than computing expected values of a function, lower and upper expectations are computed. Using this approach, we model aleatory uncertainty and epistemic uncertainty.

Numerical Example

In this section, we apply the two approaches described above to the same problem. We aim to evaluate the expected yearly availability of two components and select the component that has the highest expected yearly availability. For this example, failure and repair data of component one and component two are given in Table 5.2.

	Component 1	Component 2
Time to fail data (days)	100, 120, 60, 200, 250	110, 90, 120, 140, 70
Time to repair data (days)	1, 1, 20, 19, 3	2, 1, 5, 24, 18

Table 5.2: Table of failure and repair data used in the numerical example.

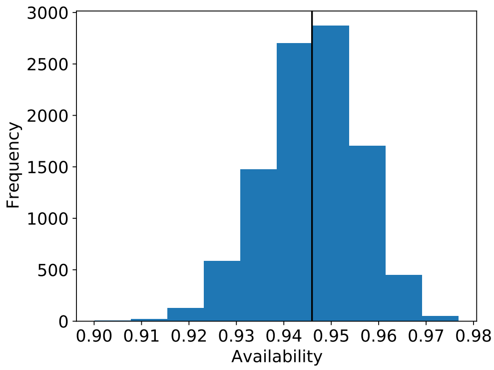


Figure 5.8: Histogram of the yearly availability of component two obtained from the simulation. The mean availability is 0.946 and shown by the black vertical line.

From the data in Table 5.2, for component one, we evaluate the MTTF to be 146 days, the MTTR to be 8.8 days and, using Eq. (5.99), the long-run availability to be 0.943. Similarly, for component two, we evaluate the MTTF to be 106 days, the MTTR to be 10 days and the long-run availability to be 0.914. This analysis suggests that component one has a higher expected yearly availability.

To model the component using a Markov chain, we assign values to the transition rates between the failed and working states. Using the data in Table 5.2, for component one we assign a failure rate of 2.5 fails per year and a repair rate of 41.4 repairs per year, and for component two we assign a failure rate of 3.4 fails per year and a repair rate of 36.5 repairs per year. These values have been assigned by taking the reciprocal of the mean times. As described above, we use these values to sample times to fail and times to repair and generate a trace for the component. This trace is used to determine the yearly availability of the component. We repeat this process to obtain a distribution for the component's yearly availability. The results are shown by Fig. 5.8 and Fig. 5.9. A summary of the expected yearly availability results obtained is presented in Table 5.3.

This modelling approach assumes that the times to fail and times to repair follow an exponential distribution. Given that we only have five data points, that vary from each other, this assumption is difficult to justify. Furthermore, assigning a single value to the transition rates does not sufficiently represent the data we have available.

Using approach B, we bound the transition rates. The choice of bounds falls to the

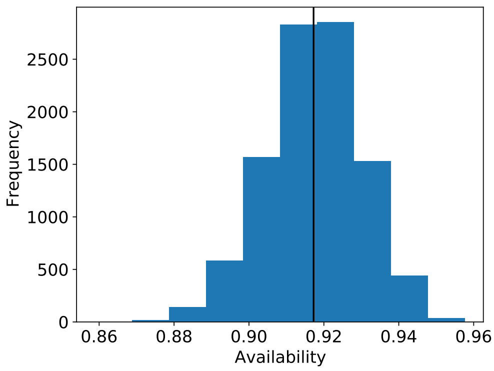


Figure 5.9: Histogram of the yearly availability of component two obtained from the simulation. The mean availability is 0.913 and shown by the black vertical line.

decision maker and remains an open topic of discussion. For now, we bound the transition rates using the minimum and maximum data values observed. This approach is simplistic and perhaps limited, but is reasonable enough for this simple example. However, we note that in practice, this approach to assigning bounds on the transition rates is rarely taken. Instead, in practice, techniques that more robustly represent our prior knowledge are used, and one way to do this is to implement a robust Bayesian model. The work by [218] gives an example of this.

For component one, we let the failure rate (transition rate to the not working state) be bounded by 1.46 fails per year and 6.08 fails per year. Similarly, we let the repair rate (transition rate to working state) be bounded by 18.25 repairs per year and 365 repairs per year. For component two, we let the failure rate be bounded by 2.61 fails per year and 5.21 fails per year, and the repair rate is bounded by 15.2 repairs per year and 365 repairs per year.

Using the bounds on the transition rate, we evaluate bounds on the expected time spent in the working state in a year (the yearly availability). This is achieved using Eqs. (5.63) and (5.64). A summary of these results is presented in Table 5.3. For component one, we bound the time spent in the working state by 273.75 days (availability is 75.0%) and 363.54 days (availability is 99.6%). Likewise, for component two, we bound the expected time spent in the working state by 270.1 days (availability is 74%) and 362.45 days (availability is 99.3%).

Using these results, we can compare the bounds on expected availability to find which component is more favourable. The bounds obtained using approach B overlap and therefore using the interval dominance criterion, as previously detailed, suggests that neither option is preferred. Using Γ-maximin, we select the option with the greatest lower bound and therefore suggests that component one is optimal.

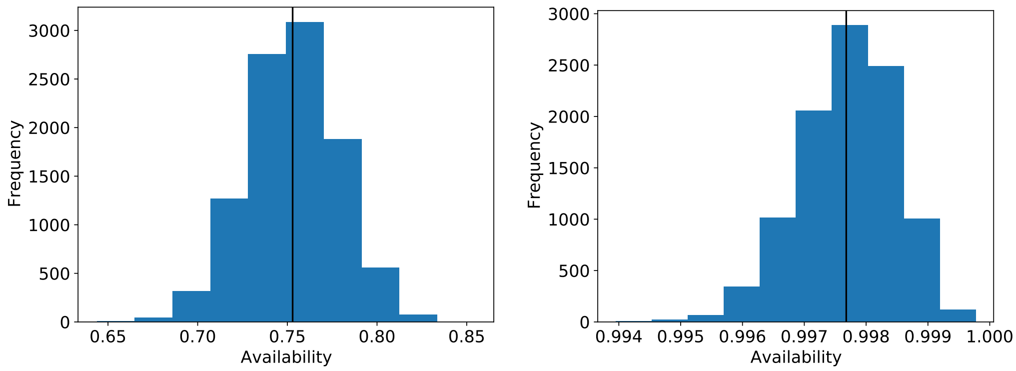


Figure 5.10: Component one. The left-hand side histogram shows the worst-case yearly availability obtained from the simulation. The mean availability is 0.753 and shown by the black vertical line. The right-hand side shows the histogram of the best-case yearly availability obtained from the simulation. The mean availability is 0.998 and shown by the black vertical line.

	Expected Yearly Availability		Decision
	Component 1	Component 2	
Approach A	0.946	0.913	Component 1
Approach B	[0.750, 0.996]	[0.740, 0.993]	Γ-maximin selects Component 1 and interval dominance selects Component 1 and 2.

Table 5.3: Summary of expected yearly availability results using approach A and approach B, and the component found to be optimal under each approach.

Using approach B, we can also simulate the behaviour of the components to find the upper and lower distributions for the yearly availability of each component. These upper and lower distributions are achieved by inputting best- and worst-case failure and repair rates. These are shown by Fig. 5.10 and Fig. 5.11.

Comparing these two techniques, we see that approach B relaxes some of the strong, and perhaps unjustified modelling assumptions that are required for approach A. Approach B uses techniques that allow for the more appropriate handling of the severe uncertainties that are present due to a limited amount of failure and repair data. Furthermore, the outputs from approach B reflect the uncertainty in the input modelling parameters, and the decision maker has more information to base their selection. Using approach B allows for indecision in the case where we do not have enough information to select one component over another. This indecision could be seen as an inconvenience to the decision maker; however, we suggest that this indecision is useful, especially if these decisions are part of

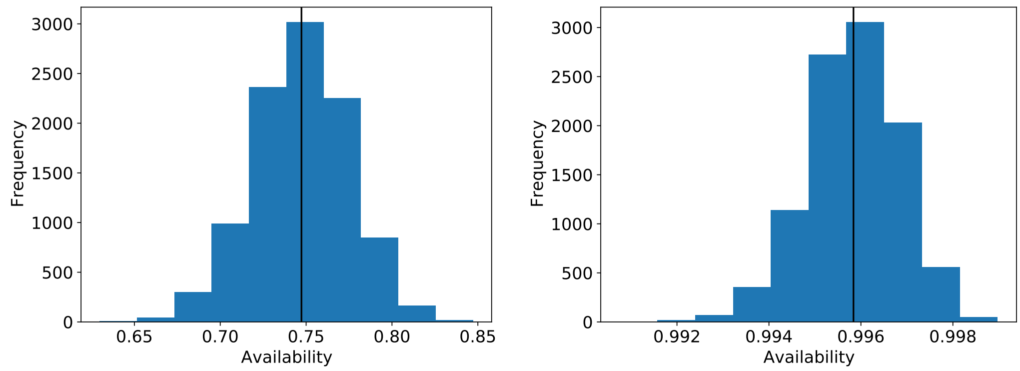


Figure 5.11: Component two. The left-hand side histogram shows the worst-case yearly availability obtained from the simulation. The mean availability is 0.748 and shown by the black vertical line. The right-hand side shows the histogram of the best-case yearly availability obtained from the simulation. The mean availability is 0.996 and shown by the black vertical line.

a significant investment decision.

5.6 Conclusions

In this chapter, we defined severe uncertainty; in summary, to be a scenario when we do not have enough information to assign a probability distribution accurately. Next, we present statistical techniques currently implemented when making decisions in offshore power transmission. We go on to show the limitations of techniques based on classical probability theory when there is severe uncertainty by presenting a cable failure example. On account of these shortcomings, we motivate the need for more suitable techniques when making decisions under severe uncertainty, as is often the case in offshore power transmission.

We present and explain a behavioural interpretation of probability that uses supremum buying and infimum selling prices, also known as lower and upper previsions. More generally, this approach is called using imprecise probability. We go on to discuss techniques within the theory of imprecise probability that are relevant to our application: imprecise continuous-time Markov chains and decision making criteria. In the final section of this chapter, we present two examples where these more robust techniques under severe certainty are applied. In these examples, we assess the benefits and limitations of taking this approach.

In the following chapters, we apply these suggested techniques to relevant decision problems in offshore power transmission. Chapters 6 and 7 demonstrate the techniques on specific decision problems. Specifically, Chapter 6 aims to find the optimal technology choice and ownership structures for an offshore transmission system (OTS). Chapter 7 considers whether it is beneficial to invest in an interlink between two offshore substations in a single project. Chapter 8 presents a more significant contribution, as we present an OTS planning tool under severe uncertainty that utilises the techniques presented in this chapter.

So far, the techniques presented show promising signs to be beneficial in the application to offshore power transmission. However, the application of theoretical techniques to practical problems may bring challenges, and these are explored in the application chapters. In particular, we investigate ways to communicate the outputs of the analysis in an effective way for those unfamiliar with imprecise probability. Furthermore, we aim to assess the extent to which these techniques are beneficial and also discuss the limitations of taking this alternative approach.

Chapter 6

Application 1: The Impact of Offshore Transmission Regulatory Regimes on Technology Choices

The work of this chapter closely follows [2].

6.1 Introduction

In Chapter 2, we discussed that many offshore transmission assessments and decisions are taken under severe uncertainty, and how, unfortunately, these technical and economic uncertainties surrounding offshore power transmission complicate decision making. In this chapter, we focus on two decisions, the first taken by policymakers regarding which regulatory regime to implement and the second taken by project planners concerning project design specifications. The exploration of these questions is of interest to those in offshore wind transmission. However, the main aim here is to demonstrate the extent to which the advanced statistical techniques described in Chapter 5 can be beneficial to decision making under severe uncertainty in offshore power transmission. The application of these techniques serves the following purposes:

- To demonstrate how the techniques can be implemented in the analysis of a practical decision problem.
- To find and overcome challenges that may arise in the application of these techniques to practical problems.
- To show the benefits of taking this alternative approach and, in particular, its ability to handle severe uncertainty in the input parameters (required to evaluate projects economically) more appropriately.

- To discuss any limitations.

Various factors contribute to a thriving offshore wind market, including its offshore transmission regulatory regime. In Chapter 2, we discussed that countries implement different ownership structures of the offshore transmission system (OTS), which can be summarised as third-party ownership, onshore transmission system operator (TSO) ownership or developer ownership. Each approach appears to have advantages and disadvantages with regards to economic security, risk management and coordination within and between projects. Assessing the benefits of existing regulatory regimes is valuable for emerging markets since there is limited information available.

To enable lessons learned, in this chapter, we summarise and contrast different regulatory regimes. Other countries are keen to install offshore wind generation assets to meet policy targets of a more significant share of renewables. Consequently, governments and stakeholders will design policies and frameworks to support this movement and may investigate current practices. Ultimately, policymakers will decide on an offshore transmission regulatory regime. Once the regime is established, developers make technology choices, including whether HVAC or HVDC is preferred. In this chapter, next-generation transmission topologies (based on current design trends) are presented as case studies. We then formulate a decision problem to assess the impact of transmission regulatory regimes and technology choices on the economic performance of an offshore transmission project.

In the formulated decision problem, we identify uncertain model inputs: cable failure rate, cable repair rate, capacity factor and wholesale energy price. Usually, as we discussed in Chapter 5, distributions are assigned to model variables but, under severe uncertainty due to limited information, it is difficult to identify the appropriate distribution. Since classical decision making techniques are unable to deal with the identified uncertainties adequately, and because these decisions could have substantial economic consequences, imprecise probability techniques are utilised. Therefore, we assign a set of distributions for each input parameter based on literature. Using these sets and imprecise probability techniques presented in Chapter 5, we bound expected profit and analyse these bounds to find economically preferable options.

When applying imprecise probability in this context, we encounter a similar problem to [220] in that we have act-state dependence the distribution of the state of nature depends on the decision. In this chapter, we discuss how we handle act-state dependence in this decision problem and how it dictates the methodology. Once the methodological approach has been established, we focus on the communication of the results and present a visualisation approach that provides a way to engage with decision makers who are unfamiliar with imprecise probability.

In summary, this chapter investigates economically preferable regulatory regimes and technology choices for emerging markets from an investor's point of view; a key player in the growth of the industry. As technical and regulatory decisions are taken under severe uncertainty, we explore techniques that are robust under severe uncertainty and present the benefits of this approach. The contributions of this work include the use of imprecise probability in a new field, and by doing so, we aim to gain a better understanding of how to implement these techniques.

The aims of this chapter are:

1. To apply imprecise probability decision making techniques to a practical decision problem in offshore power transmission.
2. To investigate which investment-driven regulatory regime and technology choice are economically preferable, from an investors perspective, under severe uncertainty.
3. To overcome the issue of act-state dependence in the decision problem by handling act-state dependent and independent variables appropriately.
4. To explore ways to present and visualise the results effectively.
5. To compare classical and imprecise probability techniques to make decisions under severe uncertainty.

The structure of the chapter is as follows. Section 6.2 summarises and contrasts current regulatory regimes. Section 6.3 discusses emerging markets and presents a HVAC and a HVDC transmission connection to act as our case studies. Section 6.4 outlines the decision problem and explains the bounding approach used to address severe uncertainty. Following this, Section 6.5 presents the input data. Section 6.6 goes on to present the results of bounding expected profit to find optimal decisions. Section 6.6 also compares the advanced statistical techniques to conventional methods, and discusses the advantages of using imprecise probability to better handle severe uncertainty. Finally, Section 6.7 discusses the conclusions of this chapter.

6.2 Offshore Transmission Regulatory Regimes and Ownership Structures

6.2.1 Individual Countries' Set-ups

In this chapter, we focus on a decision problem relating to the offshore transmission system (OTS). We begin by briefly recapping what defines an OTS (this was previously defined in Section 2.2). The OTS connects the offshore wind farm to the onshore grid and usually includes the offshore substations, offshore and onshore cable systems, and onshore substations.

Currently, the responsibility of owning and operating the OTS varies between countries. In Section 2.4, we detailed ownership structures for Belgium, Germany, China, Denmark, Netherlands and the UK. From these countries' set-ups, we see that ownership usually falls to either a third-party company, the offshore wind farm developer or the onshore TSO. Each of these ownership structures are detailed in Sections 6.2.2 to 6.2.4.

There is limited detailed literature regarding OTS regulatory regimes and ownership structures. On occasion, individual countries present outlines of their approach and these were discussed in Section 2.4. Furthermore, several studies investigate the ownership structure of an OTS. In the literature, [228] discusses the ability of current regimes to support larger offshore wind farms as well as cross-border projects. Similarly, [52] gives an in-depth report into current regulatory regimes, with a view to increasing the amount of offshore wind generation in the North and Irish Sea. Additionally, the study by [103] takes a consumer perspective to assess the value for money of third-party ownership compared to TSO ownership. The work by [103] suggests TSO ownership to be beneficial in small and medium-scale projects; however, for larger projects, third-party may be beneficial. Together these studies suggest that the optimal regime is still debatable.

Information regarding the economics of onshore transmission system operator (TSO) owned OTSs is detailed in law, and may vary from country to country. We do not have enough information to formulate a justified economic model for onshore TSO owned projects. Since this economic model is required to conduct a fair comparison, onshore TSO ownership is omitted from the analysis conducted in this chapter. Instead, this work focuses on regimes where OTS development is more competitive and investor-driven.

To date, the industry as a whole appears to prefer onshore TSO ownership; however, an emerging market will assess their options in full. We also note that regimes yet to be implemented are not considered here as this would also not be feasible; however, an emerging market may choose to implement something novel. In this next sections, we detail the three broad categories of ownership structures: onshore TSO owned (Section 6.2.2), developer owned (Section 6.2.3) and third-party owned (Section 6.2.4). Following these descriptions, in Section 6.2.5 we qualitatively compare the different ownership structures. This comparison supports the quantitative comparison that follows in the rest of this chapter.

6.2.2 Onshore Transmission System Operator (TSO) Owned

Several structures fall under onshore TSO owned. The offshore grid connection can be regulated (by the onshore regulator), non-regulated (through a third-party investor), or something in between where there might be a third-party investor, but the onshore TSO also takes on some of the expenses. These costs are then translated into tariffs.

In some cases, under onshore TSO ownership, both public and private, the responsibility of the onshore TSO to connect generating assets is extended offshore to include offshore generating assets. When a government entrusts the onshore TSO to connect offshore generation assets (perhaps through regulated power utilities), they must plan, construct and operate the required assets, while balancing costs and system availability [45]. Under this approach, costs are socialised to all users [52]. Further details on onshore TSO ownership are difficult to obtain.

6.2.3 Developer Owned

Under a developer owned structure, an offshore wind farm developer may build and operate the offshore wind farm and OTS. Information outlining this ownership structure has been drawn from [228, 52] and operational project details [48]. Under this approach, the OTS is seen as an extension of the offshore wind farm. Therefore, the responsibilities of the developer continue up to the onshore grid connection point. Approaches to developer-owned OTSs are often tailored by a specific country [52].

In this work, we consider a general developer owned approach where subsidies are not considered. This simplification could be justified in the future as we evolve towards subsidy-free offshore wind [229]. The developer generates revenue based on the amount of power transmitted to the onshore grid. Current economic models consider the revenue stream for just the offshore wind farm to be the amount of energy produced multiplied by the wholesale price of energy [24]. Extending this to include the OTS, we evaluate the annual amount of revenue acquired to be the annual amount of energy generated and transmitted multiplied by the wholesale price of energy. This is shown in Eq. (6.1).

$$R_t = \text{Energy produced and transmitted}_t \times \text{Wholesale price}_t \tag{6.1}$$

Here, R denotes revenue, t denotes the year of operation. Wholesale price refers to the price of energy when it is initially traded. The energy produced and transmitted refers to the yearly amount of energy that is transmitted to the onshore grid:

$$\text{Energy produced and transmitted}_t = 8760 \times a \times S_t \times Y_t \tag{6.2}$$

Here, a denotes project capacity, which is the amount of power the wind farm is capable of generating based on turbine ratings. In this work, a is assumed to be known at the time of decision. 8760 is the number of hours in a year. S_t represents the wind farm capacity factor which is the ratio of actual power output over potential power output. Capacity factor and wholesale price are unknown at the time of decision. Finally, Y_t represents the average yearly availability of the OTS and is a random variable.

6.2.4 Third-party Owned

Under a third-party approach (such as in the UK), a separate entity owns the OTS. This regime was presented in detail in Chapter 2, and in this section, we give a recap. A developer builds both the wind farm and OTS but only owns the wind farm during its operational phase. Therefore, when the OTS is operational, the developer hands these assets to an offshore transmission owner (OFTO). An energy regulatory body runs a competitive tender process to award an OFTO licence to a particular company. The licence determines the amount the OFTO pays the developer for the assets as well as an agreed long-term revenue stream (base revenue), regardless of generating asset performance [181].

OFTOs are incentivised to maintain high levels of availability throughout the revenue period. An offshore transmission owner's (OFTO) revenue received depends on the availability of the OTS, and is based around an annual target of 98% availability. As we have seen before, the incentive model can be described by Eq. (6.3) [49].

$$R_t = \begin{cases} 0.9 \times B, & \text{if } Y_t \leq 0.94 \\ (0.9 + (Y_t - 0.94) \times 2.5) \times B, & \text{if } Y_t \geq 0.94 \end{cases} \tag{6.3}$$

Here, R denotes revenue, t denotes the year of operation, B denotes the base revenue which is unknown at the time of decision. Y_t represents the average yearly availability of the OTS, which can be defined as the fraction of time the system is capable of transmitting power. Y_t is unknown at the time of the decision, and must be treated as a random variable.

6.2.5 Comparison of Ownership Approaches

Now that these three ownership structures have been presented, in this subsection, we set out to compare them. The third-party and developer ownership structures are similar in many respects. Both regimes require the OTS owner to finance the capital costs of the OTS. A developer has a more substantial project capital as they must also finance the offshore wind farm. Both approaches require the OTS owner to finance and coordinate operational maintenance, and there is a financial incentive to maintain high availability.

There are some key differences between the two regimes. The third-party regime involves an additional company which allows competition but leads to differences in the ability to facilitate coordination. Under a third-party regime, investors are restricted but guaranteed a revenue between 105% and 90% of a fixed base revenue. The revenue is dependent on OTS availability and therefore, independent of generating asset performance. In contrast, under developer ownership, revenue is dependent on project performance and wholesale price. The developer approach allows the developer to coordinate planned maintenance to coincide with generating asset downtime and therefore, minimise total system downtime. Although both approaches require owners to finance the transmission assets, the time frame differs. Developers must finance assets pre-construction, whereas, under the third-party approach, payment is not required until the assets are operational. Furthermore, during construction, the developer experiences years of no revenue for the offshore transmission assets, unlike in the third-party case where revenue is generated shortly after the asset transfer.

The onshore TSO owned approach is similar to the third-party approach in terms of asset management. In particular, there is still a requirement to maintain high levels of availability; however, it is not clear whether there is an explicit revenue linked incentive. Additionally, the onshore TSO owned approach is similar to the third-party approach in terms of financing since the onshore TSO finances only the OTS. The main differences between these two ownership structures arise due to a lack of competition.

6.3 Emerging Markets

6.3.1 Finding Solutions for New Market Participants

Many countries have clean energy generation targets to meet. Therefore, recently, there is increased interest by countries to install offshore wind farms. These assets need to be connected to the onshore grid, and to facilitate this the appropriate transmission infrastructure will be installed. To find optimal solutions for these grid connections and ultimately support government targets, studies to investigate ownership structures, business models and regulatory regimes are required. This chapter focuses on the regulatory and ownership aspect of this challenge.

During the planning stage of a project, many factors contribute to selecting a particular topology, including reliability, safety, environmental impact, social perspective and, possibly most important to investors, the associated costs. Therefore, this work focuses on the economic benefit of competitive investor-driven regimes.

6.3.2 Case Studies

After the regulations are in place those involved in planning an offshore transmission project will decide on design specifications. As discussed in Section 2.8, several studies explore optimal transmission topologies and technology choices including [16, 39, 89]. For

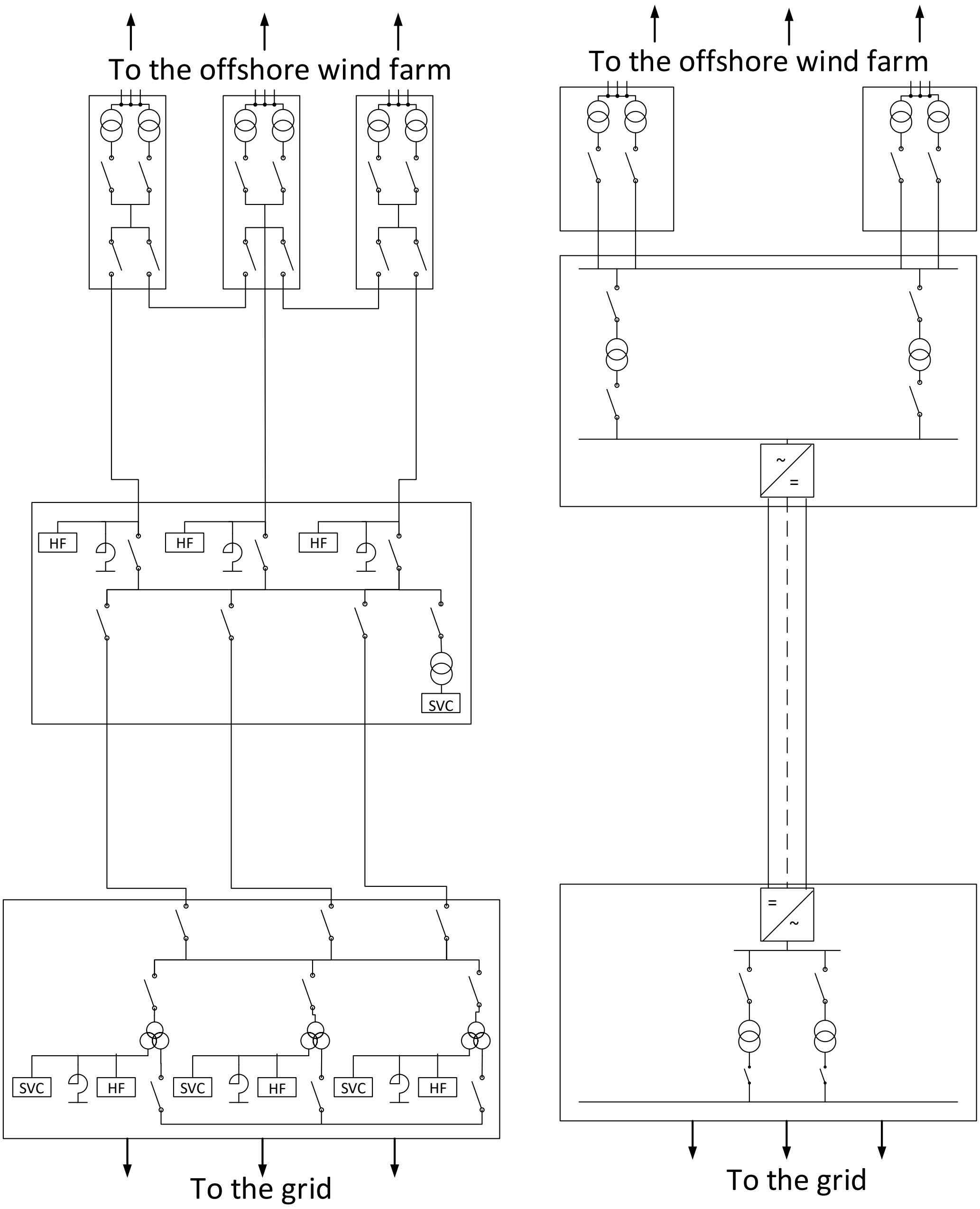


Figure 6.1: HVAC (left) and VSC-HVDC bipole (right) case study. The dashed line represents a neutral cable.

a project one hundred kilometres from shore, one decision may be whether to implement HVAC or HVDC connection technologies.

In this chapter, we take a 1.2 GW offshore wind farm case study as representative of recent projects. Guidelines that have been given in [230] are used to design two generic, far from shore, HVAC and VSC based HVDC topologies, shown in Fig. 6.1. We note that Fig. 6.1 is a simplified diagram that makes assumptions, which will affect cost and availability. Considering a topology in more detail is beyond the scope of this work, and so we take Fig. 6.1 as standard designs for this work. For this 1.2 GW project to be deployed in an emerging market, an optimal OTS regulatory regime and topology is desirable. The following analysis evaluates bounds on the expected return on investment (ROI) for each regulatory regime and technology choice while considering the associated uncertainties.

6.4 Methodology

So far, in this chapter, we have introduced and motivated the regulatory and technical decision problems that we will investigate. These decision problems are used to demonstrate how to implement imprecise probability techniques to a practical problem of interest. In this section, we more formally formulate the decision problem and explain the methodology.

6.4.1 Problem Outline

Let policymakers make a decision (j_1) between a developer and third-party ownership structures and project planners make a decision (j_2) between HVAC and HVDC technologies. In total there are four options: developer and HVAC (option one); developer and HVDC (option two), third-party and HVAC (option three); third-party and HVDC (option four). We aim to compare these four options. In this chapter, we use this decision problem to demonstrate how techniques based on the theory of imprecise probability can be applied to a practical decision problem that is taken under severe uncertainty.

In Section 6.4.2 we formulate the decision problem. Following this, Section 6.4.3 describes the limitations of using techniques based on the classical theory of probability, and Section 6.4.4 shows how techniques based on imprecise probability can be applied to the described decision problem. In Section 6.4.4, we also explain how the techniques allow for the more appropriate handling of uncertain inputs, and therefore, illustrate the benefits of applying imprecise probability.

6.4.2 Return on Investment (ROI)

So far, in this thesis, we have focused on the economic metric termed net present value (NPV). However, NPV may not be a suitable metric to compare multiple projects when the initial investment of each project is drastically different. For example, if project A has a NPV of 20 and project B has an NPV of 30, we cannot say that project B is preferable over project A without knowing their initial investments and, more importantly, whether they are similar. If these initial investments significantly differ, we may no longer think that project B is preferable; for example, if we invested 2 in project A and 28 in project B, we may not find project B to be preferable over project A.

This difference in initial investments is the case in this chapter, as we compare projects from the perspective of both a developer and a third-party owner. A developer finances the wind farm and the OTS whereas a third-party finances only the OTS. Furthermore, wind farm costs are usually significantly higher than those of the OTS, and therefore initial investments differ considerably. Consequently, in this chapter, we use the metric termed ROI, as it may be more suitable to compare projects whose initial investments vastly differ.

Usually, the choice of economic metric falls to the decision maker. There exist several metrics to choose from, and each metric has different advantages and disadvantages, which are discussed in detail in [231]. Selecting the most suitable metric is not the aim of this work; therefore, we select a reasonable and suitable metric to conduct the analysis. In this chapter, we set out to demonstrate how statistical techniques based on the theory of imprecise probability can better handle severe uncertainties in the model inputs. These techniques are applicable irrespective of the economic metric chosen; moreover, most metrics consider the same inputs. Therefore, we selected the metric termed ROI as an example to demonstrate the implementation of imprecise probability.

The metric ROI, defined for our case study by Eq. (6.4), is used to compare the options [231]. Here, R denotes revenue, t denotes the year of operation and n represents the number of operational years. OPEX represents the operational expenditure and CAPEX denotes the capital costs of the project.

$$\mathrm{ROI}(j_1, j_2) = \frac{\sum_{t=1}^{n}(R_t(j_1, j_2) - \mathrm{OPEX}_t(j_1, j_2)) - \mathrm{capex}(j_1, j_2)}{\mathrm{capex}(j_1, j_2)} \tag{6.4}$$

The metric ROI does not reflect the duration of the investment, and this may be a limitation. In this chapter, we compare projects with the same lifetime, so this limitation may not be relevant. However, one solution is to consider the annual return on investment, which can be calculated by Eq. (6.5) [232, 233].

$$\text{Annual ROI} = (1 + \mathrm{ROI})^{\frac{1}{n}} - 1 \tag{6.5}$$

Here, n is the project lifetime (number of operational years) and ROI is evaluated using Eq. (6.4). We note that in this case, the annual ROI is not evaluated by simply dividing Eq. (6.4) by the number of operational years as this would ignore the effect of compounding. We also note that ROI calculated using Eqs. (6.4) and (6.5) is a ratio. ROI is more commonly expressed as a percentage; this is achieved by simply multiplying the result of Eqs. (6.4) and (6.5) by one hundred.

6.4.3 Classical Approach

Using statistics based on the classical theory of probability, we evaluate the expected ROI for each option and suggest that the option with the highest expected ROI is optimal. The expected value (denoted by E) is discussed in Chapter 5 and can be thought of as the average value of a random variable over its possible outcomes. Furthermore, the expectation is a summary statistic used for decision making. Evaluating the expected ROI requires the expectation of capacity factor, availability and wholesale price. We do not have enough information to assign realistic distributions to these inputs.

Furthermore, in Chapter 5, we discussed how classical availability models assume failure and repairs are exponentially distributed and unfortunately, we do not have enough information to justify these modelling assumptions. Accordingly, we seek more suitable methods and implement imprecise probability techniques that we introduced in Chapter 5. The next section discusses how to apply these techniques to the decision problem introduced in this chapter. Following this explanation of the methodology, we apply these techniques in Section 6.6 and assess the benefits of doing so.

6.4.4 Bounding Approach

In Chapter 5, we discussed that strong assumptions required by classical techniques could be relaxed using the theory of imprecise probability. Applying the theory of imprecise probability, we consider lower and upper bounds on the expectation denoted by $\underline{E}$ and $\overline{E}$, respectively. We aim to find lower and upper bounds on the expected ROI. Here, we focus on the lower bound, but similar expressions are used for the upper bound.

Firstly, the following result is required. Let X be a random variable, g be a gamble which is a bounded real-valued mapping on the possibility space $\mathcal{X}$, and let $\mathcal{M}$ be a set of probability distributions. We define the lower expectation as the minimum expectation over a set of distributions [204, 234]:

$$\underline{E}(g(X)) = \min_{p \in \mathcal{M}} E_p(g(X)). \tag{6.6}$$

For all j_1 and j_2, the CAPEX is fixed and known. Additionally, under weak assumptions, the lower expectation of Eq. (6.4) satisfies:

$$\underline{E}(\mathrm{ROI}(j_1, j_2)) = \frac{\sum_{t=1}^{n} \underline{E}((R_t(j_1, j_2) - \mathrm{OPEX}_t(j_1, j_2)) - \mathrm{capex}(j_1, j_2)}{\mathrm{capex}(j_1, j_2)}. \tag{6.7}$$

Annual revenue can be formulated as:

$$R(j_1, j_2) = \begin{cases} 8760aSWY(j_2), & \text{if } j_1 = \text{developer} \\ (0.9I_{Y(j_2)\leq 0.94} - 1.45I_{0.94\geq Y(j_2)} + 2.5Y(j_2)I_{0.94\geq Y(j_2)})B(j_2), & \text{if } j_1 = \text{third-party} \end{cases} \tag{6.8}$$

Here, a denotes project capacity, S represents the capacity factor, W denotes the wholesale price of energy, $Y(j_2)$ represents the availability under technology j_2, $B(j_2)$ denotes the base revenue under technology j_2 and I_Y is the indicator function. The numerical coefficients in the bottom line of Eq. (6.8) arise from Eq. (6.3) in the following way: 0.9 is the coefficient from the top line of Eq. (6.3), -1.45 comes from the bottom line of Eq. (6.3) (specifically, $-1.45 = 0.9 + (-0.94 \times 2.5)$) and 2.5 is the coefficient of Y_t in the bottom line of Eq. (6.3). Annual operational expenditure (OPEX) can be formulated as:

$$\mathrm{OPEX}(j_1, j_2) = \begin{cases} \mathrm{opex}' + \mathrm{OPEX}''(j_2) & \text{if } j_1 = \text{developer} \\ \mathrm{OPEX}''(j_2), & \text{if } j_1 = \text{third-party} \end{cases} \tag{6.9}$$

Here, opex' refers to OPEX of the wind farm (which we assume to be is fixed and known) and $\mathrm{OPEX}''(j_2)$ refers to OPEX of the OTS.

Since CAPEX is fixed for each (j_1, j_2), we focus on $\underline{E}((R_t(j_1, j_2) - \mathrm{OPEX}_t(j_1, j_2))$. For option one (developer HVAC) and option two (developer HVDC):

$$\begin{aligned} \underline{E}((R_t(j_1, j_2) - \mathrm{OPEX}_t(j_1, j_2)) &= \underline{E}(8760aswY_t(j_2) - \mathrm{opex}' - \mathrm{OPEX}''(j_2)) & (6.10) \\ &= \min_{p\in\mathcal{M}} E_p(8760aswY_t(j_2) - \mathrm{opex}' - \mathrm{OPEX}''(j_2)) & (6.11) \\ &= \min_{p\in\mathcal{M}} 8760aswE_p(Y_t(j_2)) - \mathrm{opex}' - E_p(\mathrm{OPEX}''(j_2)) & (6.12) \end{aligned}$$

Here, $\mathcal{M}$ is the set of worst- and best-case distributions of $Y(j_2)$. The final expression is evaluated by inputting fixed values for a, s, w and opex'. $E_p(Y_t(j_2))$ is evaluated as sample mean from the availability simulation for technology j_2. $E_p(\mathrm{OPEX}''(j_2))$ is also evaluated in this simulation.

Similarly, for option three (third-party HVAC) and option four (third-party HVDC):

$$\underline{E}((R_t(j_1, j_2) - \mathrm{OPEX}_t(j_1, j_2)) \tag{6.13}$$

$$= \underline{E}((0.9 I_{Y_t(j_2) \leq 0.94} - 1.45 I_{0.94 \geq Y_t(j_2)} + 2.5 Y_t(j_2) I_{0.94 \geq Y_t(j_2)}) B(j_2) - \mathrm{OPEX}''(j_2)) \tag{6.14}$$

$$= \min_{p \in \mathcal{M}} E_p((0.9 I_{Y_t(j_2) \leq 0.94} - 1.45 I_{0.94 \geq Y_t(j_2)} + 2.5 Y_t(j_2) I_{0.94 \geq Y_t(j_2)}) B(j_2) - \mathrm{OPEX}''(j_2)) \tag{6.15}$$

$$= \min_{p \in \mathcal{M}} (0.9 E_p(I_{Y_t(j_2) \leq 0.94}) - 1.45 E_p(I_{0.94 \geq Y_t(j_2)}) + 2.5 E_p(Y_t(j_2)) E_p(I_{0.94 \geq Y_t(j_2)}))$$
$$E_p(B(j_2)) - E_p(\mathrm{OPEX}''(j_2)) \tag{6.16}$$

Here, $E_p(I_{0.94 \leq Y_t(j_2)})$ and $E_p(I_{Y_t(j_2) \geq 0.94})$ are determined from the availability simulation.

Usually, when techniques based on classical probability theory are used, we find the optimal decision by comparing point values. Since techniques based on imprecise probability give bounds on the expected value, we require techniques to compare intervals of expected ROI. In the literature there exist different approaches to this, and these were introduced in Section 5.4.5. Before recapping the decision criteria using imprecise probability, we discuss the impact of act-state dependence on the approach. We recall from Chapter 5 that act-state dependence means that the distribution of the state of nature depends on the decision taken.

In Chapter 5, we discussed how act-state dependence prevents the use of maximality as a decision criterion and requires careful handling of variables. In the decision problem presented in this chapter, we encounter act-state dependence; consequently, we need to treat those variables whose distribution depends on the decision taken differently to those variables whose distribution does not. The occurrence of act-state dependence is one challenge that arises in practical applications that is not extensively discussed in the theory. In the following paragraph, we describe how we deal with act-state dependence in the decision problem at hand.

We first classify the act-state dependent and independent variables in the ROI expression. We identify the act-state dependent variable as yearly availability, and the act-state independent variables are capacity factor and wholesale price. For the act-state dependent variables, we assign a set of distributions for each input parameter and simulate the system to obtain best- and worst-case scenarios. These scenarios are discussed in Section 6.5.2. Using these scenarios, we bound expected return on investment (conditionally on the act-state independent variables) and analyse these bounds, using interval dominance and Γ-maximin, to find economically preferable options. To handle uncertainty in the act-state independent variables, we take a sensitivity analysis approach and investigate how the decision changes as a function of fixed values of these variables.

In the remainder of this section, we recap the decision criteria presented in Chapter 5. The decision criterion called interval dominance selects options whose upper bound is greater than the greatest lower bound. In other words, interval dominance selects any option which is not interval dominated by another option, where an option is interval dominant if its interval is completely to the right-hand side of an interval for another option. Alternatively, if the decision-maker is risk-averse, they may use the Γ-maximin decision criterion which selects the option with the greatest lower bound. These two decision criteria are defined below.

For interval dominance, we define: $E^* = \max_{j_1,j_2} \underline{E}(\text{ROI}(j_1, j_2))$ and use the following decision criterion. Any option (j_1, j_2) such that $\overline{E}(\text{ROI}(j_1, j_2)) \geq E^*$ is optimal. For the Γ-maximin decision, the option (j_1, j_2) such that $\underline{E}(\text{ROI}(j_1, j_2) = E^*$ is optimal [224].

When applying statistical techniques to practical decision problems, good communication of outputs and results is vital. Consequently, we visualise the sensitivity type analysis on a 2-D plot where the x and y axes represent the act-state independent variables we are varying. In this chapter, although the theory allows us to consider more than two act-state independent variables, we restrict ourselves to just two to ensure that the visualisation is clear to interpret.

6.5 Input Data

The inputs to evaluate expected ROI are split into two categories: known inputs and random variables. Both of these types of inputs are discussed below.

6.5.1 Inputs Based on Known Data

The known inputs are project lifetime, project capacity and CAPEX. The number of operational years is taken to be twenty-five years which is typical across the industry. However, we note that project lifetimes are increasing to about thirty years. The project capacity is 1.2 GW. This capacity depends on turbine size and quantity, which is known in the design stage.

The capital expenditure (CAPEX) of the offshore transmission system (OTS) is evaluated by summing component costs found in literature [33, 36, 37]. This approach is detailed in Chapter 4. A high-level breakdown of the OTS into offshore substation(s), offshore cable(s), onshore cable(s) and onshore substation(s) is considered. This includes costs regarding electrical equipment, platform structures and installation. CAPEX of the wind farm is evaluated by summing turbine, foundation and array cable costs presented in [38]. Under developer ownership, CAPEX refers to the OTS and the offshore wind farm.

Under third-party ownership, CAPEX refers to just the OTS. The CAPEX of the OTS is evaluated to be £1.1 billion and £1.3 billion for the HVAC and HVDC case studies, respectively. The CAPEX of the OTS and offshore wind farm are evaluated to be £2.7 billion and £2.9 billion for the HVAC and HVDC case studies, respectively.

6.5.2 Random Variables

The base revenue is fixed at the time of asset transfer for, usually, twenty-five years. The base revenue is unknown at the time of the decision but can be estimated with reasonable accuracy from the project's CAPEX. Identical to the analysis in Chapter 4, using linear regression and the method of least squares on data for fully commissioned UK offshore wind projects [32], we obtained a linear model of the form presented in Eq. (6.17) with an R^2 value of 0.9783.

$$B = \beta_3 \times \text{CAPEX} + \beta_4 + \varepsilon_1 \tag{6.17}$$

Here, B denotes the base revenue, CAPEX refers to the capital costs of the OTS, $\beta_3 = 0.09023$, $\beta_4 = 3.038$ and ε_1, the residual error, is normally distributed with mean zero and a standard deviation of 1.34. The parameters β_4 and ε_1 are in units of millions of pounds.

One of the main drawbacks to offshore wind is the inherent uncertainties. The availability of an OTS depends on outage frequency and duration, which are influenced by uncertain factors including vessel availability, sea-state conditions and availability of spare parts. The capacity factor depends on wind conditions and turbine availability, while the main drivers of uncertainty in wholesale prices include matching supply to demand, fuel commodity prices and weather [235].

Single input values may fail to represent our knowledge accurately. Since it is challenging to put realistic distributions on these input parameters, we consider reasonable sets of distributions instead and assess the economic benefits over these sets. Using literature values discussed in the paragraph below, realistic ranges have been determined (shown in Table 6.1). We consider all distributions within these ranges.

In the next two paragraph, we give a summary of the literature values of the relevant input parameters. Capacity factor is quoted in literature to be between 0.24 and 0.68 in [164], 0.386 in [165], 0.473 in [165], between 0.32 and 0.63 in [166], and 0.49 in [166]. The wholesale price of energy is quoted in literature to be between £47.25/MWh and £48.10/MWh in [166], between £33.85/MWh and £67.54/MWh in [236], and between £35.00/MWh and £78.00/MWh in [237]. The operational expenditure (OPEX) of a wind farm is quoted in literature to be €76,000/MW/year in [151], £79,000/MW/year in [152], between €80,000 and €100,000/MW/year in [153], and £72,000/MW/year in [154].

Input	Range considered in this work
Capacity Factor	0.3 - 0.65
Failure Rate of HVDC Export Cable (fails/year/km)	0.00001 - 0.0007
Failure Rate of HVAC Export Cable (fails/year/km)	0.000705 - 0.003
Wholesale price of energy (£/MWh)	35.00 - 65.00
Export Cable Repair Time (days)	30 - 150

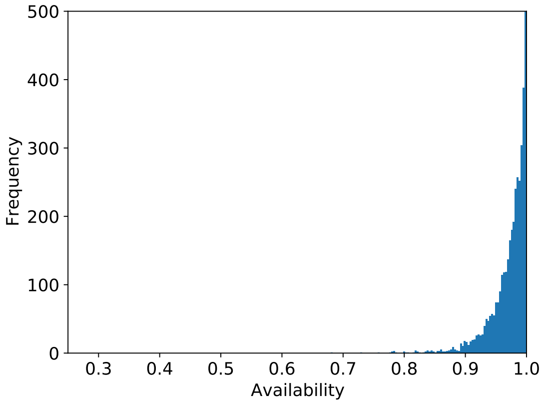
Table 6.1: Input ranges considered in this chapter for uncertain model parameters.

The failure rate of a HVDC export cable is quoted to be 0.0007 fails/year/km in [149], 0.00001107 fails/year/km in [238], 0.0000213 fails/year/km in [238], and 0.00036889 fails/year/km in [238]. The failure rate of a HVAC export cable is quoted to be 0.000705 fails/year/km in [142], 0.00024 fails/year/km in [150], 0.0016 fails/year/km in [82], and 0.003 fails/year/km in [83]. The export cable repair time is quoted in literature to be sixty days in [142], sixty days in [238], and between thirty and one hundred and fifty days in [141]. These input values are used to determine ranges given in Table 6.1.

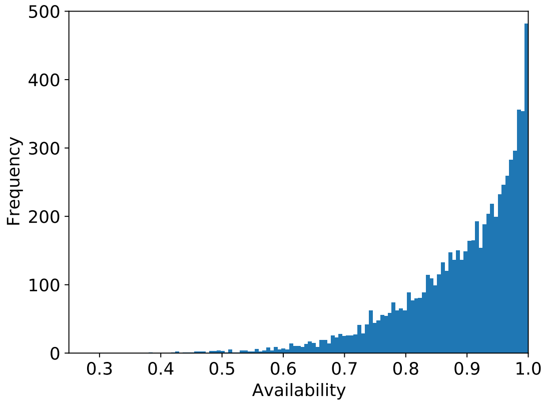
A probability distribution for OTS availability under each technology is required for the analysis. This was evaluated using Monte Carlo simulations performed in `Python` using `Numpy` [27]. The state of each major component, and in turn, the system, is determined each hour in a year using failure and repair rates given by [99] and Table 6.1. This system trace determines the availability each year. The simulation has been repeated for 10,000 years to obtain a probability distribution for availability. Best- and worst-case scenarios have been considered by inputting best- and worst-case failure and repair rates. The results are shown in Fig. 6.2. Each simulation resulted in a peak at 100% availability that has been removed for clarity. The number of counts at 100% availability, out of $10,000$, are $6,345$, $3,059$, $2,478$ and $1,648$ for Figs. 6.2a to 6.2d, respectively.

Another random variable is operational expenditure (OPEX), which refers to the costs associated with the maintenance and repairs required to keep the assets in a good working condition. OPEX evaluation is complex and often commercially sensitive. Consequently, a simplistic but reasonable approach is taken. Interval analysis indicates that OPEX of the wind farm has little impact on the decision choice (see Section 6.5.3). Therefore, OPEX of the wind farm is fixed at £$75,000$ per MW per year.

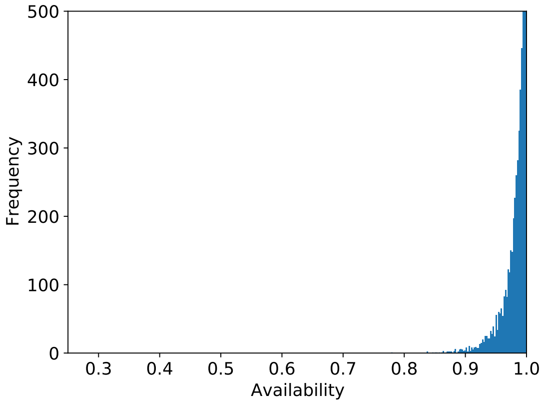
OPEX of the OTS is evaluated using the previously described availability simulation. In the simulation, when a component fails a repair cost is assigned (based on component costs given by [33, 36, 37] and vessel hire rates given by [93]). Due to a limited amount of



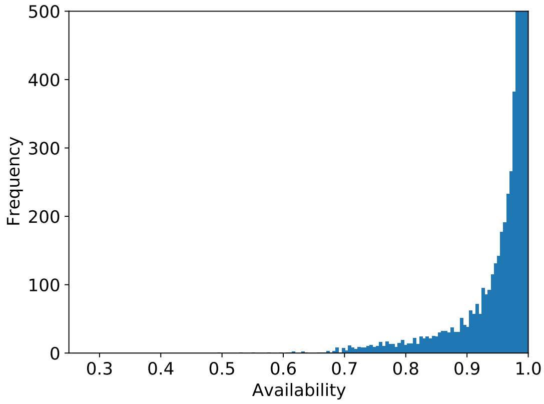
(a) Histogram of best-case HVAC availability.



(b) Histogram of worst-case HVAC availability.



(c) Histogram of best-case HVDC availability.



(d) Histogram of worst-case HVDC availability.

Figure 6.2: HVAC and HVDC availability from Monte Carlo simulations of the case studies. Each simulation resulted in a peak at 100% availability that has been removed for clarity.

operational information available, replacement upon failure is assumed except for cables (typically 200 metres is replaced [187]) and converters (OPEX of the offshore converter and onshore converter is assumed to be 2% and 0.7% of the component costs, respectively [148]). In the simulation, these costs are summed over the year and used to find an average yearly OPEX.

6.5.3 Interval Analysis for Wind Farm Operational Costs

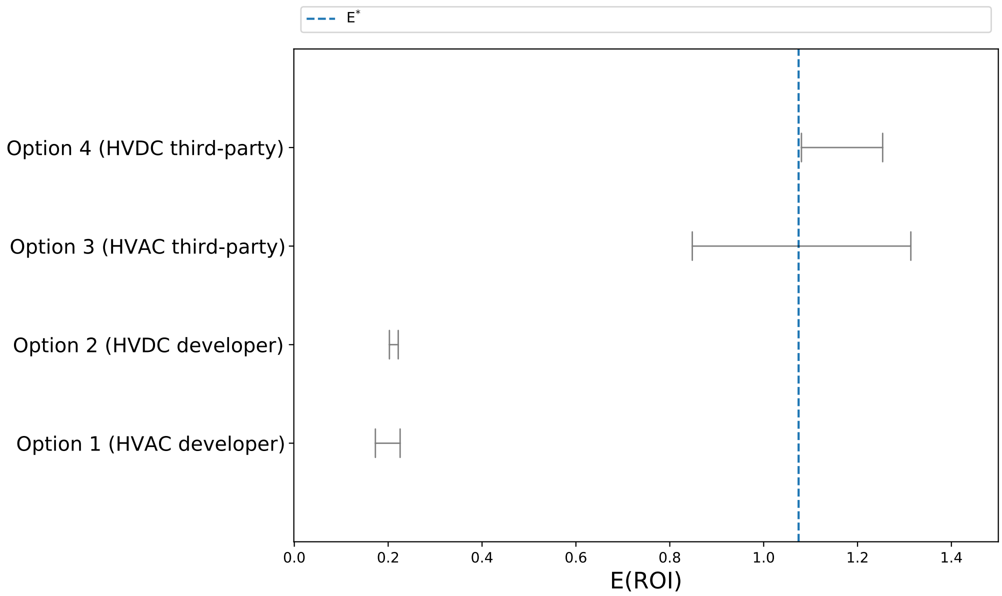
In this section, we investigate the impact of OPEX associated with the wind farm on the decisions made. Based on literature values, the analysis has been conducted with wind farm OPEX at £70,000 and £80,000 per MW per year. These results are shown in Figs. 6.3 to 6.7. Fig. 6.3 shows bounds on the expected ROI for each option with OPEX of the wind farm fixed at £70,000 per MW per year in Fig. 6.3a and £80,000 per MW per year in Fig. 6.3b. From these figures, we see very little difference, and therefore this input has a small impact on decision choice. This is further confirmed by Figs. 6.4 to 6.7, which shows that as we handle uncertainty in capacity factor and wholesale price, the decisions do not change considerably for these two wind farm OPEX values.

6.6 Results & Sensitivity Analysis

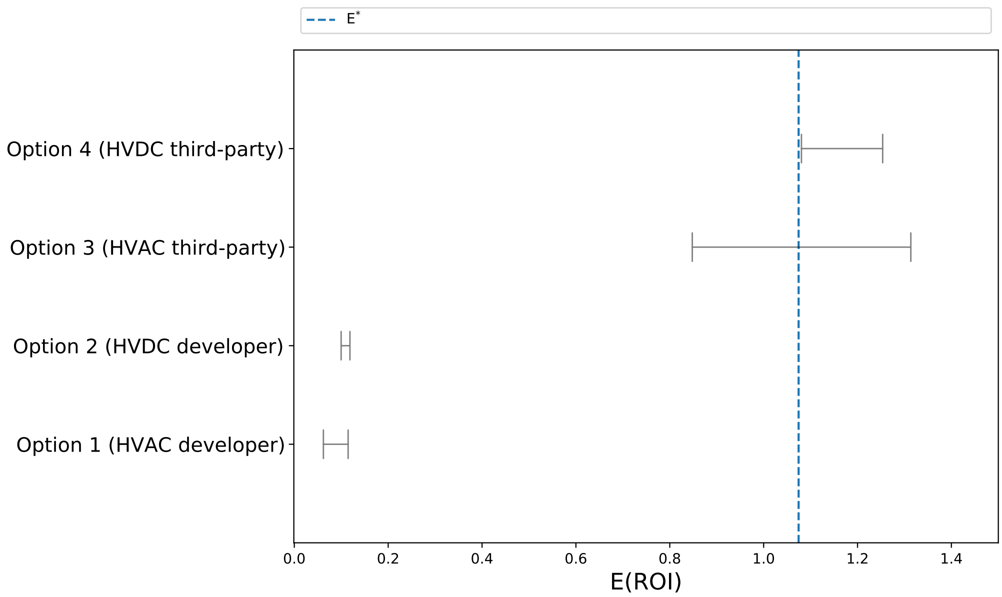
6.6.1 Results

In the previous section, we detailed the methodology that would be applied to the described decision problem of this chapter. In this section, we present the results of this application. In the analysis, capacity factor and wholesale price are initially fixed at 0.45 and £50 /MWh, respectively. For each option, the upper and lower bounds of expected ROI are shown in Fig. 6.8 and the bounds on expected annual ROI are shown in Fig. 6.9. In this example, we see that the results and decision between ROI and annual ROI do not differ. We also note that an expected ROI of 0.01 equates to 1%. In Fig. 6.8, under option one, the lower expected ROI is 0.11, and the upper expected ROI is 0.18. These are represented by vertical lines which are connected to represent an interval of expected values. The vertical dashed line represents the greatest lower bound (considering all of the options), E^*, and can be used to assist with identifying optimal options.

The results are dependent on the decision maker's inputs. Using the described input data and modelling approach, Fig. 6.8 shows that under interval dominance, HVAC third-party and HVDC third-party are deemed optimal. Under the risk-averse decision criterion called Γ-maximin, Fig. 6.8 shows HVDC third-party to be optimal. A decision maker can tailor the inputs and pick a decision criterion that meets their needs. Therefore, this

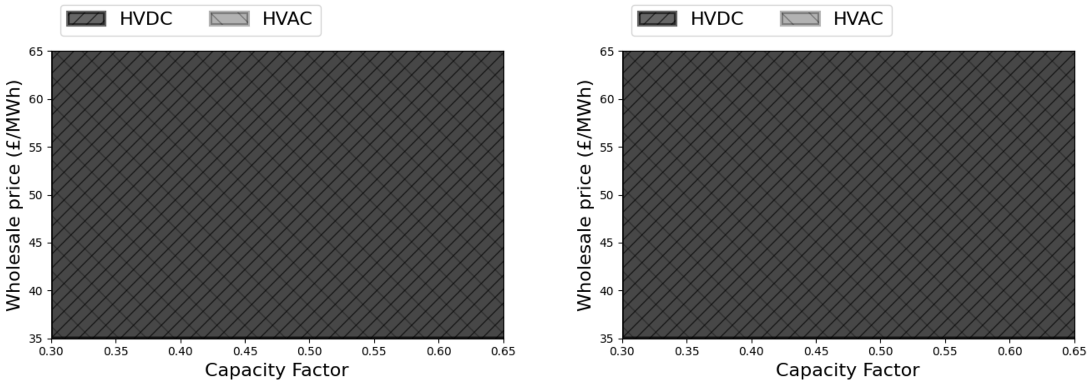


(a) In this analysis the OPEX of the wind farm is fixed at £70,000 per MW per year.



(b) In this analysis the OPEX of the wind farm is fixed at £80,000 per MW per year.

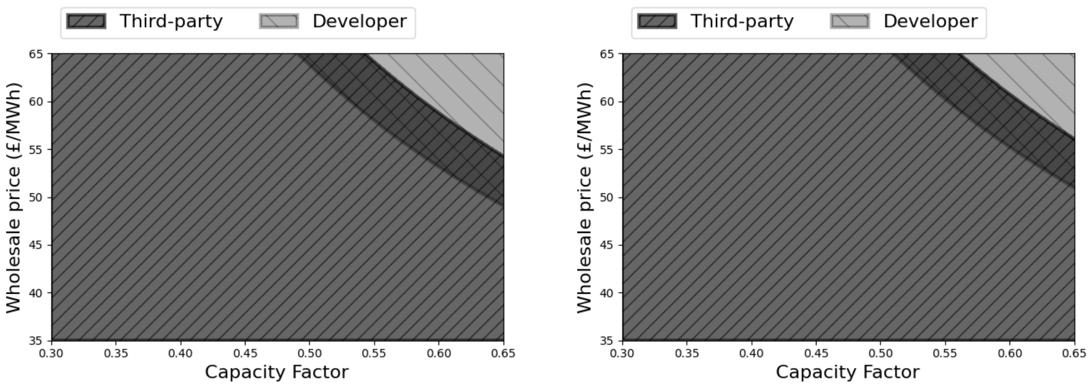
Figure 6.3: Bounds on the expected return on investment (ROI) for each option. Here, capacity factor (s) and wholesale energy price (w) are fixed at 0.45 and £50/MWh respectively.



(a) OPEX of the wind farm is fixed at £70,000 per MW per year.

(b) OPEX of the wind farm is fixed at £80,000 per MW per year.

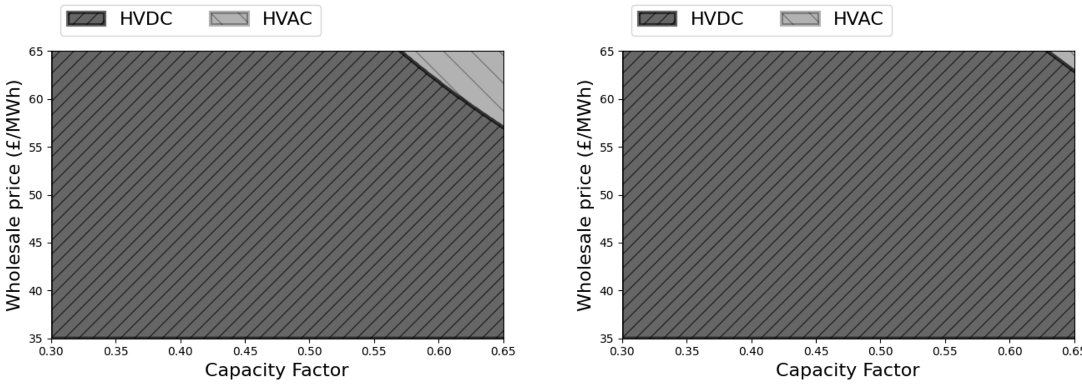
Figure 6.4: The technology choice for different values of wholesale price and capacity factor when interval dominance is used as the decision criterion.



(a) OPEX of the wind farm is fixed at £70,000 per MW per year.

(b) OPEX of the wind farm is fixed at £80,000 per MW per year.

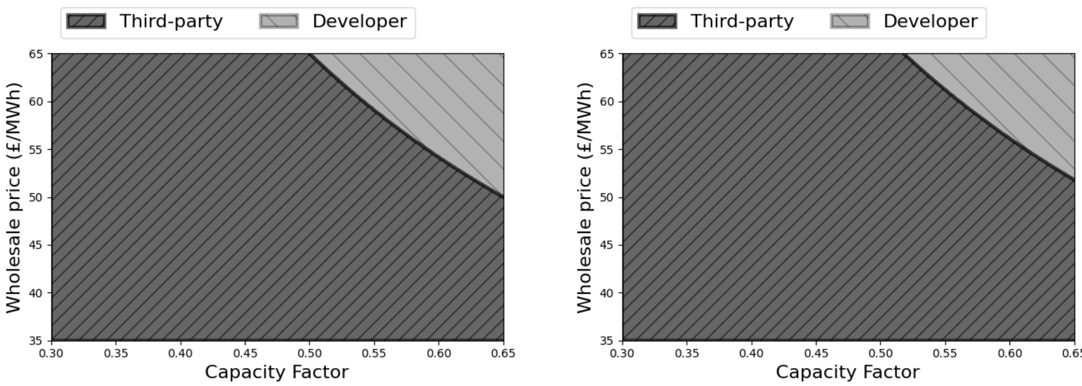
Figure 6.5: The regime choice for different values of wholesale price and capacity factor when interval dominance is used as the decision criterion.



(a) OPEX of the wind farm is fixed at £70,000 per MW per year.

(b) OPEX of the wind farm is fixed at £80,000 per MW per year.

Figure 6.6: The technology choice for different values of wholesale price and capacity factor when Γ-maximin is used as the decision criterion.



(a) OPEX of the wind farm is fixed at £70,000 per MW per year.

(b) OPEX of the wind farm is fixed at £80,000 per MW per year.

Figure 6.7: The regime choice for different values of wholesale price and capacity factor when Γ-maximin is used as the decision criterion.

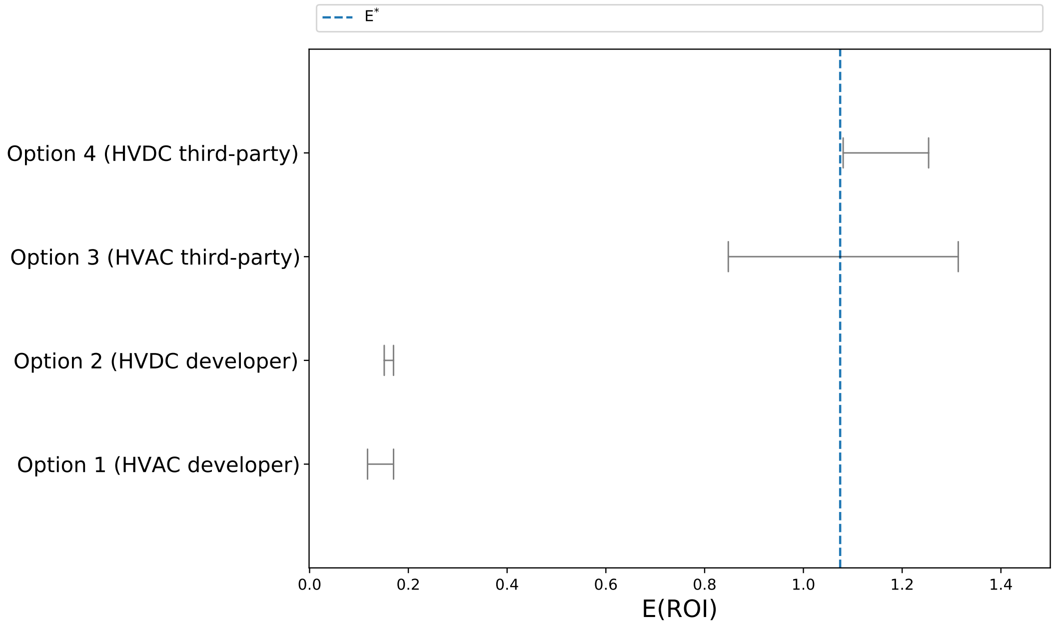


Figure 6.8: Bounds on the expected ROI for each option. Here, capacity factor and wholesale price are fixed at 0.45 and £50/MWh respectively.

approach could be adopted in decision making under severe uncertainty.

6.6.2 Sensitivity Analysis

To handle uncertainty in the act-state independent inputs, we assess how the decision changes as a function of fixed values of capacity factor and wholesale price. To achieve this, capacity factor and wholesale price are varied across values given in Table 6.1, and we assess their impact on expected ROI. For each capacity factor and wholesale price input combination, we find and visualise the optimal options under each decision criterion. Fig. 6.10 and Fig. 6.11 shows how the decision changes as these inputs are varied. We only include the sensitivity analysis plots for expected ROI since the results for expected annual ROI are identical.

6.6.3 Technique Comparison

So far, in this chapter, we have demonstrated how to implement techniques based on imprecise probability to two practical decision problems in offshore transmission. We now compare the approach taken in this chapter to more conventional techniques based on the classical theory of probability. In this chapter, we conduct this comparison qualitatively, and in the next chapter (for a different decision problem), we will present the comparison more quantitatively.

To conduct the same analysis using conventional techniques, we evaluate the expected

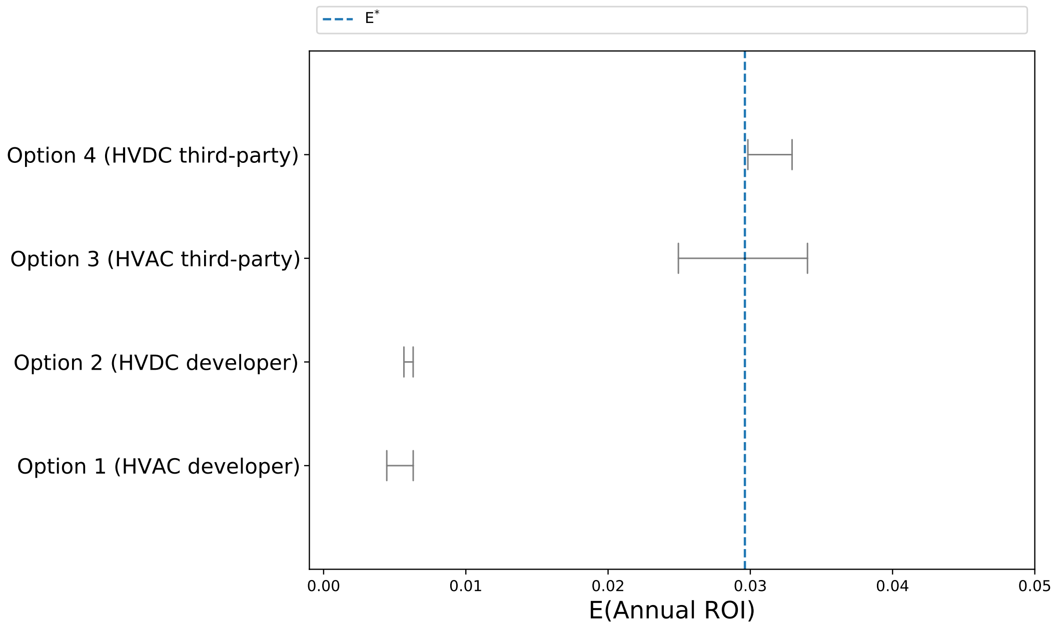


Figure 6.9: Bounds on the expected annual ROI for each option. Here, capacity factor and wholesale price are fixed at 0.45 and £50/MWh respectively.

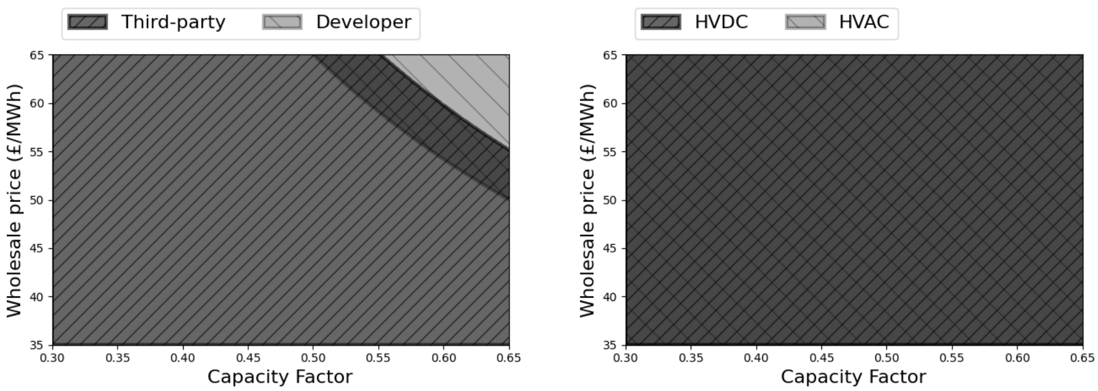


Figure 6.10: The regime (left) or technology (right) choice for different values of wholesale price and capacity factor when interval dominance is used as the decision criterion.

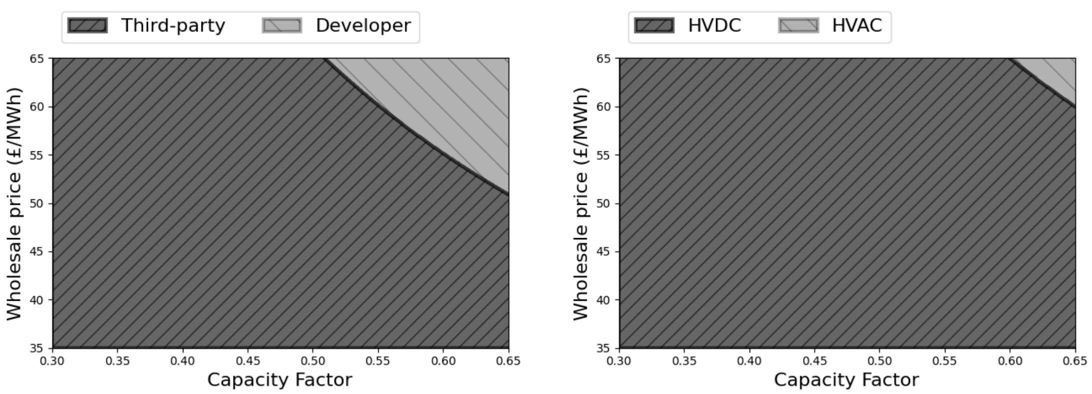


Figure 6.11: The regime (left) or technology (right) choice for different values of wholesale price and capacity factor when Γ-maximin is used as the decision criterion.

ROI, $E(\text{ROI})$, for each option. To evaluate the expected ROI requires inputs such as capacity factor, the wholesale price of energy, and component failure and repair rates. In particular, we must assign values or distributions to these inputs. However, due to a limited amount of relevant data and information, we do not have enough information to assign probability distributions accurately. Therefore, if we were to assign a distribution, it may not adequately represent the data available. This limitation of techniques based on classical probability theory motivated us to seek out and apply alternative techniques that are more robust under severe uncertainty.

For now, we ignore these more robust techniques and proceed to consider an approach based on the classical theory of probability. At this point, due to the severe uncertainties described, a methodology based on classical probability theory is weakened. Moreover, situations where the inputs significantly impact the output can be problematic. Unfortunately, in Chapter 4, we saw that this is the case for failure and repair rates, as they have a significant impact on a project's economic performance. Consequently, in this scenario, the outputs of analysis based on classical probability theory under severe uncertainty are inadequate, and it could be unwise to base investment decisions on these outputs.

To complete the analysis using classical probability theory, we assign values or distributions to inputs and evaluate the expected ROI, (we may also evaluate confidence intervals around this expected ROI). However, this analysis used inputs that do not accurately represent the information we have available. Furthermore, evaluating the expected ROI requires the availability of the system. Conventionally, this is evaluated by modelling the components within the system as Markov chains. Unfortunately, as we have previously noted, under severe uncertainty, we do not have enough information to justify the assumptions required for a Markov chain, notably stationarity and the Markov property. Therefore, the expected availability, the expected ROI and any inferences made are not representative of the information available, and therefore, should be treated with care.

As we have seen, there exists a more general approach called imprecise probability, and these techniques allow more appropriate handling of severe uncertainties in the input parameters. Therefore, in this chapter, we applied these techniques. Techniques based on imprecise probability have several benefits in applications that have severe uncertainty. Here, we limit the discussion of advantages to those relevant to the decision problem in this chapter.

In this chapter, we used imprecise Markov chains to allow strong modelling assumptions required for precise Markov chains to be relaxed. Additionally, the approach allows us to deal with epistemic uncertainty by considering inputs within more suitable ranges, and therefore consider a set of processes. Ultimately, this approach evaluates bounds on the expected ROI rather than a single value; these bounds allow a better representation of the available information. Another advantage of techniques based on imprecise probability is that the approach allows for indecision this is important for scenarios where there is insufficient information to arrive at a justified decision. Focusing more specifically on the decision problem presented in this chapter, the described approach allows us to handle uncertainty in act-state independent variables by evaluating how the decision changes as a function of fixed values within a range. Overall, the techniques allow more appropriate handling of severe uncertainty in the input parameters and allow us to make decisions under severe uncertainty.

Although the techniques based on imprecise probability allow more appropriate handling of severe uncertainty in the input parameters, compared to techniques based on the classical theory of probability, there exist some limitations to this approach. Firstly, the results depend on the sets of distributions we assign to the input parameters. Therefore, the decision maker must be able to assign these sets or know which regions to consider in the resulting sensitivity analysis plot. In the case where sets of distributions are challenging to identify, we may end up considering a wide range of values. Ultimately, this may mean we obtain large sets of distributions for the outputs that may not be informative. However, if the primary purpose is to compare different options to make a decision, these large intervals may not be so much of a limitation.

Secondly, we do not investigate aleatory uncertainty (the uncertainty due to variability), as we aim to maximise the expected return on investment. Instead, we focus on epistemic uncertainties and handling severe uncertainty in the input modelling parameters. To consider the aleatory uncertainty, we could look at confidence bounds around the expected values. This limitation is to be discussed further and addressed in Chapter 8.

6.7 Conclusion

As the offshore wind industry matures, new markets will install assets and design policies to facilitate this. One consideration will be optimising offshore transmission regulatory regimes to the situation of a particular market. If a competitive and investor-driven approach is desirable for the offshore transmission system (OTS) development, the regime must be attractive to investors and therefore maximise return on investment (ROI). Furthermore, an emerging market will investigate the current operational practices. From a developer's perspective, they will make several decisions relating to the design of the OTS, including, in the initial stages, whether to install HVAC or HVDC technologies. The study of this chapter set out to find solutions to these regulatory and technical decision problems under severe uncertainty. Moreover, the aim was to apply advanced statistical techniques to appropriately handle severe uncertainty in the input parameters (due to a limited amount of relevant data) and assess the application of these techniques to decision problems in offshore power transmission.

In this chapter, we summarised and contrasted current regulatory regimes, before formulating two decision problems: firstly, which ownership structure to implement and secondly, which technology choice to install. For the HVAC and HVDC case studies considered (and contingent on model choices), the study found third-party ownership to be optimal. These results were obtained using advanced statistical methods as approaches based on the classical theory of probability were unable to deal with the identified severe uncertainties adequately. This chapter demonstrated the benefits of this approach over classical techniques, and they included addressing and more accurately representing the uncertainty in our knowledge. The analysis conducted, and the resulting optimal decision choice depends heavily on the availability distribution and associated operational costs. In this chapter, we based these inputs on literature values. A more realistic analysis could be obtained, following the same methodology, provided that we have access to relevant data.

When applying imprecise probability in this chapter, we encountered act-state dependence (the distribution of the state of nature depends on the decision), and showed a way to overcome the issue of act-state dependence. We explored how to present the results in a way that is simple to interpret and achieved this using a two-dimensional visualisation of the sensitivity analysis. This chapter showed that taking this sensitivity analysis approach facilitates clear communication of results. In particular, the approach allows decision makers to use their expert knowledge to simply read off the optimal decision(s) from the visual output, rather than input their knowledge into the model.

Overall, we presented a more in-depth insight into the benefits of using imprecise probability for decision making in offshore wind and identified that careful consideration of how to handle variables is required when there is act-state dependence. The study contributes to our understanding of applying imprecise probability to offshore power decision problems and confirms that we can more suitably handle severe uncertainty by implementing these advanced statistical techniques. These findings suggest that the application of imprecise probability to offshore power transmission advances the current practice. Finally, this chapter demonstrated that where there is severe uncertainty, and classical statistical techniques are no longer justified, we should seek more suitable approaches, such as techniques based on imprecise probability. Consequently, these findings will be of interest to others who make decisions under severe uncertainty.

Chapter 7

Application 2: Assessing the Benefit of Investing in Redundancy for Offshore Transmission Under Severe Uncertainty

7.1 Introduction

In Chapter 6, we demonstrated how to apply techniques based on imprecise probability to two decision problems (one taken by policymakers and one taken by project planners). We showed that applying imprecise probability to these decision problems can be beneficial to offshore power transmission, in particular, to handle severe uncertainty due to insufficient data. In this chapter, we focus on another decision problem; however, this application concentrates on project design. Furthermore, we demonstrate how to implement imprecise probability to handle severe uncertainty in this particular investment problem.

We recall that each wind farm installed offshore is connected to the onshore grid by an offshore transmission system (OTS). As offshore wind projects increase in capacity and move further offshore, there is an increased importance for the OTS to have high availability and reliability levels. Unfortunately, some offshore transmission projects have experienced costly, in terms of time and money, cable failures [82]. Furthermore, these cable failures occurred more frequently than initially expected [83, 82]. On account of this challenge, steps must be taken to reduce the number and impact of offshore cable failures when planning future projects. Consequently, research into proactive cable maintenance, cable installation practices, cable testing, cable fault detection methods, and redundancy has emerged.

The reliability of offshore wind systems is studied in [94, 95, 96, 18, 97, 16]. However, as we discussed in Chapter 2, most studies in the field focus on evaluating offshore network reliability from a wind farm owner's perspective [18]. Consequently, there has been limited research to assess the impact of cable failures from an offshore transmission owner's perspective. The failure behaviour of offshore cables introduces uncertainty when making investment decisions; accordingly, we require a suitable decision making method.

In this chapter, we apply techniques based on imprecise probability to aid decision making under severe uncertainty from the perspective of multiple stakeholders. Specifically, we utilise imprecise probability to assess whether to invest in an interlink between two offshore substations to provide increased redundancy. Furthermore, we explain the methodology and motivation behind the approach taken to handle uncertainty (in particular surrounding the export cable), as well as discuss how the presence of act-state dependence, again, dictates our approach. Overall, we demonstrate how imprecise probability could be beneficial to decision makers who require the appropriate handling of severe uncertainty in offshore power transmission.

The aims of this chapter are:

1. To investigate whether to invest in an interlink between two offshore substations from the perspective of multiple stakeholders.
2. To demonstrate how to apply imprecise probability to a practical decision problem where there is severe uncertainty that must be handled suitably.
3. To explain the methodology and motivation behind the approach taken to handle uncertainty in this decision problem. In addition, to discuss the handling of uncertainty in the presence of act-state dependence.
4. To compare techniques based on the classical theory of probability and imprecise probability to take decisions under severe uncertainty.

This chapter is structured as follows. Section 7.2 describes the interlink decision problem and details the case studies. Section 7.3 introduces two stakeholder perspectives and formulates the decision problem by outlining the metrics of interest for both stakeholders. In Section 7.3, we first present a methodology based on the classical theory of probability and then explain how uncertainty can be handled more appropriately using imprecise probability. Next, we apply the techniques described in Section 7.3 to the case study given in Section 7.2, and in Section 7.4 present and discuss the results of this work. Finally, Section 7.5 concludes the chapter.

7.2 Case Study: Interlink or No interlink?

In Chapter 2 and Section 7.1, we highlighted that the reliability of the OTS is critical and that, currently, research is being carried out to improve the reliability of these systems. One option to increase reliability is to invest in redundancy by installing duplicate components. Current regulation in the UK specifies that each offshore substation must have at least two offshore transformers unless the single transformer substations are interlinked [115]. However, to the best of our knowledge and to date, no regulation specifies that offshore substations hosting two offshore transformers should be interlinked. Nonetheless, recent projects have installed an interlink in this situation, and therefore in this chapter, we assess the advantages of this investment.

For the rest of the chapter, we focus on an OTS with two offshore substations. We design a case study based on operational OTSs [30] that is capable of transmitting 800 MW. The array cables from the offshore wind turbines collect at two offshore substations, each capable of carrying 400 MW, and each hosting two 220/34 kV offshore transformers. Each offshore substation is connected onshore via an eighty kilometre 220 kV XLPE offshore cable, that at the landfall meets an onshore cable. The 220 kV XLPE onshore cable takes power twenty kilometres to the onshore substation. In this work, a branch includes an offshore and onshore cable segment (as shown by Fig. 7.1). In practice, there could be multiple branches connecting each offshore substation to the onshore substation, but for simplicity, we restrict this analysis to just one branch per offshore substation. The onshore substation hosts two 400/220 kV onshore transformers.

Based on the information presented in [30], we consider that, in the event of an outage of an offshore cable or onshore cable, the normally de-energised interlink cable is switched into service. To ensure that the rating of the remaining cables is not exceeded, both offshore substations are curtailed to 50%. The interlink ensures that some of the power collected at each offshore substation can be transmitted to the onshore grid. Figure 7.1 and Fig. 7.2 show simplified diagrams of the case studies without and with the interlink, respectively.

7.3 Method

7.3.1 Investor Perspectives

The planning, installation and operation of an offshore wind power plant involve multiple stakeholders, including developers, customers, regulators, and insurers. Preferably, the installed system is optimal from all perspectives involved. Based on the UK set-up,

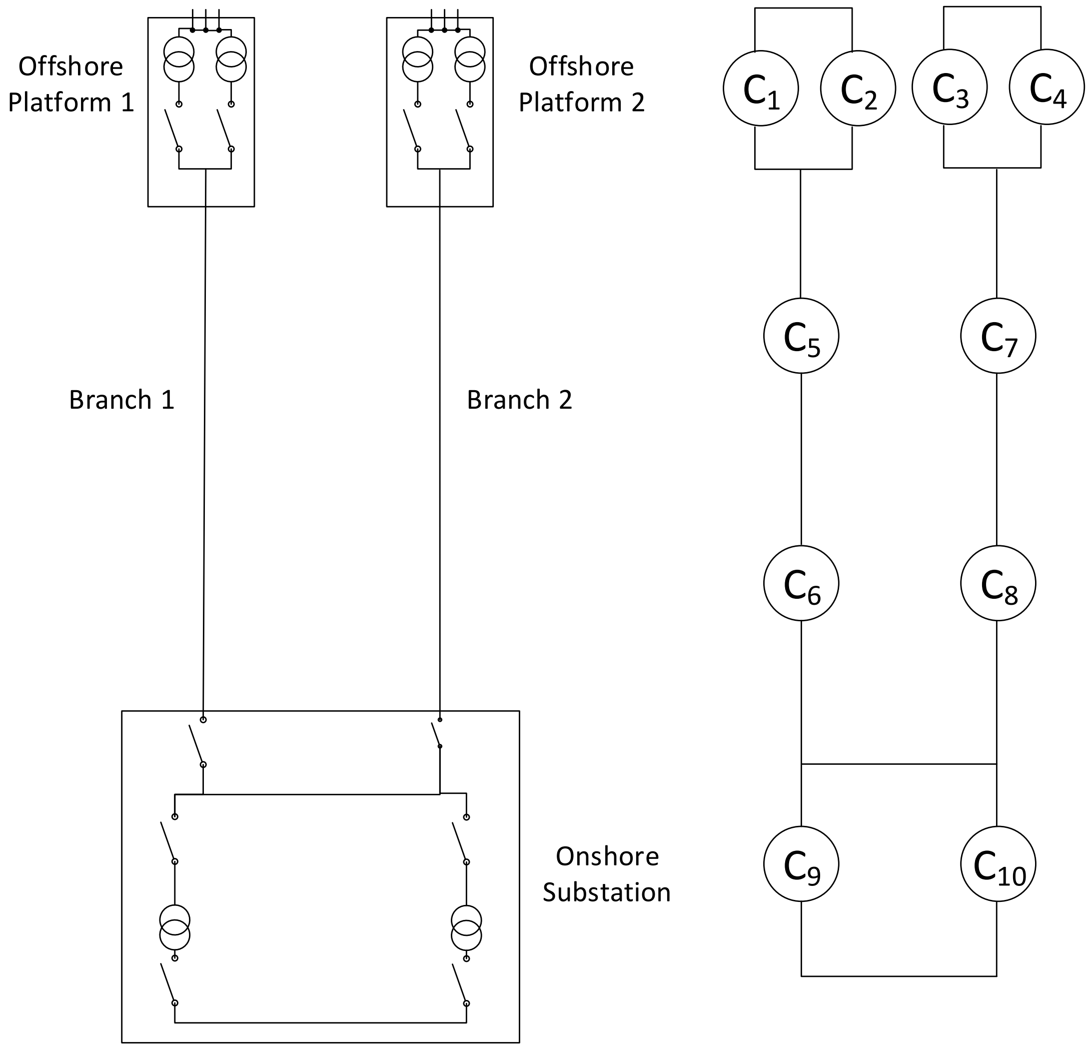


Figure 7.1: A case study that does not have an interlink between the two offshore substations. Each branch includes an offshore and onshore cable segment. The left-hand side shows a simplified single line diagram of the case study, and the right-hand side numbers the major components. These numbers will be referred to later in the chapter to describe and evaluate quantities such as system availability and energy transferred.

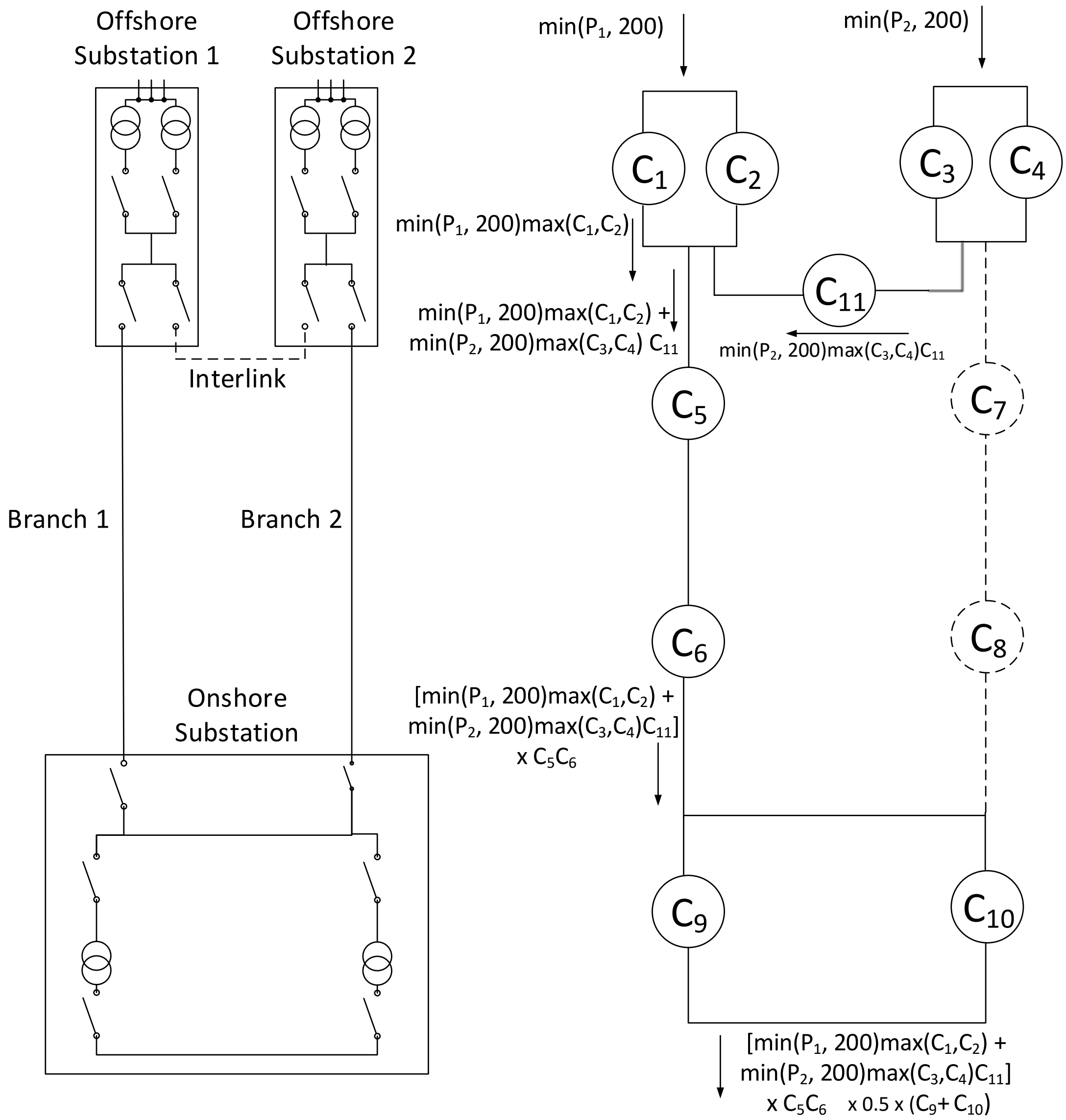


Figure 7.2: A case study with an interlink between the two offshore substations. The left-hand side shows a simplified single line diagram of the case study, and the right-hand side numbers the major components. These numbers will be referred to later in the chapter to describe and evaluate quantities such as system availability and energy transferred. The arrows aid the description of how the interlink works, and describes the power flow should a component in branch two fail. Again, these annotations will be referred to later in the chapter.

we focus on two perspectives: offshore transmission owner (OFTO) and offshore wind farm owner. From each perspective, we investigate whether investing in a system with an interlink (j = interlink) is preferred to a system without an interlink (j = no interlink). This decision problem consists of two options, denoted by j.

Offshore Transmission Owner (OFTO) Perspective

The first perspective we consider is from an OFTO. To compare the two investment options, from an offshore transmission owner's perspective, we evaluate the economic metric termed NPV, for option j, by:

$$\text{NPV}(j) = \sum_{t=1}^{n} \frac{V_t(j)}{(1+d)^t}. \tag{7.1}$$

Here, d denotes the discount factor and $V_t(j)$ denotes the cash flow in year t, for option j, which we evaluate by Eq. (7.2).

$$V_t(j) = \begin{cases} V_t'(j) = R_t(j) - \text{OPEX}_t(j) - L_t(j), & \text{for } 0 \leq t \leq n_1 \\ V_t''(j) = R_t(j) - \text{OPEX}_t(j), & \text{for } n_1 \leq t \leq n \end{cases} \tag{7.2}$$

Here, $R_t(j)$ denotes revenue in year t, $\text{OPEX}_t(j)$ denotes the operational expenditure in year t, $L_t(j)$ denotes the loan repayment amount in year t, n denotes the number of operational years, and n_1 denotes the loan duration in years. Eq. (7.2) shows that the cash flow is different in the first n_1 years as it includes the loan repayments. As we have seen in Chapters 2 and 4, according to the OFTO regime [49], annual revenue can be formulated as:

$$R_t(j) = (0.9 I_{Y_t(j) \leq 0.94} - 1.45 I_{Y_t(j) \geq 0.94} + 2.5 Y_t(j) I_{Y_t(j) \geq 0.94}) B(j) \tag{7.3}$$

Here, $Y_t(j)$ represents the yearly availability under option j, $B(j)$ denotes the annual base revenue defined in the OFTO licence of option j and $I_{Y(j)}$ is the indicator function. We note that $R_t(j)$ was called as contractual income in Chapter 4. We also note that Eq. (7.3) is presented in a slightly different format to previous chapters, as this format is more convenient in this chapter.

Wind Farm Developer Perspective

The second perspective we consider is from an offshore wind farm owner; they design, build and operate the offshore wind farm. The wind farm owner relies on the OTS to transmit the generated power back to shore and therefore values a reliable system. Consequently, to compare the two investment options, from a wind farm owner's perspective, we evaluate the annual amount of energy generated and transmitted to shore for each option

j. This quantity is denoted by $U_t(j)$ and can be evaluated by:

$$U_t(j) = \sum_{h=1}^{8760} Z_h(j) \tag{7.4}$$

Here, $Z_h(j)$ denotes the hourly energy transferred to shore for option j, which is evaluated by Eq. (7.5) and Eq. (7.6). If $j =$ no interlink:

$$Z_h(j) = P_{1h}Y_{1h} + P_{2h}Y_{2h} \tag{7.5}$$

If $j =$ interlink:

$$Z_h(j) = \begin{cases} P_{1h}Y_{1h} + P_{2h}Y_{2h}, & \text{if } C_{5h}C_{6h} = 1 \text{ and } C_{7h}C_{8h} = 1 \\ Q_{1h}, & \text{if } C_{5h}C_{6h} = 0 \text{ and } C_{7h}C_{8h} = 1 \\ Q_{2h}, & \text{if } C_{5h}C_{6h} = 1 \text{ and } C_{7h}C_{8h} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{7.6}$$

Here, P_{1h} and P_{2h} are the hourly power output arriving at offshore substation one and two, respectively. Y_{1h} and Y_{2h} are the hourly availability of branch one and two in the transmission system. Q_{1h} and Q_{2h} denote the energy transferred when the interlink is energised, and are discussed in more detail later in this section. Let C_{ih} denote the availability of component i at hour h where the component indexing corresponds to Fig. 7.1 and Fig. 7.2.

For clarity, $C_{1h}, \ldots, C_{4h}$ correspond to the offshore transformers. C_{5h} and C_{6h} correspond to the offshore cable and onshore cable in branch one. Similarly, C_{7h} and C_{8h} correspond to the offshore cable and onshore cable in branch two. C_{9h} and C_{10h} correspond to the onshore transformers, and C_{11h} corresponds to the interlink.

Detailed modelling of wind farm power output is beyond the scope of this work, and therefore a simplified approach is taken. We ignore wake effects and therefore, do not consider the spatial variation of the wind speed caused by the impact of turbines on each other. We assume that the power output of one turbine is equal to the power output of the other turbines connected to the same substation. Therefore, the hourly amount of power reaching offshore substation m, denoted by P_{mh}, can be evaluated by:

$$P_{mh} = \sum_{l=1}^{\eta_m} P_{lmh} = \eta_m P_{1mh} \tag{7.7}$$

Here, η_m denotes the number of turbines connected to offshore substation m. In this case study $m \in \{1, 2\}$ since we have two offshore substations. P_{lmh} denotes the power output of turbine l, connected to offshore substation m, at hour h. The hourly power output of a single turbine can be evaluated by [239]:

$$P_{1mh} = \begin{cases} 0 & \text{if } \nu_h < \nu', \\ 0.5\rho\kappa\omega\nu_h^3 & \text{if } \nu' < \nu_h < \nu'', \\ P^* & \text{if } \nu'' < \nu_h < \nu''', \\ 0 & \text{if } \nu_h > \nu''' \end{cases} \tag{7.8}$$

Here, ρ denotes air density taken to be 1.225 kg m^{-3}, κ denotes power coefficient, ω denotes the rotor swept area of the turbine, and P^* denotes the wind turbine rated power. ν_h, ν', ν'' and ν''' denotes the wind speed at hour h, cut-in wind speed, rated wind speed and cut-out wind speed, respectively. In this work, we use the eight MW reference turbine for input values [240].

The evaluation of $Z_h(j)$, for $j =$ interlink, given by Eq. (7.6) is motivated by how the interlink works. While both branches are working the system behaves as if there is no interlink. In the event of an outage of an offshore cable or onshore cable, the interlink cable is switched into service. To ensure that the rating of the remaining cables is not exceeded, both offshore substations are curtailed to 50%. Figure 7.2 describes the power flows corresponding to when the interlink is in use due to a failure in branch two. This reasoning leads to Eq. (7.10). Similarly, Eq. (7.9) corresponds to hourly energy transferred if branch one experienced a failure.

$$Q_{1h} = [\min(P_{1h}, 200)\max(C_{1h}, C_{2h})C_{11h} + \min(P_{2h}, 200)\max(C_{3h}, C_{4h})]\left(\frac{C_{9h} + C_{10h}}{2}\right) \tag{7.9}$$

$$Q_{2h} = [\min(P_{1h}, 200)\max(C_{1h}, C_{2h}) + \min(P_{2h}, 200)\max(C_{3h}, C_{4h})C_{11h}]\left(\frac{C_{9h} + C_{10h}}{2}\right) \tag{7.10}$$

In this subsection, we have detailed the metric of interest relevant to each stakeholder. When making investment decisions, the decision making process may involve aiming to maximise this metric. From the offshore transmission owner's (OFTO) perspective, we detailed how to evaluate the NPV of a project. Similarly, from the wind farm owner perspective, we detailed how to evaluate the energy generated and transmitted to the onshore grid.

7.3.2 Techniques Based on the Classical Theory of Probability

Up to this point, in this chapter, we have set up the decision problem and described the metrics that will be used to assess whether to invest in an interlink between two offshore platforms from the perspective of two key stakeholders. We now move on to outline the techniques implemented in this decision making analysis. We begin by describing methods based on the classical theory of probability. Although these techniques are not used in the final analysis (due to the limitations that we will discuss), we will use this approach to compare conventional techniques to methods proposed in this thesis.

Offshore Transmission Owner (OFTO) Perspective

From the offshore transmission owner's (OFTO) perspective, using techniques based on the classical theory of probability, we evaluate the expected NPV. These techniques were detailed in Chapter 4, and therefore, here, we only present a summary of the approach. From the offshore transmission owner's (OFTO) perspective, we evaluate the expectation of Eq. (7.1) by:

$$
\begin{aligned}
E(\mathrm{NPV}(j)) &= E\left(\sum_{t=1}^{n} \frac{V_t(j)}{(1+d)^t}\right) && (7.11)\\
&= E\left(\sum_{t=1}^{n_1} \frac{V_t'(j)}{(1+d)^t} + \sum_{t=n_1+1}^{n} \frac{V_t''(j)}{(1+d)^t}\right) && (7.12)\\
&= \sum_{t=1}^{n_1} \frac{E(V_t'(j))}{(1+d)^t} + \sum_{t=n_1+1}^{n} \frac{E(V_t''(j))}{(1+d)^t} && (7.13)\\
&= \lambda_1 E(V_{(t=1)}'(j)) + \lambda_2 E(V_{(t=n_1+1)}''(j)). && (7.14)
\end{aligned}
$$

Here,

$$
\begin{aligned}
\lambda_1 &= \sum_{t=1}^{n_1} \frac{1}{(1+d)^t} && (7.15)\\
\lambda_2 &= \sum_{t=n_1+1}^{n} \frac{1}{(1+d)^t} && (7.16)
\end{aligned}
$$

Focusing on $E(V_{(t=1)}'(j))$:

$$
\begin{aligned}
E(V_{(t=1)}'(j)) &= E(R_{(t=1)}(j) - \mathrm{OPEX}_{(t=1)}(j) - L_{(t=1)}(j)) && (7.17)\\
&= E(R_{(t=1)}(j)) - E(\mathrm{OPEX}_{(t=1)}(j)) - L_{(t=1)}(j). && (7.18)
\end{aligned}
$$

Here, we use the fact that $L_t(j)$ is constant. Similarly, for $E(V_{(t=n_1+1)}''(j))$:

$$
\begin{aligned}
E(V_{(t=n_1+1)}''(j)) &= E(R_{(t=n_1+1)}(j) - \mathrm{OPEX}_{(t=n_1+1)}(j)) && (7.19)\\
&= E(R_{(t=n_1+1)}(j)) - E(\mathrm{OPEX}_{(t=n_1+1)}(j)). && (7.20)
\end{aligned}
$$

Focusing on the first term in Eqs. (7.18) and (7.20) (the expected value of the yearly revenue), we assume independent years, and by taking the expectation of Eq. (7.3), we obtain:

$$E(R_{(t=n_1+1)}(j)) = E(R_{(t=1)}(j)) \tag{7.21}$$
$$= E((0.9I_{Y_{(t=1)}(j)\leq 0.94} - 1.45I_{Y_{(t=1)}(j)\geq 0.94} \tag{7.22}$$
$$+ 2.5Y_{(t=1)}(j)I_{Y_{(t=1)}(j)\geq 0.94})B(j))$$
$$= (0.9P(Y_{(t=1)}(j) \leq 0.94) - 1.45P(Y_{(t=1)}(j) \geq 0.94) \tag{7.23}$$
$$+ 2.5E(Y_{(t=1)}(j))P(Y_{(t=1)}(j) \geq 0.94))E(B(j))$$

Here, we evaluate $P(Y_{(t=1)}(j) \geq 0.94)$ and $E(Y_{(t=1)}(j))$ from the availability simulation which we will describe later in this section. To evaluate B, the base revenue, we refer back to Section 4.4.1, where we obtained:

$$B(j) = \beta_3\text{CAPEX}(j) + \beta_4 + \varepsilon_1 \tag{7.24}$$

Here, $\beta_3 = 0.09023$, $\beta_4 = 3.038$ and ε_1 is the residual error. For the expectation of OPEX, we have:

$$E(\text{OPEX}_{(t=n_1+1)}(j)) = E(\text{OPEX}_{(t=1)}(j)) \tag{7.25}$$
$$= E(\text{Planned OPEX}_{(t=1)}(j) + \text{Unplanned OPEX}_{(t=1)}(j)) \tag{7.26}$$
$$= E(\text{Planned OPEX}_{(t=1)}(j) + E(\text{Unplanned OPEX}_{(t=1)}(j)) \tag{7.27}$$

Here, $E(\text{Planned OPEX}_{(t=1)}(j))$ is evaluated following the approach outlined in Section 4.6, and $E(\text{Unplanned OPEX}_{(t=1)}(j))$ is evaluated during the availability simulation described below.

The evaluation of $E(\text{NPV}(j))$ outlined above requires the following inputs:

- Capital expenditure (CAPEX): we evaluate the capital expenditure of a project by summing individual component costs. For more details we refer back to Section 4.5.1.
- Loan repayments: we evaluate the loan repayments each year as a function of CAPEX, loan duration, number of loan repayment instalments per year and interest rate. For further details and the equations used to evaluate the yearly loan repayment, we refer back to Section 4.5.2.
- Revenue stream: we evaluate the yearly revenue stream as a function of the base revenue and the distribution of availability. Details of how we obtain a distribution for availability are given in the next bullet point. We evaluate the base revenue as function of CAPEX. For more details we refer back to Section 4.4 and in this chapter to Eq. (7.3).
- Availability: the distribution for availability is required in this analysis. The conventional approach to obtain a distribution for availability, based on the classical

theory of probability, is to model the components in the system as a Markov chain. Modelling a component as a Markov chain requires strong modelling assumptions which we discussed in Chapter 5. Nonetheless, since we are restricted to using techniques based on the classical theory for the purpose of this technique comparison, we model a component's behaviour as a Markov chain. We evaluate the distribution for availability using Monte Carlo simulations, where the state of each major component, and in turn, the system, is determined each hour in a year using failure and repair rates of the components considered. This system trace determines the availability each year. The simulation is repeated to obtain a probability distribution for availability.

- Operational expenditure (OPEX): we evaluate the expected annual operational expenditure as a sum of the expected annual planned operational expenditure and the expected annual unplanned operational expenditure. In this work, we evaluate annual planned OPEX as a percentage of the project's CAPEX, and we evaluate unplanned OPEX during the availability simulation described above. For more details we refer back to Sections 4.6 and 6.5.2.
- Discount factor, d: the discount factor is a rate that discounts future cash flows to the present-day value [178].
- Project lifetime, n: the number of operational years for the offshore wind project.

Wind Farm Developer Perspective

To analyse from the perspective of an offshore wind farm developer, we use techniques based on the classical theory of probability to evaluate the expected annual amount of energy generated and transmitted, $U_t(j)$. Taking the expectation of Eq. (7.4), we find:

$$E(U_t(j)) = E\left(\sum_{h=1}^{8760} Z_h(j)\right). \tag{7.28}$$

Here, we evaluate $E(\sum_{h=1}^{8760} Z_h(j))$ by Monte Carlo simulation. This simulation calculates an availability trace of the offshore transmission system (OTS) and a power output trace of the wind farm. The availability trace is obtained in the same way as in the OFTO case using component failure and repair rates and modelling components using a Markov chain. The power trace is obtained using hourly historical wind speed data, the number of turbines, and turbine model specification. For further details, we refer back to Eq. (7.8).

Numerical Example

Next, we turn to evaluate the expected NPV and expected energy generated and transmitted using techniques based on the classical theory of probability that have been

Component	Failure rate (fails/year)	Repair rate (repairs/year)	Cost per failure (£million)	Cost per day of downtime (£million)
Offshore transformer	0.0105	8.69	3.75	0.0035
Offshore cable	$0.000705 \times c_1$	8.76	0.0042	0.1426
Onshore transformer	0.0105	5.79	2.25	0
Onshore cable	$5.77 \times 10^{-6} \times c_2$	14.6	0.0841	0

Table 7.1: Component failure and repair rates are from the literature [99, 142]. Here, c_1 and c_2 stands for the cable length of the offshore and onshore cables, respectively. We note that the cost per failure for the offshore cable is related to the material cost of a 200 m cable replacement.

described above. From the offshore transmission owner's (OFTO) perspective, we use the following inputs: a project lifetime of twenty-five years, a discount rate of 3.5% [178], a planned OPEX factor of 0.5%, component failure and repair rates shown in Table 7.1, unplanned OPEX inputs also outlined in Table 7.1, capital expenditure (evaluated to be £500 million for the system without an interlink and £530 million for a system with an interlink), the loan repayments (evaluated to be £45.6 million (no interlink system) and £48.3 million (interlink system) considering the loan duration to be twelve years, with four repayment instalments per year and an interest rate of 1.5%). Using this input data, we evaluated the expected NPV to be £285.4 million (no interlink system) and £300.3 million (interlink system).

From the offshore wind farm developer's perspective, we use the following inputs: availability simulation inputs (as detailed in Table 7.1), wind speed data (we use historical wind speed data for a specific location given by [160, 161, 162, 163]), the number of turbines (we assume one hundred 8 MW turbines) and turbine characteristics (we use the 8 MW reference turbine for input values [240]). Using this input data, we evaluated the expected annual energy generated and transmitted to be 3.95 TWh (no interlink system) and 3.98 TWh (interlink system). These results will be used later in this chapter to compare conventional techniques to methods proposed in Chapter 5.

7.3.3 Handling Uncertainty in Decision Making

So far, we have evaluated the metrics of interest for both the OFTO and wind farm developer using techniques based on the classical theory of probability. However, we recall that these types of investment decision assessments are taken under severe uncertainty for the following reasons: wind power transmission assets (especially at current distances from shore and capacities) are still in their infancy; project conditions are site-specific making it difficult to generalise; and technology advancements between projects result in a limited amount of relevant historical data to base analysis. Unfortunately, severe uncertainty complicates the decision making process and makes it challenging to justify the modelling assumptions required for techniques based on classical probability theory. Notably, we may not have enough information to assign probability distributions. In the case of this work, we do not have enough information to assume that a component's time to fail and time to repair are exponentially distributed; and therefore, model a component's failure and repair behaviour as Markov chains.

In the classical theory of probability, there exist ways to handle uncertainty. For example, we may evaluate confidence intervals around the expected value; however, this only considers aleatory uncertainty (the variability in realisations of an event). Another approach, which we took in Chapter 4, is through a sensitivity analysis where individually one factor is varied within an interval. This approach does consider epistemic uncertainty in the input parameters (required to evaluate projects economically); however, strong modelling assumptions are still required. Therefore, we argue that these techniques are not adequate when there is severe uncertainty in the input parameters.

In the absence of relevant data, and confidence to make these assumptions, in other words, the presence of severe uncertainty, a more suitable approach to decision making is required. Therefore, in the rest of this chapter, we use decision making techniques that are based on imprecise probability to handle the severe uncertainties more appropriately. We recall from Chapter 5 that we are using probability to model epistemic uncertainty; in this application, this is due to uncertainty in the input parameters due to insufficient relevant data. We take a subjective interpretation of probability using betting rates, and in particular, take a more general approach using imprecise probability. The term imprecise probability covers theories related to generalised uncertainty quantification, including lower and upper previsions (see Chapter 5 for more details). In short, using imprecise probability, we consider sets of probability distributions.

As we have seen in previous chapters, instead of evaluating the expectation, using imprecise probability, we calculate lower and upper bounds on the expectation using the theory of lower and upper provisions. These upper and lower bounds on the expectation, denoted by $\underline{E}$ and $\overline{E}$ respectively, form intervals that represent sets of probability distributions. These intervals, for each option, can be compared to select the optimal option(s). In Chapter 5, we introduced several decision criteria using imprecise probability that exists in the literature, including interval dominance and Γ-maximin that will be implemented in this chapter.

7.3.4 Lower and Upper Bounds on the Expectation

We recall from Chapters 5 and 6 that there are properties that coherent lower previsions satisfy. In this section, we use these properties to find the lower bounds on the expectation of the metrics of interest. Details of how to evaluate the upper bounds follow similarly but are omitted. Taking the lower expectation of Eq. (7.1), we find:

$$\underline{E}(\mathrm{NPV}(j)) = \underline{E}\left(\sum_{t=1}^{n} \frac{V_t(j)}{(1+d)^t}\right) \tag{7.29}$$

$$= \underline{E}\left(\sum_{t=1}^{n_1} \frac{V_t'(j)}{(1+d)^t} + \sum_{t=n_1+1}^{n} \frac{V_t''(j)}{(1+d)^t}\right) \tag{7.30}$$

$$= \min_{p\in\mathcal{M}} E_p\left(\sum_{t=1}^{n_1} \frac{V_t'(j)}{(1+d)^t} + \sum_{t=n_1+1}^{n} \frac{V_t''(j)}{(1+d)^t}\right) \tag{7.31}$$

$$= \min_{p\in\mathcal{M}} \left(\sum_{t=1}^{n_1} \frac{E_p(V_t'(j))}{(1+d)^t} + \sum_{t=n_1+1}^{n} \frac{E_p(V_t''(j))}{(1+d)^t}\right) \tag{7.32}$$

$$= \min_{p\in\mathcal{M}} \left(\lambda_1 E_p(V'_{(t=1)}(j)) + \lambda_2 E_p({V''}_{(t=n_1+1)}(j))\right) \tag{7.33}$$

Here, $\mathcal{M}$ is the set of worst- and best-case distributions of $Y_t(j)$. $\lambda_1 = \sum_{t=1}^{n_1} \frac{1}{(1+d)^t}$ and $\lambda_2 = \sum_{t=n_1+1}^{n} \frac{1}{(1+d)^t}$. $E_p(V'_{(t=1)}(j))$ and $E_p(V''_{(t=n_1+1)}(j))$ can be evaluated by:

$$E_p(V'_{(t=1)}(j)) = E_p(R_{(t=1)}(j) - \mathrm{OPEX}_{(t=1)}(j) - L_{(t=1)}(j)) \tag{7.34}$$

$$= E_p(R_{(t=1)}(j)) - E_p(\mathrm{OPEX}_{(t=1)}(j)) - L_{(t=1)}(j) \tag{7.35}$$

and

$$E_p(V''_{(t=n_1+1)}(j)) = E_p(R_{(t=n_1+1)}(j) - \mathrm{OPEX}_{(t=n_1+1)}(j)) \tag{7.36}$$

$$= E_p(R_{(t=n_1+1)}(j)) - E_p(\mathrm{OPEX}_{(t=n_1+1)}(j)). \tag{7.37}$$

Here, $E_p(\mathrm{OPEX}_{(t=1)}(j)) = E_p(\mathrm{OPEX}_{(t=n_1+1)}(j))$ is evaluated as a sample mean from the availability simulation. The loan repayments in a year is known and fixed and therefore $E_p(L_{(t=1)}(j)) = L_{(t=1)}(j)$ as we see in Eq. (7.35). The loan repayment structure is detailed in Chapter 4, and specifically the equations to evaluate the loan repayment in a year are given by Eqs. (4.14) to (4.16). $E_p(R_{(t=1)}(j)) = E_p(R_{(t=n_1+1)}(j))$, and (recalling Eq. (7.3)) is evaluated by:

$$E_p(R_{(t=1)}(j)) = (0.9P(Y_{(t=1)}(j) \leq 0.94) - 1.45P(Y_{(t=1)}(j) \geq 0.94) + 2.5E_p(Y_{(t=1)}(j))P(Y_{(t=1)}(j) \geq 0.94))E_p(B(j)) \quad (7.38)$$

Here, $E_p(Y_{(t=1)}(j))$ is evaluated as sample mean from the availability simulation. $P(Y_{(t=1)}(j) \leq 0.94)$ and $P(Y_{(t=1)}(j) \geq 0.94)$ are also determined from the availability simulation.

From the wind farm owner's perspective we aim to maximise the energy transmitted. Taking the lower expectation of Eq. (7.4) we obtain:

$$\underline{E}(U_t(j)) = \underline{E}\left(\sum_{h=1}^{8760} Z_h(j)\right) = \min_{p\in\mathcal{M}} E_p\left(\sum_{h=1}^{8760} Z_h(j)\right) \quad (7.39)$$

Here, $\mathcal{M}$ is the set of worst- and best-case distributions of $Y_t(j)$, and $E_p(\sum_{h=1}^{8760} Z_h(j))$ is evaluated by Monte Carlo simulation. This involves combining the availability trace of the OTS with the wind farm power output. The wind farm power output is evaluated using historical wind speed data for a specific location [160] and the turbine power relation given by Eq. (7.8).

7.3.5 Act-state Dependence

In the described decision problem, we, again, encounter act-state dependence. Act-state dependence occurs when the distribution of the state of nature depends on the decision taken. We discussed act-state dependence in Chapters 5 and 6. In this section, we explain how we handle act-state dependence in the decision problem at hand.

We first identify the act-state dependent and independent variables in our decision problem. In the OTS owner's evaluation, the act-state dependent variable is availability since the distribution of availability depends on the decision taken. Annual revenue and operational expenditure depend on the availability. In the wind farm owner's evaluation, availability is also an act-state dependent variable and turbine power output is an act-state independent variable.

To handle uncertainty in the act-state dependent variable, we simulate over best- and worst-case distributions of this variable. To obtain a distribution for the yearly availability of the system, $Y_t(j)$, we simulate $Y_t(j)$ for ten thousand years. We evaluate $Y_t(j)$ by Eq. (7.40).

$$Y_t(j) = \frac{1}{8760}\sum_{h=1}^{8760} Y'_h(j). \quad (7.40)$$

Here, $Y_t(j)$ denotes the yearly availability of option j in year t and $Y'_h(j)$ denotes the availability of option j at hour h. $Y'_h(j)$ depends on the components in option j. If $j =$ no interlink:

$$Y'_h(j) = \frac{1}{2}\left(\frac{C_{1h}+C_{2h}}{2}C_{5h}C_{6h} + \frac{C_{3h}+C_{4h}}{2}C_{7h}C_{8h}\right)\frac{C_{9h}+C_{10h}}{2}. \tag{7.41}$$

If $j =$ interlink:

$$Y'_h(j) =$$
$$\begin{cases} \frac{1}{2}\left(\frac{C_{1h}+C_{2h}}{2}C_{5h}C_{6h} + \frac{C_{3h}+C_{4h}}{2}C_{7h}C_{8h}\right)\frac{C_{9h}+C_{10h}}{2}, & \text{if } C_{5h}C_{6h}=1 \text{ and } C_{7h}C_{8h}=1 \\ \frac{1}{2}\left(\frac{\max(C_{1h},C_{2h})}{2}C_{11h} + \frac{\max(C_{3h},C_{4h})}{2}\right)C_{7h}C_{8h}\frac{C_{9h}+C_{10h}}{2}, & \text{if } C_{5h}C_{6h}=0 \text{ and } C_{7h}C_{8h}=1 \\ \frac{1}{2}\left(\frac{\max(C_{1h},C_{2h})}{2} + \frac{\max(C_{3h},C_{4h})}{2}C_{11h}\right)C_{5h}C_{6h}\frac{C_{9h}+C_{10h}}{2}, & \text{if } C_{5h}C_{6h}=1 \text{ and } C_{7h}C_{8h}=0 \\ 0, & \text{otherwise.} \end{cases} \tag{7.42}$$

Here, C_{ih} denotes the availability of component i at hour h. A component's availability at hour h takes the value zero or one. To evaluate a component's availability, using techniques based on the classical theory of probability we sample times to fail and times to repair from the exponential distribution as detailed by Eq. (7.43) and Eq. (7.44). These samples give a trace for each component and in turn a trace for the OTS.

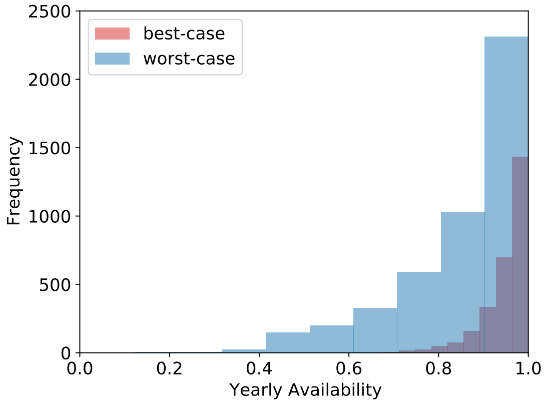
$$\text{time to fail}_i \sim \exp(f_i) \tag{7.43}$$

$$\text{time to repair}_i \sim \exp(r_i) \tag{7.44}$$

Here, f_i and r_i denote component i's failure rate and repair rate, respectively.

Due to the short operational history of offshore wind transmission and technology advancements between projects, it is difficult to assign precise values to the repair and failure rates required in Eq. (7.44) and Eq. (7.43). In particular, the failure and repair rates of the offshore cable are thought to be uncertain [83]. Furthermore, this limited data also means that we may not have enough information to validate the assumption that the times to fail and times to repair for an offshore cable are exponential; and therefore, that the component's behaviour can be modelled as a Markov chain.

Since it is challenging to put realistic distributions on the input parameters required to model the failure and repair of an offshore cable, we alternatively consider reasonable sets of distributions. Since we now consider a set of distributions rather than a single distribution (the exponential distribution), we no longer model the failure and repair behaviour of an offshore cable as a Markov chain. Instead, as we demonstrated in Chapter 6, we model the behaviour of an offshore cable as an imprecise Markov chain which we introduced in Section 5.4.4. Literature values are used to determine ranges for which we consider all distributions within.



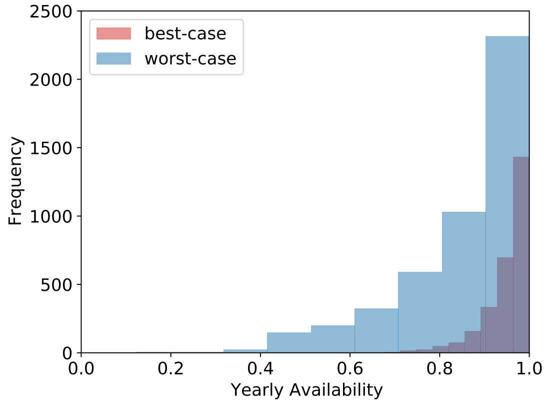


Figure 7.3: Histogram of yearly availability values from the Monte Carlo simulations for the interlink (left) and no interlink (right) case studies. In both plots, the peak at 100% availability has been removed for clarity.

In the literature, failure rates of HVAC offshore cables vary considerably. For example, 0.000705 fails/year/km is quoted in [142], 0.0016 fails/year/km in [82] and 0.003 fails/year/km in [83]. In this work, we consider HVAC offshore cable failure rates between 0.000705 and 0.003 fails/year/km. Similarly, the repair time for a HVAC offshore cable depends on factors such as weather, sea conditions, and the availability of vessels and spare parts. Based on values given in [95] and [142], and operational experiences [141], we consider repair times between 30 and 150 days. These inputs give us the best- and worst-case distributions of availability for each option.

The results for the Monte Carlo simulation are shown in Fig. 7.3. Each simulation resulted in a peak at 100% availability that has been removed for clarity. The number of counts at 100% availability, out of 10,000, are 7,282, 5,434, 7,282 and 5,434 for worst-case interlink, best-case interlink, worst-case no interlink and best-case no interlink case studies, respectively. In Fig. 7.3, the availability distribution for the interlink and no interlink case studies appear identical. We will return to this observation in the results of this chapter.

Next, we treat uncertainty in the wind speed, which is an act-state independent variable. Initially, we fix the hourly wind speed input using historical data and use this input to bound the metric of interest (energy output). We analyse these bounds using the decision criteria detailed in Section 7.3.6. Then, we investigate how the decision changes as a function of fixed values of the wind speed.

To vary the wind speed, we are no longer able to use historical wind speed data. Therefore, we need a method to generate simulated wind speed data. Various models are implemented in the literature to generate simulated wind speed data such as the Weibull distribution [241, 242] and auto-regressive moving average (ARMA) [243]. In this chapter, to investigate how the decision changes as a function of fixed values of the wind speed, we employ the Weibull distribution to generate wind speed data.

The Weibull distribution is an independently and identically distributed process, and therefore, sampling from this distribution ignores time correlations. In contrast, the ARMA model does consider time correlation. When the analysis requires wind speeds on an hourly level, time correlations between hourly wind speeds matter. However, in this work, since we are considering the yearly expected value, we justify taking a simple approach and sample the wind speeds from the Weibull distribution. Nevertheless, it is necessary to note that the Weibull distribution is limited. To the best of our knowledge, there is no universal wind model; furthermore, the model may be location dependent. Further work could investigate how modelling the wind speed using different models, for example, Weibull and ARMA, impacts this analysis. However, this is beyond the scope of this study, and therefore, we proceed with the simple Weibull model.

The Weibull distribution, whose probability density function is shown by Eq. (7.45), requires two model parameters: the shape parameter (θ) and the scale parameter (τ).

$$\mathrm{pdf}(\nu_h) = \frac{\theta}{\tau}\left(\frac{\nu_h}{\tau}\right)^{\theta-1} e^{-\left(\frac{\nu_h}{\tau}\right)^{\theta}} \tag{7.45}$$

We assume the hourly wind speed, ν_h, follows a Weibull distribution with mean (μ_ν) and standard deviation (σ_ν). The study by [244] shows a method to approximate the Weibull distribution parameters from μ_ν and σ_ν using Eq. (7.46) and Eq. (7.47). Since there may be uncertainty about the mean and standard deviation of the wind speed, we vary the value of both of these inputs and evaluate the bounds on the expected energy generated and transmitted.

$$\hat{\theta} = \left(\frac{\sigma_\nu}{\mu_\nu}\right)^{-1.086} \tag{7.46}$$

$$\hat{\tau} = \frac{\mu_\nu}{\Gamma(1+\frac{1}{\hat{\theta}})} \tag{7.47}$$

In this chapter, we vary the mean wind speed between 3 m/s and 17 m/s. This approach allows the decision maker to select wind speeds that are appropriate to their specific project and therefore, read off the results that are relevant to them. Secondly, we vary the wind speed standard deviation between 2 m/s and 5 m/s based on historical wind speed data. Again, the decision maker can select which value or range of values that are relevant to them. Furthermore, the decision maker can see if and how these inputs affect the decisions made. In terms of visualisation, we plot the results for varied mean wind speeds for a fixed standard deviation. We then repeat this visualisation for different standard deviations.

7.3.6 Γ-maximin and Interval Dominance

To find the optimal option(s), we recall two decision criteria from Chapter 5, Γ-maximin [224, 225, 226] and interval dominance [222, 223]. Γ-maximin is a more conservative decision criterion, and selects the option with the greatest lower bound. From the offshore transmission owner's perspective, using Γ-maximin, we define:

$$E^* = \max_j \underline{E}(\mathrm{NPV}(j)) \tag{7.48}$$

Any option, j such that $\underline{E}(\mathrm{NPV}(j)) = E^*$ is optimal. A similar equation can be written from the wind farm owner's perspective. Alternatively, interval dominance selects any option which is not interval dominated by another option, where an option is interval dominant if its interval is completely to the right-hand side of an interval for another option. In other words, from the offshore transmission owner's (OFTO) perspective, option j_1 interval dominates option j_2 if:

$$\underline{E}(\mathrm{NPV}(j_1)) > \overline{E}(\mathrm{NPV}(j_2)). \tag{7.49}$$

Again, a similar expression exists from the wind farm owner's perspective.

7.4 Results and Discussion

To assess the benefit of investing in an interlink between offshore substations, we apply the methodology based on imprecise probability detailed in Section 7.3 to the case study detailed in Section 7.2. The results are shown in Figs. 7.4 to 7.8. From the offshore transmission owner's (OFTO) perspective, Fig. 7.4 shows the upper and lower bounds on NPV for each option (an OTS with an interlink and an OTS with no interlink). From the offshore wind owner's perspective, Fig. 7.8 shows the upper and lower bounds on energy transferred for each option.

Fig. 7.4 shows that the bounds on the expected NPV for each option overlap significantly. Using the described input data and modelling approach, from the offshore transmission owner's (OFTO) perspective, Fig. 7.4 shows that Γ-maximin selects the system with an interlink and interval dominance suggests neither option is preferred over the other. However, we note that the NPV of a system with an interlink may be higher than the system without an interlink because the initial investment is more significant for the interlinked system. In Chapter 6, we discussed that using the metric NPV may not be a suitable metric to compare multiple projects when the initial investment of each option are drastically different.

Although the initial investments in this study only differ slightly, we explore other metrics to assess further which option is preferable. Therefore, Figs. 7.5 and 7.6 shows

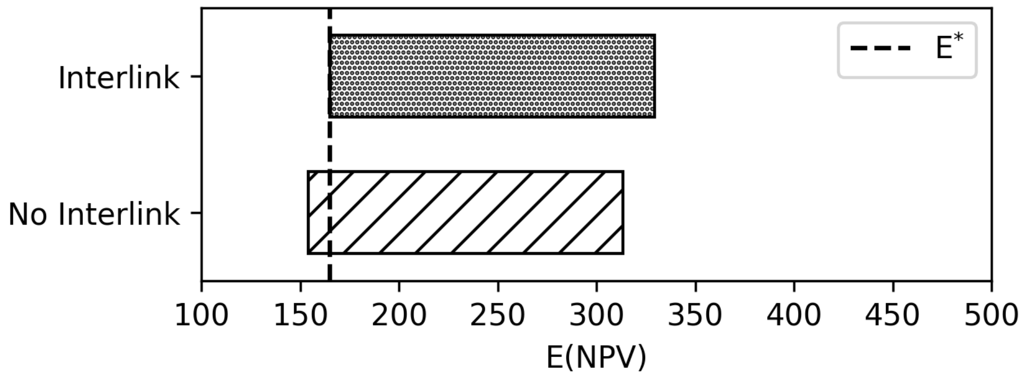


Figure 7.4: Results from the offshore transmission owner perspective, showing bounds on the expected NPV for each option.

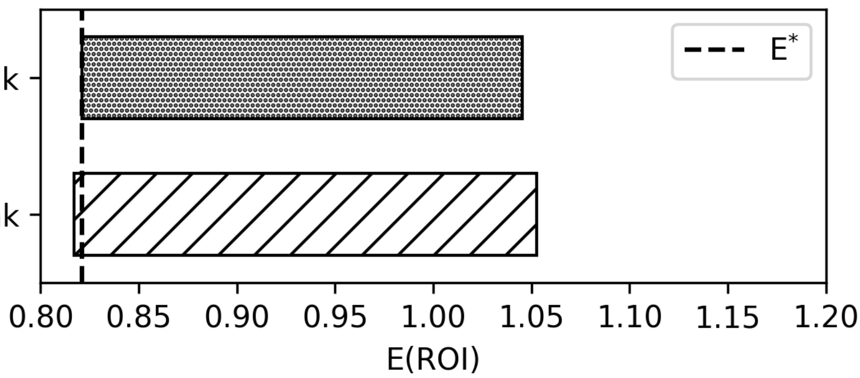


Figure 7.5: Results from the offshore transmission owner perspective, showing bounds on the expected ROI for each option.

bounds on the return on investment (ROI) and annual ROI from the offshore transmission owner's (OFTO) perspective, respectively. These metrics have been evaluated in a similar way to the application in Chapter 6. Figs. 7.5 and 7.6 suggest that the options are incomparable. Here, we note that an expected annual ROI of 0.025 is equivalent to 2.5%.

To understand the findings of this study further, in Fig. 7.7, we investigate bounds on the expected yearly availability. Fig. 7.7 shows that both options have identical values. The identical availability values arise since when the interlink is energised, the offshore substations are curtailed to 50%. Therefore, usually, the availability of the system with an interlink is identical to a system without an interlink. There exist some rare scenarios where the availability differs between the interlink and no interlink options. Table 7.2 shows two scenarios where the availability values are identical and two where they differ; this table is useful to understand how the failure of different components in the system affects the availability of the system. Importantly, the availability of the interlink and no

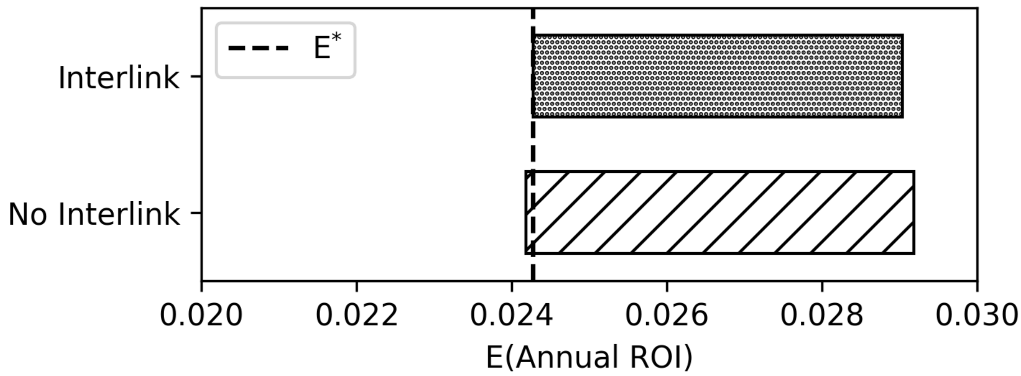


Figure 7.6: Results from the offshore transmission owner perspective, showing bounds on the expected annual ROI for each option.

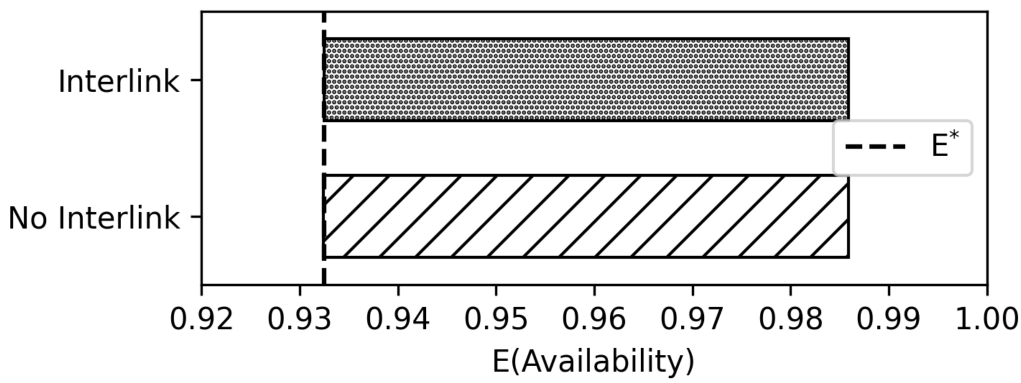


Figure 7.7: Results from the offshore transmission owner perspective, showing bounds on the expected yearly availability for each option.

interlink systems only differ in 0.1% (best-case simulation) and 0.4% (worst-case simulation) of the hours simulated. Overall, the results suggest that from an offshore transmission owner's (OFTO) perspective, an interlink is not anymore economically favourable than a system without an interlink; however, they pay for this asset.

From the wind farm owner's perspective, we evaluate bounds on the expected energy generated and transmitted. These results are presented in Fig. 7.8 which shows that Γ-maximin selects an interlink and interval dominance suggests neither option is preferred over the other. Here, the wind resource is fixed using historical data (with a mean wind speed of 9.8 m/s and a standard deviation of 3.7 m/s).

Next, we handle uncertainty in the act-state independent variable. We now model the wind speed using the Weibull distribution described in Section 7.3.5, and estimate the Weibull model parameters from the mean and standard deviation of the wind speed (also described in Section 7.3.5). Figures 7.9 to 7.11 shows how the decision changes as

Failed components	Availability		Power (MW)	
	Interlink	No Interlink	Interlink	No Interlink
C_1, C_8	0.5	0.25	120	30
C_4, C_5	0.5	0.25	400	200
C_4	0.75	0.75	115	115
C_8	0.5	0.5	395	221

Table 7.2: Availability and power output simulation values for the interlink and no interlink case studies. Four hour slots have been chosen, with the failed components in that hour identified for clarity.

a function of fixed mean wind speed between 3 m/s and 17 m/s. In Fig. 7.9, Fig. 7.10, Fig. 7.11 the standard deviation is fixed at 2 m/s, 3 m/s and 5 m/s, respectively. As the wind resource increases, interval dominance suggests that the two options are incomparable from a wind farm owner's perspective.

At this point, it is important to interpret the amount of energy transferred. In Fig. 7.8, the lower bounds for the expected annual energy transferred are 3.84 TWh for the interlinked system and 3.77 TWh for the no interlink system. Based on these lower bounds, the difference between the energy transferred in each option is 0.07 TWh. To understand the value of this energy difference to the offshore wind owner, we evaluate the monetary value of this extra energy. To do this, we multiply the amount of energy by the wholesale price of energy. We recall from Chapter 6 that the wholesale price of energy is quoted in literature to be between £47.25/MWh and £48.10/MWh in [166], between £33.85/MWh and £67.54/MWh in [236], and between £35.00/MWh and £78.00/MWh in [237]. For this example, let's assume the wholesale price of energy is £50/MWh. Therefore, an energy difference of 0.07 TWh is worth £3.5 million per year. Over the project's lifetime of twenty-five years, this is equivalent to £87.5 million.

Figs. 7.9 to 7.11 show that the difference between the two options decreases at higher wind speeds. At higher wind speeds, the amount of energy generated increases; however, when the energy generated by each substation exceeds 50% of the total capacity, there is no benefit to rerouting the power. This lack of gain occurs since when the interlink is energised, the system is limited to 50%. Therefore, when there is a failure in one transmission branch, the system can only transmit 50% of the capacity in both the interlink and no interlink scenario. As a result, we see a reduced difference in the energy from the interlinked system and no interlink system at higher wind speeds in Figs. 7.9 to 7.11. From this study, we find that installing an interlink does not (in almost all cases) change the

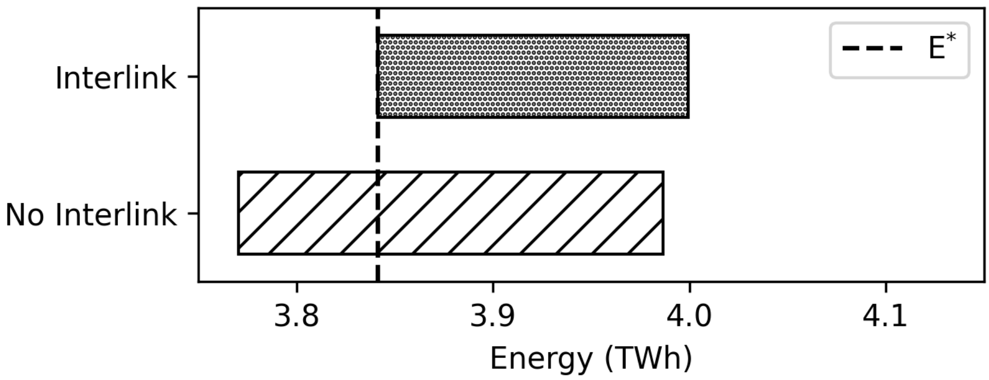


Figure 7.8: Results from the offshore wind farm owner's perspective, showing bounds on the expected energy generated and transmitted for each option. Here, the mean wind speed is fixed at 9.8 m/s and standard deviation is fixed at 3.7 m/s.

system's availability. However, from the offshore wind owner's perspective, the interlink allows some energy from both offshore substations to be transmitted and can increase the amount of energy transferred.

Finally, we recall the results from Section 7.3.2, where we conducted the same analysis using conventional techniques. We evaluated the E(NPV) to be £285.4 million (no interlink system) and £300.3 million (interlink system). Additionally, we evaluated the expected amount of energy yearly generated and transmitted to be 3.95 TWh (no interlink system) and 3.98 TWh (interlink system). Fig. 7.4 and Fig. 7.8 shows that these values are within the intervals obtained using techniques based on imprecise probability. However, there are some key differences between the ways these results were obtained. The intervals obtained using imprecise probability did not require a probability distribution to be assigned to uncertain inputs. This approach is beneficial to the application in this chapter, as it was challenging to assign probability distributions due to limited data.

Furthermore, the techniques provided a way to better express our knowledge by considering sets of probability distributions. In the case of modelling the offshore cable's failure and repair behaviour, this meant that the strong and usually unjustified modelling assumptions could be relaxed. This relaxation of unjustified assumptions is important if substantial investment decisions are going to be made based on the analysis.

Additionally, the techniques based on imprecise probability allow for indecision (unlike methods based on the classical theory of probability). For the case study considered in this chapter, we found that using interval dominance generally, neither option is preferred over the other from both perspectives (for the metrics of interest considered). Overall, considering these points, the outputs obtained using imprecise probability are more robust

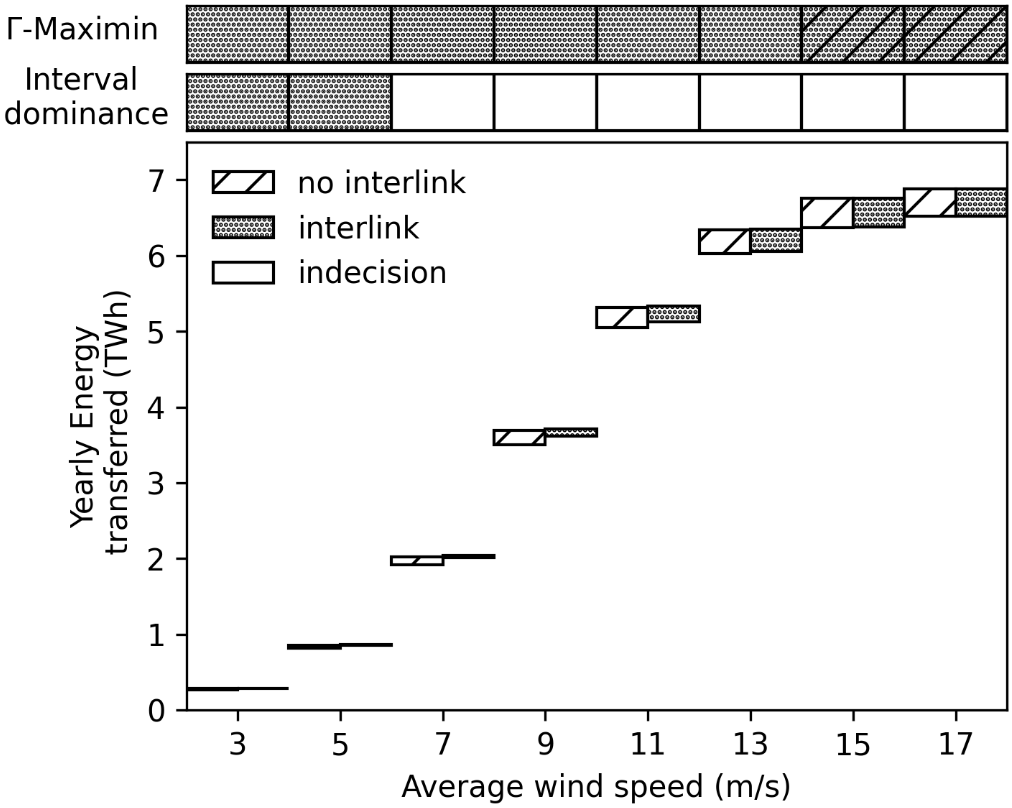


Figure 7.9: Bounds on yearly energy transferred (for interlink and no interlink systems) at varying wind resource inputs. Here, the wind speed standard deviation is fixed at 2 m/s. The two rows above the main plot show how the selected options varies (using Γ-maximin and interval dominance decision criteria) as the wind resource varies.

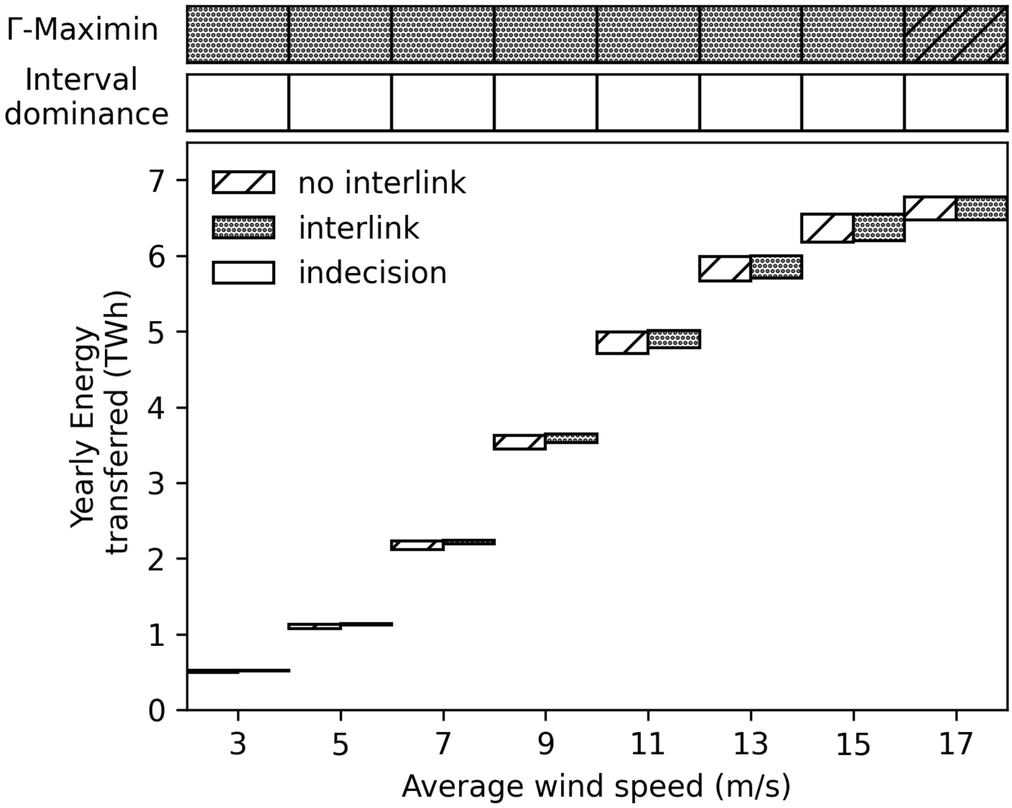


Figure 7.10: Bounds on yearly energy transferred (for interlink and no interlink systems) at varying wind resource inputs. Here, the wind speed standard deviation is fixed at 3 m/s. The two rows above the main plot show how the selected options varies (using Γ-maximin and interval dominance decision criteria) as the wind resource varies.

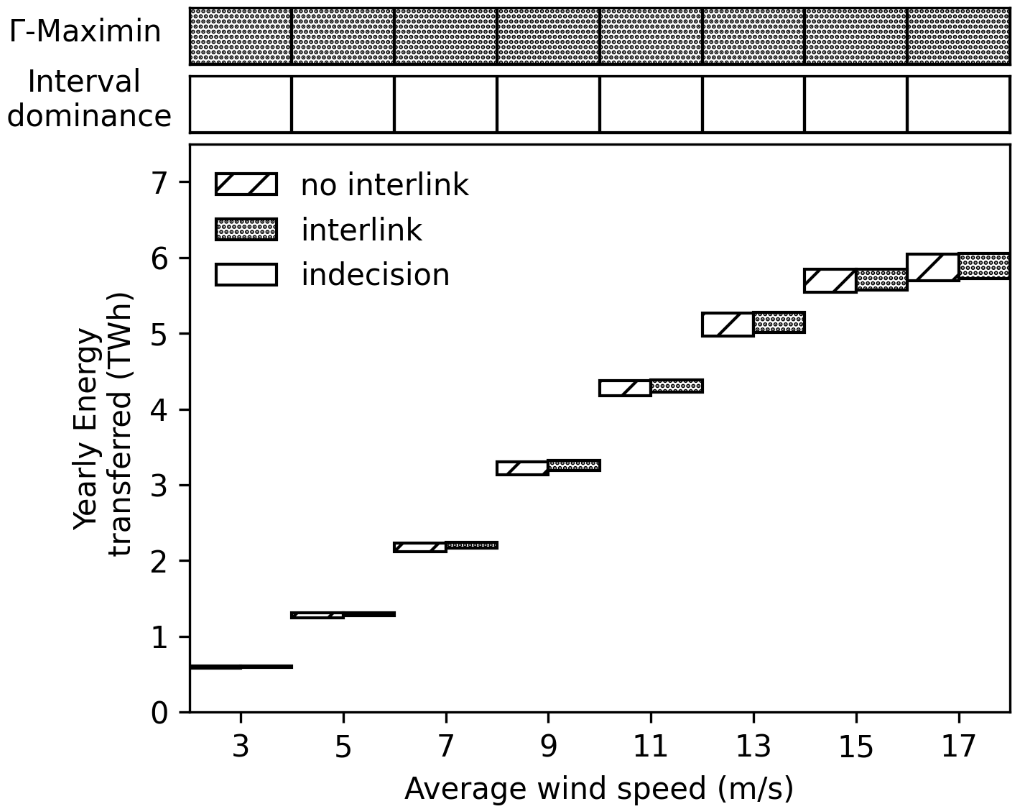


Figure 7.11: Bounds on yearly energy transferred (for interlink and no interlink systems) at varying wind resource inputs. Here, the wind speed standard deviation is fixed at 5 m/s. The two rows above the main plot show how the selected options varies (using Γ-maximin and interval dominance decision criteria) as the wind resource varies.

under severe uncertainty than those based on conventional techniques.

7.5 Conclusion

In this chapter, we set out to demonstrate how to apply imprecise probabilities to handle severe uncertainty in a specific project design decision problem. This investigation assessed the benefit of investing in an interlink between two offshore substations from two perspectives: an offshore wind farm owner and an offshore transmission owner. Each stakeholder has their view and therefore has a different metric of interest. In this chapter, we formulated the decision problem from both perspectives by detailing the net present value (NPV) evaluation from the offshore transmission owner's (OFTO) perspective and the energy generated and transmitted evaluation from the wind farm owner's perspective. We discussed that this investment decision, like others in offshore transmission planning, is taken under severe uncertainty due to a limited amount of relevant data. This severe uncertainty necessitates a suitable decision making approach, and therefore, we utilised imprecise probability.

While applying imprecise probability, we encountered act-state dependence as the distribution of availability depends on the decision selected. Therefore, we explained how act-state dependence impacts the handling of uncertainty in different variable types. To handle uncertainty in availability (act-state dependent variable), we assigned a set of distributions for each input parameter and simulated the systems to obtain best- and worst-case scenarios. These scenarios bounded NPV and energy transmitted, and we analysed these bounds using Γ-maximin and interval dominance to select the optimal option. To handle uncertainty in the wind resource (act-state independent variable), we investigated how the decision changes as a function of fixed values of the wind speed parameters. In conclusion, this work presented decision making techniques to handle severe uncertainty in offshore power transmission.

We found that for the 800 MW case study and described modelling approach, the two stakeholders select different sets of optimal decisions. As the wind resource increases, the wind farm owner cannot decide between the two options as the extra power generated cannot be rerouted without overloading the cables. In conclusion, we found that, for this case study and modelling approach, an interlink makes economic sense for the offshore wind farm owner. However, there is a weak business case for an interlink from the offshore transmission owner's (OFTO) perspective.

Furthermore, the work of this chapter demonstrated how techniques based on imprecise probability differ from conventional methods based on the classical theory of probability.

We discussed how the approaches differ, in particular, how the conventional techniques require enough information to assign a probability distribution. In contrast, the methods based on imprecise probability relax this requirement and instead consider a set of distributions. This relaxation provided a way to consider epistemic uncertainty in the input parameters. Therefore, we showed how techniques based on imprecise probability give a more robust way to handle severe uncertainty than conventional approaches. Consequently, this chapter has illustrated (through the application of imprecise probability to a practical decision problem) that the proposed advanced statistical methods can be beneficial to decision problems in offshore power transmission, that are taken under severe uncertainty.

This chapter raises further design decision problems, such as investigating to what extent should a cable be overdesigned in wealthy wind resource regions. Additionally, a further study could assess whether the same conclusions are obtained for future meshed and increased redundancy grids. Finally, further research might also explore in more detail the ability of transmission regulation to support systems with increased redundancy.

Chapter 8

Application 3: Designing Offshore Transmission System (DOTS)

8.1 Introduction

In this chapter, we present a more comprehensive application of advanced statistical techniques to offshore power transmission. So far, in Chapters 6 and 7, we have demonstrated how to apply the proposed techniques to specific decision problems. In this chapter, we extend the decision problem by including a framework to construct the decision space. Specifically, we create possible topologies given the market conditions, rather than selecting between predesigned systems for a given project specification.

Accordingly, this advancement allows the techniques to aid in the handling of severe uncertainty when planning future offshore transmission systems (OTSs). In particular, we allow the decision maker to specify design parameters, for example, project capacity; and therefore, the implementation in this chapter is more directly applicable to an extensive range of projects. In summary, this work presents a novel investment planning tool to support decision makers in offshore power transmission by facilitating a more appropriate way to handle uncertainty.

This study investigates and designs optimal OTSs for varying distances offshore and wind farm generation capacities. Although offshore wind is still in its infancy, trends in OTSs can be explored by considering current and planned projects. In Chapter 3, we explored characteristics of operational OTSs in the UK. In particular, how project capacity, export cable length, export cable voltage and the number of export cables have evolved. We noted that there had been a shift to larger offshore wind generation capacities (from 90 MW in 2008 to 1200 MW in 2020 [30, 31]) due to larger turbines installed further offshore. Consequently, longer export cables have been installed, and more recent HVAC projects have installed cables with a higher nominal voltage of 220 kV [38].

The requirements of an OTS are changing to accommodate the needs of the industry. As offshore wind farms grow in capacity, higher power rated equipment and more offshore platforms are required. As projects move further offshore, longer export cables are installed, as well as either the installation of reactive compensation units or a change to HVDC technologies. Furthermore, as the size of the wind farms grows, the greater the importance of the OTS to be in good working order and consequently, the significance of reliability. Ultimately, how we connect wind farms is an increasingly crucial question [18].

There is limited literature publicly available that investigates how to design optimal OTSs from components available in the market. However, the work by [89], which we discussed in Chapter 2, does present a methodology to design the transmission system under risk. The decision process in [89] includes selecting HVAC or VSC-HVDC technologies, the nominal voltage of the system, the size of the cable, the rating of the transformer and the compensation type. Furthermore, the work by [89] uses a criterion that incorporates the decision maker's risk tolerance through a risk tolerance parameter. However, the analysis by [89], like other economic assessments in this field, is based on classical probability theory. We argue that decisions made in offshore transmission are taken under severe uncertainty, and hence require techniques that are more robust under uncertainty.

We have previously discussed that, unfortunately, decisions made during the planning stage of an OTS are taken under severe uncertainty due to limited data. This challenge arises due to the short operational history of these technologies; each project has its specific requirements; and the limited amount of knowledge sharing within the industry. Conventional techniques used in traditional power systems analysis, are based on the classical theory of probability and do not sufficiently handle uncertainty. Therefore, we apply imprecise probability [25] to aid in the design of future OTSs. In Chapter 5, we introduced imprecise probability and explained how the theory provides techniques to handle uncertainty.

In this chapter, we aim to present a methodology that allows the decision maker to input components that are available in the current market, and based on these inputs, output an optimal topology. To carry out this process, we take a two-step approach: firstly, we design a set of optimal options (we refer to this as the modelling step) and secondly, we find which of these options is optimal using probability bounding techniques (we refer to this as the inference step). The presented methodology can be used to plan future OTSs by specifying design parameters such as project capacity and distance offshore.

Several factors contribute to the final selection of a particular OTS including cost, reliability, safety, environmental impact, social perspective, supply chain and previous project experience. In this study, we focus on the economics of an OTS, which also includes other considerations such as availability. To assess which topology is economically optimal, we must take a stakeholder's perspective, and previously, we discussed that the ownership structure of the OTS varies between countries. Here, again, we consider the UK market and analyse from the perspective of an offshore transmission owner (OFTO). We recall that in the UK setting an OFTO finances, owns and operates the OTS. Unfortunately, taking a specific view can appear to limit the applicability of the techniques. Therefore, in this work, we discuss how the methodology could be adapted to suit the needs of other markets and stakeholders.

To summarise, the aims of this chapter are:

1. To design feasible OTSs from components available in the market using physical and logical constraints.
2. To demonstrate the application of imprecise probability to a more comprehensive offshore power transmission decision problem. Furthermore, to present a novel investment planning tool to aid decision makers when designing an OTS under severe uncertainty.
3. To illustrate how techniques based on imprecise probability could be beneficial to decision makers in offshore power transmission when the analysis is conducted under severe uncertainty.

This chapter is structured as follows. Sections 8.2 and 8.3 presents the methodology of this chapter to design and find optimal OTSs. Section 8.2 describes how we design a set of feasible OTSs from the components available in the market (the modelling step). Then, Section 8.3 explains how we select the optimal design from the set of viable OTSs (the inference step). In Section 8.3.6, we discuss how the methodology outlined could be adapted to other markets. Next, Section 8.4 shows the results of this chapter for three case studies. Finally, Section 8.5 concludes the chapter.

8.2 Methodology: Modelling

This work aims to develop an approach to planning future offshore wind transmission systems under severe uncertainty. We propose to design and find an optimal OTS in two steps:

- **Step 1:** For a given project capacity and distance offshore, design a set of viable OTSs. This step is the main modelling part of the decision making analysis and where we construct the decision space. Therefore, this step is referred to as the modelling step.

- **Step 2:** From the set of feasible topologies obtained in the modelling step, we find which system is optimal. This step is the inference part of the decision making analysis; and therefore, this step is referred to as the inference step.

Planning an OTS involves designing a set of feasible topologies. To do this, we suggest that the decision maker (who could be the project planner) first identifies the range of components available in the market. In this work, we consider the offshore platforms, offshore transformers, offshore cables, onshore cables, offshore transformers, offshore voltage source converters (VSCs) and onshore VSCs when designing the OTS. We use logical and physical constraints to design possible topologies from these components. These constraints, detailed below, are motivated from previous projects, design standards and expert knowledge; however, the constraints could be modified to consider non-standard systems should the decision maker prefer. In Sections 8.2.1 to 8.2.3, we design HVAC and HVDC systems. Table 8.1 sets up the notation that is used throughout the modelling step explanation.

In this work, we design HVDC monopole and bipole configurations. These types of systems have been implemented in current HVDC offshore wind connections and electricity interconnectors between different countries [245]. Furthermore, we focus on point-to-point and multi-infeed point-to-point systems. Several studies (including [16, 20, 21, 95] and the research project by [246]) suggest that other types of grid connection layouts, such as multi-terminal HVDC, could be advantageous, especially as offshore wind farms grow in capacity.

The suggested advantages of multi-terminal HVDC systems include lower CAPEX, lower OPEX, improved reliability, lower environmental impact and, importantly, a lower cost of energy [20, 21, 246]. Currently, there are still believed to be some challenges with installing HVDC multi-terminal systems, including regulatory aspects [246]. In this work, we do not design multi-terminal systems; however, the methodology presented below could be extended to consider these systems and the economic evaluation would follow similarly.

A consideration when designing OTSs is that all selected components in a topology are compatible with the nominal voltage of the system. To achieve this, we must first identify a set of components compatible for a given nominal voltage and design a set of possible topologies from this set of components. For example, to design a HVAC system with a nominal voltage of 220 kV, we must identify components in the market that are suitable for such a system and then apply the logical and physical constraints presented below to design possible topologies for this nominal voltage. In order to design and compare systems with different nominal voltages, we should repeat the modelling step for a suitable set of components (that are available in the market) for each nominal voltage.

We note that this modelling step makes many assumptions and simplifications, including usually designing a project for 100% of the rating where no over or underrating is considered. On account of this limitation, this work could be implemented in the early design phase of a project to narrow down topologies before more detailed system studies are conducted.

8.2.1 Designing High Voltage Alternating Current (HVAC) Systems

In this subsection, we design offshore transmission systems (OTSs) that use HVAC technology. We begin by identifying and outlining the logical and physical constraints associated with each component considered in the system. For a HVAC system, we consider offshore platforms, offshore transformers, offshore cables, onshore cables, and onshore transformers. Each of these components is discussed below.

- Offshore platform
  - All platforms are the same type of platform and support the same amount of capacity.
  - Together, all the offshore platforms in the system are able to carry the total project capacity.
  - We allow the platforms to be overrated (by rounding up).
  - Therefore, for $s_1 \in \mathcal{S}_1$ we evaluate the number of offshore platforms to be:

    $$NS_1 = \left\lceil \frac{a}{s_1} \right\rceil. \tag{8.1}$$

    For clarity, s_1 is a one platform chosen from the set of platforms available (S_1 in Table 8.1). This notation follows similarly for all components.

- Offshore transformer
  - All platforms host the same number of offshore transformers.
  - All transformers are the same type (carry the same capacity), i.e. the same $k_1 \in \mathcal{K}_1$.
  - Together, all the offshore transformers in the system are able to carry the total project capacity.
  - Physically, the number of offshore transformers is a natural number.
  - Therefore, we evaluate the number of offshore transformers per platform to be:

    $$NK_1 = \frac{a}{NS_1 \times k_1} \in \mathbb{N}. \tag{8.2}$$

- Offshore cable
  - All offshore cables in the project are of the same type, i.e. the same $c_1 \in \mathcal{C}_1$.

Symbol	Definition
a	Project capacity
$\mathcal{C}_1$	Offshore HVAC cable capacities in the market
$\mathcal{C}_2$	Onshore HVAC cable capacities in the market
$\mathcal{C}_3$	Offshore HVDC cable capacities in the market
$\mathcal{C}_4$	Onshore HVDC cable capacities in the market
$\mathcal{K}_1$	Offshore transformer capacities in the market
$\mathcal{K}_2$	Onshore transformer capacities in the market
$\mathcal{S}_1$	Offshore HVAC platform capacities in the market
$\mathcal{S}_2$	Offshore HVDC platform capacities in the market
$\mathcal{V}_1$	Offshore voltage source converter (VSC) capacities in the market
$\mathcal{V}_2$	Onshore voltage source converter (VSC) capacities in the market
NC_1	Number of offshore cables per transformer
NC_2	Number of onshore cables per transformer
NC_3	Number of HVDC offshore cables
NC_4	Number of HVDC onshore cables
NK_1	Number of offshore transformers per platform
NK_2	Number of onshore transformers required for this topology
NS_1	Number of offshore platforms required for this topology
NS_2	Number of HVDC offshore platforms
NV_1	Number of offshore voltage source converters (VSCs)
NV_2	Number of onshore voltage source converters (VSCs)

Table 8.1: Symbol definitions for quantities used throughout this chapter; in particular, in the logical and physical constraints that are described in the modelling step of the decision analysis.

- The number of cables connected to each platform is the same for all platforms.
- The offshore cables combined are able to carry the total project capacity.
- Physically, the number of offshore cables connected to each platform is a natural number.
- To ensure the system is symmetric, the number of cables connected to a transformer or the number of transformers connected to a cable is a natural number. If the number of offshore cables is greater than the number of offshore transformers, then we require that the number of cables connected to each transformer ($\frac{NCS_1}{NK_1}$) is a natural number. Here, NCS_1 denotes the number of cables per platform. Similarly, if the number of offshore transformers is greater than the number of offshore cables, then we require that the number of transformers connected to each cable ($\frac{NK_1}{NCS_1}$) is a natural number. This constraint leads to Eq. (8.10).
- Therefore, we evaluate the number of offshore cables per transformer to be:

$$NC_1 = \frac{a}{c_1 \times NS_1 \times NK_1}. \tag{8.3}$$

- Onshore cable
  - All onshore cables in the project are the same type, i.e. the same $c_2 \in \mathcal{C}_2$.
  - Due to physical constraints, the number of onshore cables is equal to the number of offshore cables. In Chapter 3, we observed that the number of offshore cables is equal to the number of onshore cables in operational projects in the UK.
  - The offshore cable rating must be compatible with the rating of onshore cables available in the market.
  - The onshore cable rating is equal to the offshore cable rating.
  - Therefore, we check that $c_1 \in \mathcal{C}_2$ and if satisfied, assign $c_2 = c_1$ and $NC_2 = NC_1$.
- Onshore transformer
  - All onshore transformers in the project are the same type, i.e. the same $k_2 \in \mathcal{K}_2$.
  - Each system has the same number of onshore transformers as the number of offshore cables. This constraint ensures that the system is symmetric. The exception is systems with only one offshore cable. In this case, two onshore transformers are installed due to reliability. In Chapter 3, we observed that operational projects support these constraints.
  - The rating of the offshore cable is compatible with the ratings of onshore transformers available in the market.

- Therefore, the number of onshore transformers is evaluated by:

$$NK_2 = \max\{2, NTC_1\}. \tag{8.4}$$

Here, NTC_1 denotes the total number of cables in the project.

- Reactive compensation unit
  - For projects that are located significantly far offshore, transmission losses in the cables becomes a challenge. One option is to install HVDC technologies; however, if HVAC is preferred, a reactive power compensation unit could be installed along the cable route [11]. The additional unit would host additional reactive power compensation equipment.
  - The distance offshore at which HVDC is preferred over HVAC technologies is, as we discussed in Chapter 2, a highly debated topic [16, 84]. In general, this distance is thought to be greater than fifty kilometres. Therefore, for HVAC projects located more than eighty kilometres offshore, we factor into the analysis an additional cost due to the need to install a reactive compensation unit.
  - Without detailed costings of this type of infrastructure, due to limited numbers of reactive compensation units installed in operational projects, we assume that the CAPEX of a reactive compensation unit is £0.13 million per MVA. This figure is based on costs given in [33, 36, 37] which suggest that the cost of the platform is approximately £0.1 million per MVA and the installation costs are approximately £0.01 million per MVA. Additionally, data from [148] suggests that costs relating to reactive compensation equipment are approximately £0.02 million per MVA.

Using these described logical and physical constraints presented above, we formulate a framework to design HVAC systems. This framework is described by the equations below. To determine the number of offshore platforms, we choose s_1 from $\mathcal{S}_1$ and calculate:

$$NS_1 = \left\lceil \frac{a}{s_1} \right\rceil. \tag{8.5}$$

Then, we determine the number of offshore transformers by choosing k_1 from $\mathcal{K}_1$ and calculate:

$$NK_1 = \frac{a}{NS_1 \times k_1}. \tag{8.6}$$

Before proceeding with this topology, we check that $NK_1 \in \mathbb{N}$. If $NK_1 \notin \mathbb{N}$, we stop this loop and try the next option (in other words, the next k_1 from $\mathcal{K}_1$). Next, we determine the number of offshore cables. We choose c_1 from $\mathcal{C}_1$ and calculate:

$$NC_1 = \frac{a}{c_1 \times NS_1 \times NK_1}. \tag{8.7}$$

We then calculate the number of cables per platform (NCS_1) by:

$$NCS_1 = NC_1 \times NK_1. \tag{8.8}$$

Before proceeding with this topology, we check that $NCS_1 \in \mathbb{N}$. Then, we calculate the total number of cables in the project (NTC_1) by:

$$NTC_1 = NC_1 \times NK_1 \times NS_1. \tag{8.9}$$

The final check for the offshore cable is to check that the system is symmetric. To achieve this, we check that the following is true:

$$\frac{\max\{NCS_1, NK_1\}}{\min\{NCS_1, NK_1\}} \in \mathbb{N}. \tag{8.10}$$

Now, we move on to determine the number of onshore cables. Firstly, we check that $c_1 \in \mathcal{C}_2$, and then assign $c_2 = c_1$, $NC_2 = NC_1$. Finally, we determine the number of onshore transformers. We check $c_1 \in \mathcal{K}_2$ and calculate:

$$NK_2 = \max\{2, NTC_1\}. \tag{8.11}$$

If all the checks are satisfied, we have found a feasible OTS. This option can be described by $[NS_1, NK_1, NC_1, NC_2, NK_2]$. We then repeat the process for all components in the sets of components to find all feasible HVAC options. Should any of the checks not be satisfied, the framework loops through the next component in the set, and only proceeds if and when the constraints are satisfied.

8.2.2 Designing high voltage direct current (HVDC) systems (point-to-point monopole link)

So far, the methodology has detailed how to design HVAC OTSs. Although the UK, so far, has favoured HVAC technologies, to conduct a complete analysis, we move on to also design HVDC systems. In this section, we motivate and explain the process of planning HVDC systems. These technologies have been installed in offshore wind projects in Germany [45]. We start by identifying the logical and physical constraints associated with the components that constitute a HVDC point-to-point monopole system. Here, we consider point-to-point and multi-infeed point-to-point systems [230]. A physical constraint that applies to all components is the need for the quantity of each component to be a natural number.

- Offshore voltage source converter (VSC)
  - We start by selecting the VSC as it is one of the most expensive components in the system.

- All offshore VSCs in a system are the same type, i.e. the same $v_1 \in \mathcal{V}_1$.
- Together, all the offshore VSCs in the system are able to carry the total project capacity.
- We allow the offshore VSC to have a rating higher than the project rating, but restrict the amount of overdesigning to 25% of the total capacity.
- Therefore, the number of offshore VSCs is evaluated by:

$$NV_1 = \left\lceil \frac{a}{v_1} \right\rceil. \tag{8.12}$$

- Offshore platform
  - Each platform hosts one VSC.
  - The capacity of the platform is greater than or equal to the capacity of the VSC it hosts.
  - All platforms are the same type of platform, i.e. the same $s_2 \in \mathcal{S}_2$.
  - Together, all the offshore platforms in the system are able to carry the total project capacity.
  - We consider combined HVAC offshore substations and HVDC converter offshore platforms in-line with state-of-the-art technology [34, 22] (for more details see Section 3.8.2).
- Offshore transformer
  - All transformers are the same type and carry the same capacity, i.e. the same $k_1 \in \mathcal{K}_1$.
  - All offshore VSCs are connected to the same number of offshore transformers.
  - Together, all the transformers in the system can carry the total project capacity.
- Offshore cable
  - All offshore cables in the project are the same type, i.e. the same $c_3 \in \mathcal{C}_3$.
  - As we are considering point-to-point systems, each converter is connected to one HVDC link.
  - The cables combined are able to carry the total project capacity.
- Onshore cable
  - All onshore cables in the project are the same type, i.e. the same $c_4 \in \mathcal{C}_4$.
  - In point-to-point topologies, each offshore cable is connected to one onshore cable.

  - Together, all the onshore cables in the system can carry the total project capacity.

- Onshore VSC
  - In point-to-point topologies, each option has the same number of onshore VSCs as offshore VSCs.
  - All onshore VSCs in a system are the same type, i.e. the same $v_2 \in \mathcal{V}_2$.
  - Together, all of the onshore VSCs in the system are able to carry the total project capacity.

- Onshore transformer
  - All onshore transformers in the project are the same type, i.e. the same $k_2 \in \mathcal{K}_2$.
  - Together, all the onshore transformers in the system can carry the total project capacity.

Using these described logical and physical constraints, we formulate a framework to design HVDC systems. This framework is described by the equations below. We begin with determining the number of offshore VSCs. We choose v_1 from $\mathcal{V}_1$ and calculate:

$$NV_1 = \left\lceil \frac{a}{v_1} \right\rceil. \tag{8.13}$$

Before proceeding with this topology, we check that we have not overdesigned by more than 25% of the total capacity:

$$NV_1 \times v_1 \leq 1.25a. \tag{8.14}$$

Next, we determine the number of offshore platforms. We choose s_2 from $\mathcal{S}_2$ such that $v_1 \leq s_2$ and assign:

$$NS_2 = NV_1. \tag{8.15}$$

Next, we turn to the offshore transformer. We choose k_1 from $\mathcal{K}_1$ and calculate the number of offshore transformers in the topology, NK_3, by:

$$NK_3 = \left\lceil \frac{a}{k_1} \right\rceil. \tag{8.16}$$

Before proceeding, we check that the number of offshore transformers per platform, NK_1, is an integer:

$$NK_1 = \frac{NK_3}{NV_1} \in \mathbb{N}. \tag{8.17}$$

Then, we determine the number of offshore cables. We choose c_3 from $\mathcal{C}_3$ such that $v_1 \leq c_3$ and assign:

$$NC_3 = NV_1. \tag{8.18}$$

Next, we move on to the onshore cable. We choose c_4 from $\mathcal{C}_4$ such that $c_3 \leq c_4$ and then assign:

$$NC_4 = NC_3. \tag{8.19}$$

Next, we determine the number of onshore VSCs. We choose v_2 from $\mathcal{V}_2$ such that $v_1 \leq v_2$ and then assign:

$$NV_2 = NV_1. \tag{8.20}$$

Finally, we determine the number of onshore transformer by choosing k_2 from $\mathcal{K}_2$ and calculate:

$$NK_2 = \left\lceil \frac{a}{k_2} \right\rceil. \tag{8.21}$$

Similar to the HVAC case, if all the checks are satisfied, we have found a feasible OTS. This option can be described by [(NV_1, v_1), (NS_2, s_2), (NK_1, k_1), (NC_3, c_3), (NC_4, c_4), (NV_2, v_2), (NK_2, k_2)]. We then repeat the process to find all feasible HVDC options with a monopole configuration.

8.2.3 Designing high voltage direct current (HVDC) systems (point-to-point bipole link)

In Section 8.2.2, we presented a methodology to design HVDC systems with monopole configurations. In this section, we aim to extend the decision space to include bipole configurations. In general, the logical and physical constraints presented in Section 8.2.2 also apply to HVDC bipole configurations; however, some important considerations are specific to a topology utilising bipole technology.

A significant benefit of a bipole configuration is the increased redundancy; the system can operate at half capacity in the event of a cable fault [95]. The reliability advantages come at higher CAPEX due to the additional return cable. The study by [95] investigates the reliability of different grid connection options, including bipole configurations. Furthermore, [95] details two areas for bipole configurations that result in extra costs: specially designed converters and an additional return cable. In the absence of published data for these costs, we follow the approach taken by [95]. Consequently, we assume an additional ten per cent to the CAPEX of the converters and the CAPEX of the additional return cable is fifty per cent of the costs of the standard cables. We note that the decision maker can adjust these values to suit their needs; for example, they could assume that bipole VSC converters are about the same price as a monopole.

Figure 8.1: A high voltage alternating current (HVAC) point-to-point system.

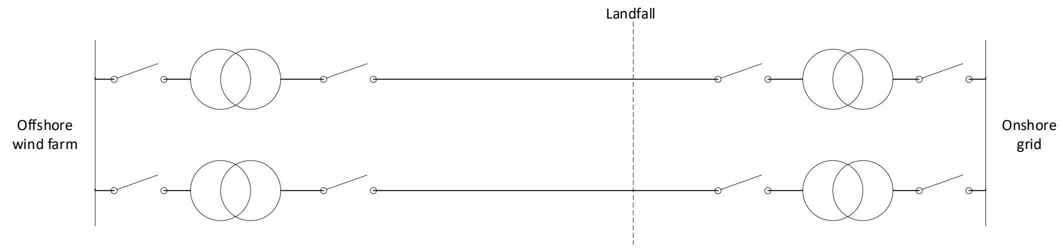


Figure 8.2: A high voltage alternating current (HVAC) multi-infeed point-to-point system.

8.2.4 Sketches of types of topologies considered

In Figs. 8.1 to 8.6, we present sketches of the offshore transmission systems (OTSs) designed in the modelling step of the decision making analysis. In summary, the framework outlined in Sections 8.2.1 to 8.2.3 allows a project planner to input the components that they have access to (and the ratings of these components), apply these equations, and ultimately find all the possible topologies.

8.2.5 Case Study Example of Modelling Step

Next, we turn to apply the methodology of the modelling step (step one) to a case study. We take the components listed in Table 8.2 and Table 8.3 and apply the described methodology of the modelling step to a 1200 MW project located one hundred kilometres offshore. Carrying out this step designs all possible topologies (based on the identified constraints) for this project. The viable topologies for this case study are presented in Table 8.4 and Table 8.5. We note that in the tables below $[x, y]$ corresponds to x number of components (where the component is given by the column heading) at rating y MW.

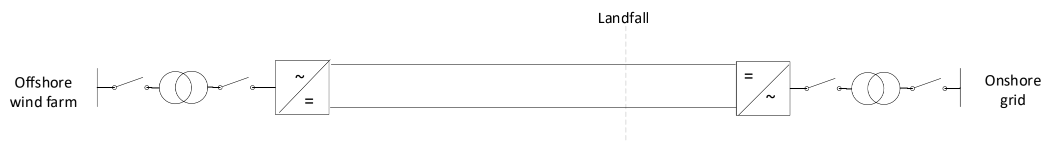


Figure 8.3: A high voltage direct current (HVDC) (monopole) point-to-point system.

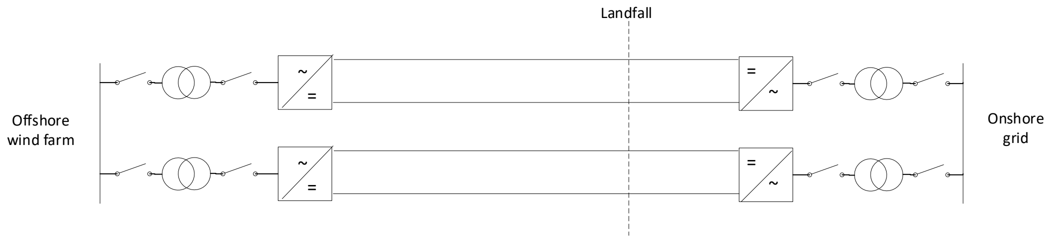


Figure 8.4: A high voltage direct current (HVDC) (monopole) multi-infeed point-to-point system.

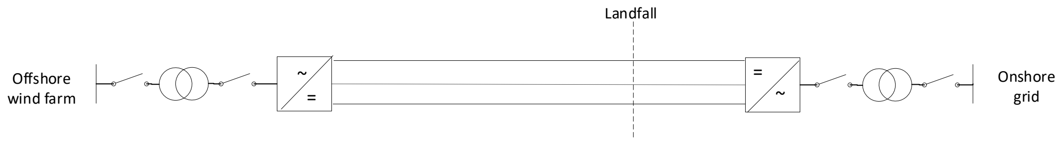


Figure 8.5: A high voltage direct current (HVDC) (bipole) point-to-point system.

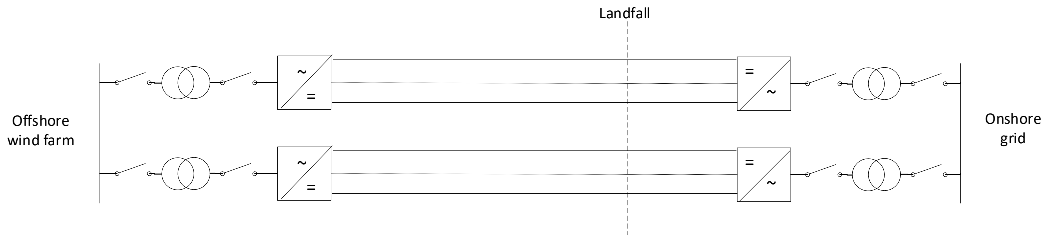


Figure 8.6: A high voltage direct current (HVDC) (bipole) multi-infeed point-to-point system.

Component	Capacity ratings available in the market (MW)
Offshore VSC	800, 1000, 1200, 1800, 2200
Onshore VSC	800, 1000, 1200, 1800, 2200
Offshore cable	600, 800, 1000, 1200, 1500, 1800
Onshore cable	600, 800, 1000, 1200, 1500, 1800
Offshore platform	1000, 1250, 1500, 1750, 2000, 2250, 2500
Offshore transformer	200, 250, 300, 350
Onshore transformer	200, 250, 300, 350

Table 8.2: An example of high voltage direct current (HVDC) components available in the market. These components are used in the case studies and examples throughout this chapter.

Component	Capacity ratings available in the market (MW)
Offshore cable (220 kV)	150, 200, 250, 300, 350, 400
Onshore cable (220 kV)	150, 200, 250, 300, 350, 400
Offshore platform	300, 400, 700, 1200
Offshore transformer	200, 250, 300, 350
Onshore transformer	200, 250, 300, 350, 400

Table 8.3: An example of high voltage alternating current (HVAC) components available in the market. These components are used in the case studies and examples throughout this chapter.

8.3 Methodology: Inference

Up to this point, we have designed a set of possible topologies for the offshore transmission system (OTS). Next, we aim to find the economically optimal topology from this set; this is the inference step. To achieve this, we evaluate and compare the economic benefit of the options. A decision maker must decide between the options such that some quantity of interest (e.g. net present value (NPV)) is maximised (or minimised). However, usually, some inputs required to evaluate the quantity of interest are uncertain, to a degree where it becomes hard to identify a probability distribution for these inputs that accurately describes our knowledge.

Throughout this thesis, we have discussed that both literature and operational experience indicates that offshore wind grid integration, and in particular the planning of OTSs, is subject to severe epistemic uncertainty. Due to each project having its specific situation, the advancement of technology and the short operational history of the assets, there is a limited amount of useful information to input into the analysis. Unfortunately, this complicates the decision making process.

In Chapter 5, we introduced imprecise probability, and in Chapters 6 and 7, we applied these techniques to specific decision problems. We recall that imprecise probability can be described as a more general theory of uncertainty quantification. The techniques can be implemented when we do not have enough information (for example, about our input parameters) to use techniques based on the classical theory of probability. Since many uncertainties surround offshore power transmission, taking investment decisions based on analysis that uses imprecise probability could be beneficial. In this chapter, we demonstrate how to apply imprecise probability in the proposed investment planning tool and investigate the advantages of these methods.

Option		Offshore VSC	Offshore platform	Offshore transformer*	Offshore cable	Onshore cable	Onshore VSC	Onshore transformer
Monopole	Bipole							
Option 1	Option 17	[1, 1200]	[1, 1250]	[6, 200]	[1, 1200]	[1, 1200]	[1, 1200]	[6, 200]
Option 2	Option 18	[1, 1200]	[1, 1250]	[6, 200]	[1, 1200]	[1, 1200]	[1, 1200]	[5, 250]
Option 3	Option 19	[1, 1200]	[1, 1250]	[6, 200]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 300]
Option 4	Option 20	[1, 1200]	[1, 1250]	[6, 200]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 350]
Option 5	Option 21	[1, 1200]	[1, 1250]	[5, 250]	[1, 1200]	[1, 1200]	[1, 1200]	[6, 200]
Option 6	Option 22	[1, 1200]	[1, 1250]	[5, 250]	[1, 1200]	[1, 1200]	[1, 1200]	[5, 250]
Option 7	Option 23	[1, 1200]	[1, 1250]	[5, 250]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 300]
Option 8	Option 24	[1, 1200]	[1, 1250]	[5, 250]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 350]
Option 9	Option 25	[1, 1200]	[1, 1250]	[4, 300]	[1, 1200]	[1, 1200]	[1, 1200]	[6, 200]
Option 10	Option 26	[1, 1200]	[1, 1250]	[4, 300]	[1, 1200]	[1, 1200]	[1, 1200]	[5, 250]
Option 11	Option 27	[1, 1200]	[1, 1250]	[4, 300]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 300]
Option 12	Option 28	[1, 1200]	[1, 1250]	[4, 300]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 350]
Option 13	Option 29	[1, 1200]	[1, 1250]	[4, 350]	[1, 1200]	[1, 1200]	[1, 1200]	[6, 200]
Option 14	Option 30	[1, 1200]	[1, 1250]	[4, 350]	[1, 1200]	[1, 1200]	[1, 1200]	[5, 250]
Option 15	Option 31	[1, 1200]	[1, 1250]	[4, 350]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 300]
Option 16	Option 32	[1, 1200]	[1, 1250]	[4, 350]	[1, 1200]	[1, 1200]	[1, 1200]	[4, 350]

Table 8.4: Feasible HVDC topology options identified using the methods described in the modelling step of the decision making analysis. These topologies have been designed for a 1200 MW project located 100 km offshore. Here, * denotes when the quantity is given per platform.

Option	Offshore platform	Offshore transformer*	Offshore cable**	Onshore cable**	Onshore transformer
Option 33	[4, 300]	[1, 300]	[1, 300]	[1, 300]	[4, 300]
Option 34	[3, 400]	[2, 200]	[1, 200]	[1, 200]	[6, 200]
Option 35	[3, 400]	[2, 200]	[0.5, 400]	[0.5, 400]	[3, 400]
Option 36	[3, 500]	[2, 200]	[1, 200]	[1, 200]	[6, 200]
Option 37	[3, 500]	[2, 200]	[0.5, 400]	[0.5, 400]	[3, 400]
Option 38	[2, 600]	[3, 200]	[1, 200]	[1, 200]	[6, 200]
Option 39	[2, 600]	[2, 300]	[1, 300]	[1, 300]	[4, 300]
Option 40	[2, 700]	[3, 200]	[1, 200]	[1, 200]	[6, 200]
Option 41	[2, 700]	[2, 300]	[1, 300]	[1, 300]	[4, 300]
Option 42	[1, 1200]	[6, 200]	[1, 200]	[1, 200]	[6, 200]
Option 43	[1, 1200]	[6, 200]	[0.5, 400]	[0.5, 400]	[3, 400]
Option 44	[1, 1200]	[4, 300]	[1, 300]	[1, 300]	[4, 300]

Table 8.5: Feasible HVAC topology options identified using the methods described in the modelling step of the decision making analysis. These topologies have been designed for a 1200 MW project located 100 km offshore. We note that since this project is 100 km offshore, the design includes a reactive compensation unit. Here, * denotes when the quantity is given per platform and ** denotes when the quantity is given per transformer.

8.3.1 Economic Metrics of Interest

We recall that using imprecise probability, instead of evaluating the expectation, we calculate lower and upper and bounds on the expectation using the theory of lower and upper previsions. These upper and lower bounds on the expectation for each option form intervals that represent sets of distributions, and are denoted by $\underline{E}$ and $\overline{E}$, respectively. These intervals are compared to select the optimal option. To compare the different connection options from the offshore transmission owner's (OFTO) perspective, we consider two economic metrics: net present value (NPV) and return on investment (ROI). In this section, we detail how to evaluate the lower bound of these two metrics of interest. Details of how to evaluate the upper bound follow similarly but are omitted.

In Chapter 6 we detailed the metric ROI and in Chapter 7 we detailed the metric NPV. We repeat the resulting expressions here for convenience. Each topology is referred to as an option, denoted by j, and for each option, we evaluate its ROI by Eq. (8.22).

$$\mathrm{ROI}(j) = \frac{\sum_{t=1}^{n}(R_t(j) - \mathrm{OPEX}_t(j)) - \mathrm{capex}(j)}{\mathrm{capex}(j)}. \tag{8.22}$$

Here, $R_t(j)$ denotes revenue in year t, $\mathrm{OPEX}_t(j)$ denotes the operational expenditure in year t, capex is the capital expenditure, and n is the total number of operational years. As we have seen before, annual revenue can be formulated as:

$$R_t(j) = (0.9 I_{Y_t(j)\leq 0.94} - 1.45 I_{Y_t(j)\geq 0.94} + 2.5 Y_t(j) I_{Y_t(j)\geq 0.94}) B(j). \tag{8.23}$$

Here, $Y_t(j)$ represents the availability under option j, $B(j)$ denotes the base revenue under option j and I_Y is the indicator function. Taking the lower expectation of Eq. (8.22), in Chapter 6 we obtained:

$$\underline{E}(\mathrm{ROI}(j)) = \frac{\min_{p\in\mathcal{M}} n(E_p(R_t(j)) - E_p(\mathrm{OPEX}_t(j))) - \mathrm{capex}(j)}{\mathrm{capex}(j)}. \tag{8.24}$$

Here, $\mathcal{M}$ is the set of worst- and best-case distributions of $Y_t(j)$. In this work, the worst- and best-case scenarios are a result of the export cable behaviour. $E_p(\mathrm{OPEX})$ is evaluated as a sample mean from an availability simulation for each option j. Using Eq. (8.23), we find that:

$$\begin{aligned} E_p(R_t(j)) = (0.9 E_p(I_{Y_t(j)\leq 0.94}) &- 1.45 E_p(I_{Y_t(j)\geq 0.94}) \\ &+ 2.5 E_p(Y_t(j)) E_p(I_{Y_t(j)\geq 0.94})) E_p(B(j)). \end{aligned} \tag{8.25}$$

Here, $E_p(Y_t(j))$ is evaluated as a sample mean from an availability simulation for each option j. $E_p(I_{0.94\leq Y_t(j)})$ and $E_p(I_{Y_t(j)\geq 0.94})$ are also determined from the availability simulation. If the metric annual ROI is preferred, then we recall Eq. (6.5) from Chapter 6, and the analysis follows in a similar same way to the approach described here.

Similarly, we repeat the expressions for NPV that we detailed in Chapter 7. For each option j, the NPV can be evaluated by:

$$\mathrm{NPV}(j) = \sum_{t=1}^{n_1} \frac{R_t(j) - \mathrm{OPEX}_t(j) - L_t(j)}{(1+d)^t} + \sum_{t=n_1+1}^{n} \frac{R_t(j) - \mathrm{OPEX}_t(j)}{(1+d)^t}. \tag{8.26}$$

Here, d denotes the discount factor, $R_t(j)$ denotes revenue in year t, $\mathrm{OPEX}_t(j)$ denotes the operational expenditure in year t, $L_t(j)$ denotes the loan repayment amount in year t, n denotes the number of operational years, and n_1 denotes the loan duration in years. Eq. (8.26) shows that the cash flow is different in the first n_1 years as it includes the loan repayments. Taking the lower expectation of Eq. (8.26), we find:

$$\begin{aligned} \underline{E}(\mathrm{NPV}(j)) = \min_{p \in \mathcal{M}} \Bigg(& \left(\sum_{t=1}^{n_1} \frac{1}{(1+d)^t} \right) (E_p(R_{(t=1)}(j)) - E_p(\mathrm{OPEX}_{(t=1)}(j)) - L_{(t=1)}(j)) \\ & + \left(\sum_{t=n_1+1}^{n} \frac{1}{(1+d)^t} \right) (E_p(R_{(t=n_1+1)}(j)) - E_p(\mathrm{OPEX}_{(t=n_1+1)}(j))) \Bigg). \end{aligned} \tag{8.27}$$

8.3.2 Model Inputs that Contain Uncertainty

Several of the model parameters required in the expressions presented above (for ROI and NPV) contain uncertainty. The type of uncertainty can be described by two broad categories: aleatory uncertainty and epistemic uncertainty (see Section 5.2 for more details). Aleatory uncertainty comes from variability, whereas epistemic uncertainty arises due to a lack of completeness in our knowledge. In our analysis, we concentrate on handling uncertainty due to limited information (the epistemic uncertainty) for the following model inputs:

1. The failure and repair rates of an offshore cable which are used to evaluate a component's availability.
2. The interest rate on the loan taken out to repay the capital costs.
3. The hire cost of an offshore cable repair vessel.
4. The amount of planned operational costs.

In this work, we encounter act-state dependence, which can be defined as instances in which the distribution of the state of nature depends on the decision taken. We discussed act-state dependence in Chapters 5 to 7. The act-state dependent variable that contains uncertainty in this decision problem is the availability of the OTS. To handle uncertainty in the act-state dependent variable, we simulate the best- and worst-case distributions of availability, for fixed values of the act-state independent variables. These simulations bound the expectation of NPV and ROI (conditionally on the act-state independent variables) and can be used with the interval dominance and Γ-maximin decision criteria.

The act-state independent variables, that contain uncertainty and that we focus on in this study, are the hire cost of an offshore cable repair vessel, the interest rate on the loan taken out to repay the capital costs and the amount of planned operational costs. To treat the act-state independent variables, we investigate how the decision changes as a function of fixed values of these variables. The following subsections discuss four model variables that contain uncertainty, and that will be is addressed in the analysis that follows.

Failure and repair rates of an offshore cable

We begin by discussing the act-state dependent variable: system availability. The availability of an OTS depends on the frequency and duration of component outages. To model the availability of each component, we use failure and repair rates. In this study, we concentrate on uncertainty in the export cable failure and repair rates. Operational experience has seen unexpected cable failures that have had costly implications [82]; therefore, these incidents suggest that cables could be an area of concern. Furthermore, the cable reliability parameters commonly used in assessments are suggested to be unrealistic [83].

This paragraph recaps the failure rates and repair times quoted in the literature. Failure rates of HVAC offshore cables are quoted to be 0.000705 fails/year/km in [142], 0.0015873 fails/year/km in [82], 0.00021 fails/year/km in [247], and 0.003 fails/year/km in [83]. Similarly, failure rates of HVDC offshore cables are quoted to be 0.0001 fails/year/km in [238], 0.0007 fails/year/km in [149], and 0.00021 fails/year/km in [247]. Repair times are quoted in the literature between two and five months [142], and 60 days in [95]. Performance reports by National Grid indicate that UK cable failures have lasted between a couple of hours and 125 days [141].

The limited amount of data means that it is difficult to assign distributions to model the system and justify any modelling assumptions. In particular, as we have discussed in Chapters 5 to 7, conventional techniques model cable failure and repair behaviour using Markov chains. Unfortunately, under severe uncertainty due to limited data, we cannot justify the modelling assumptions required to use Markov chains. Instead, to more robustly handle the severe uncertainty, we work with a set of processes (for more details see Section 5.4). By assigning bounds to the transition rates (between the working and not working states), we consider a set of transition matrices that may depend on the full time and history of the system. This approach means we no longer have to specify transition rates as precise values.

Fig. 8.7 shows a simplified block diagram to explain the analysis and uncertainty handling of the act-state dependent variable. In these diagrams input parameters are represented by a double circle, a box represents simulation processes, a single circle represents outputs of one process that are used by another, and a diamond shape represents the final outputs of the analysis. In Fig. 8.7, the grey filled nodes show where epistemic uncertainty in the act-state dependent variables is included in the analysis. The input node termed 'component properties' includes four input parameters shown on the left-hand side of Fig. 8.8: component failure rate, repair rate, daily repair cost and one-off repair cost.

As there is limited data regarding the failure behaviour of offshore cables, there is epistemic uncertainty in the analysis. On account of this epistemic uncertainty, we assign reasonable ranges to the offshore cable failure rate and repair rate and consider all distributions with these ranges. Figs. 8.7 and 8.8 shows that these inputs feed into the availability simulation which results in bounds on the simulation outputs: expected yearly availability, the probability that availability is greater than 94% and the expected OPEX. Ultimately, this bounds the expected NPV and ROI, which are then visualised and used in the inference part of the decision making process.

During the modelling process, we consider aleatory uncertainty, and this is denoted in the block diagrams by nodes with red font. In the availability simulation, we obtain traces of the system using a Monte Carlo simulation; this modelling process introduces aleatory uncertainty into the model. The right-hand side of Fig. 8.8 shows this in more detail. However, as we focus on expectations and usually only visualise expectations, the resulting plots do not show the aleatory uncertainty.

The interest rate of the loan used to repay the capital costs

Another model input that contains uncertainty is the loan interest rate, which is an act-state independent variable. In the NPV analysis, capital investment is modelled through a loan repayment structure. This loan repayment structure requires a model parameter called the interest rate. Interest rates change throughout time, and its future value is uncertain. Over the last twenty-years this value, according to the bank of England, has ranged between 0.1% and 6% [189].

Vessel hire costs for offshore cable repairs

We also consider the uncertainty in the model input termed vessel hire costs, which is an act-state independent variable. Upon the failure of an export cable, a repair process begins, which may involve locating the cable fault and replacing the damaged cable section [187]. The repair of a cable may require a specialist vessel, and unfortunately, hiring a vessel at short notice can be expensive. Additionally, there may be a delay to the vessel arriving on site (due to vessel availability or weather), which increases the cable downtime [24, 142]. The exact cost of vessel hire depends on several factors, including the availability

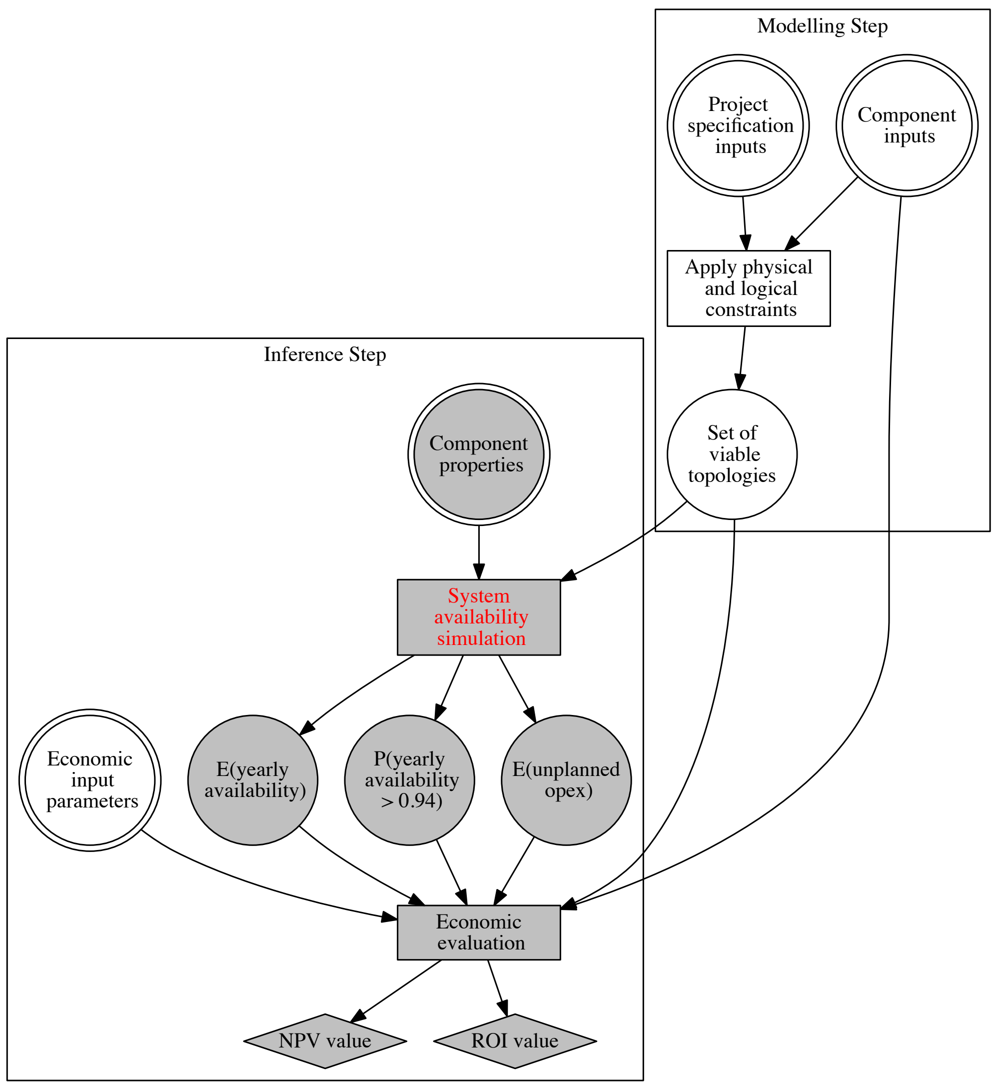


Figure 8.7: Simplified block diagram to explain epistemic and aleatory uncertainty in our analysis. The grey filled nodes show where epistemic uncertainty is included in the modelling process. The nodes written in red font indicate where we consider aleatory uncertainty in our analysis. The diagram also shows the modelling step and the inference step.

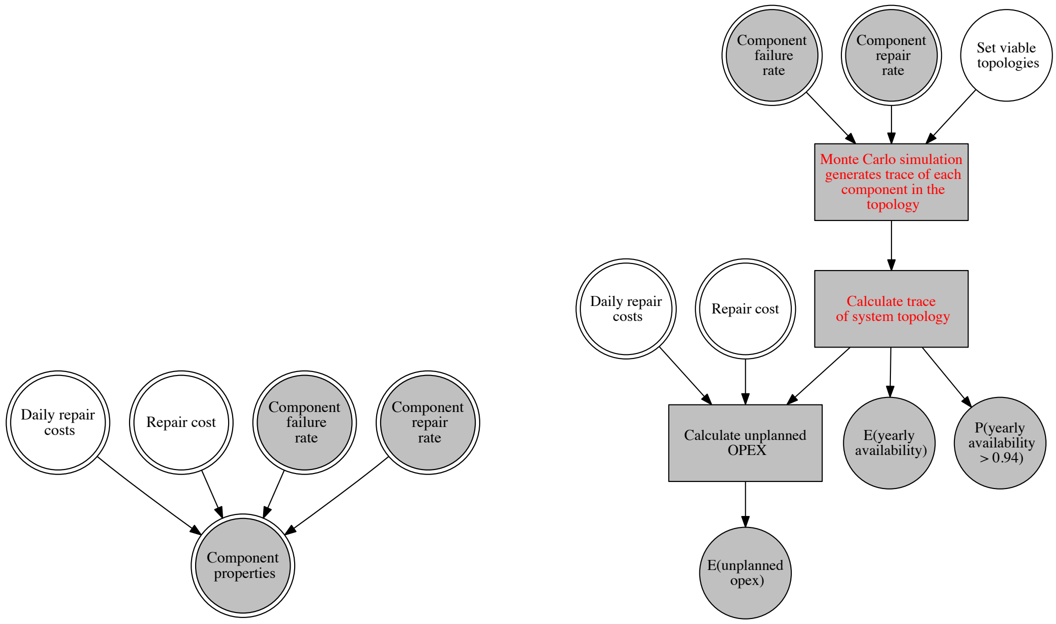


Figure 8.8: Block diagrams for component properties (on the left-hand side) and availability simulation (on the right-hand side).

of vessels. Below, we list the daily vessel hire rates quoted in the literature:

- The day rate of a heavy lift vessel is quoted between £50,000 and £125,000 in [93].
- Vessel daily rates are quoted to be £102,000, £147,300, and £192,600 for a 800, 1000, 1200 tonne jack up crane capacity, respectively [155].
- Daily rates for the spot market are quoted between £95,300 and £287,400 in [71].
- In a recent export cable repair, the rate for vessel and crew hire per day in UK waters was approximately £100,000 [190].

The amount of planned operational expenditure

Finally, we consider uncertainty in the model input required to evaluate the planned OPEX, which is also an act-state independent variable. In Chapter 4, we discussed that OFTOs conduct planned maintenance to ensure good system conditions. When detailed data is unavailable, yearly planned operational expenditure is estimated as a percentage, α, of the capital cost of the OTS [104, 177, 17]. There is uncertainty around the input parameter α as it is often determined by expert knowledge.

Literature estimates the operational expenditure of cables to be 0.4% of the capital costs [177]. Similarly, the study by [104] uses a yearly maintenance cost of the substation to be 0.4% of the capital costs of the transmission link. Furthermore, the work by [17] takes the annual maintenance costs of a HVDC connection to be 0.5% of the transmission

Input Parameter	Values considered
Loan interest Rate	0.01, 0.03, 0.05, 0.065
Vessel hire per day (£)	50,000, 100,000, 150,000, 200,000
Planned OPEX factor	0.005, 0.01, 0.015, 0.02

Table 8.6: Summary of input values for act-state independent variables that contain uncertainty.

capital costs and the lifetime maintenance costs of HVAC connection to be 15%. In this study, we assess how the decision changes for different input values of α between 0.5% and 2%.

One limitation of this work is that the model does not account for unavailability due to planned maintenance. Further work could investigate including this.

Summary of input values considered

In the section, we have detailed the model inputs that contain uncertainty. We also presented literature values for the act-state dependent variables (offshore cable failure and repair rate), and the act-state independent variables (loan interest rate, vessel hire, and planned OPEX factor). Table 8.6 shows a summary of input values for the act-state independent inputs, and they will be used to obtain the results in Section 8.4.

In this section, we also explained that it is challenging to assign distributions to model the failure and repair behaviour of offshore cables. Consequently, we consider a reasonable set of distributions by assigning ranges to these inputs and considering all distributions within these ranges. Therefore, the analysis that follows uses the following bounds on the offshore cable failure rates: 0.000705 fails/year/km to 0.0016 fails/year/km (for HVAC systems) and 0.0001 fails/year/km to 0.0007 fails/year/km (for HVDC systems). In this study, we also assume that an offshore cable repair takes between 40 days and 150 days.

8.3.3 Decision Criteria

So far, in step two (the inference part of the decision analysis), we have presented a methodology to evaluate bounds on the expected value of two economic metrics. Additionally, we have discussed and detailed the input data, in particular, the ranges for which we consider all distributions within. This methodology allows us to obtain bounds on the expected NPV and ROI for each viable offshore transmission system (OTS). Next, we explain how to analyse and compare these intervals to select the optimal option.

In Chapter 5, we introduced several decision criteria that exist to make decisions under severe uncertainty using imprecise probability. On account of the presence of act-state dependence, we use interval dominance and Γ-maximin as the decision criterion to select the optimal OTS. These criteria were discussed in Chapter 5. Here, we repeat a brief description of these criteria for convenience.

Firstly, Γ-maximin is a more conservative decision criterion, and selects the option with the greatest lower bound. The second decision criterion that we use is called interval dominance, and may be chosen if the decision maker is more tolerant to risk. Interval dominance selects any option which is not interval dominated by another option, where option A interval dominates option B if the interval for option A is entirely to the right-hand side of interval B.

8.3.4 Sensitivity Analysis

To handle uncertainty in the act-state independent variables, we investigate how the decision changes as a function of fixed values of the act-state independent variables. To explain the methodology, and to aid the interpretation of future plots, Fig. 8.9 shows how to construct the sensitivity analysis plot. For this example, we use topologies designed for a 1200 MW project located one hundred kilometres offshore. To aid clarity, we only show the results for eleven of the possible topologies that were designed in the modelling step; these are labelled A to K.

The first plot (shown in the top-left of Fig. 8.9) shows the bounds on the expected net present value (NPV) for each option when the value of the loan interest rate is fixed at 1%. The Γ-maximin decision criterion selects the option with the greatest lower bound. A vertical dotted line is added to the plots at the value of the greatest lower bound, the Γ-maximin value, to aid readability. In the first plot, the Γ-maximin line (shown in blue), is in-line with the lower bound of option E. The plot shows that option J has bounds completely below the Γ-maximin line. Accordingly, using the decision criterion termed interval dominance, option J is dominated by the other options. Therefore, the optimal set of options contains all the options except for option J.

On the next plot (shown in the top-right of Fig. 8.9), the bounds on the expected NPV when the loan interest rate is 3% are added. Next, we find the Γ-maximin option, which remains unchanged as option E. We add a purple dotted line at the Γ-maximin value and see that there are no options whose bounds fall below this line. Consequently, the set of options selected using the interval dominance decision criterion includes all options. Therefore, the decision, using interval dominance has changed as the value of the loan interest rate changes from 1% to 3%.

The third plot (shown in the bottom-left of Fig. 8.9) shows the bounds on the expected

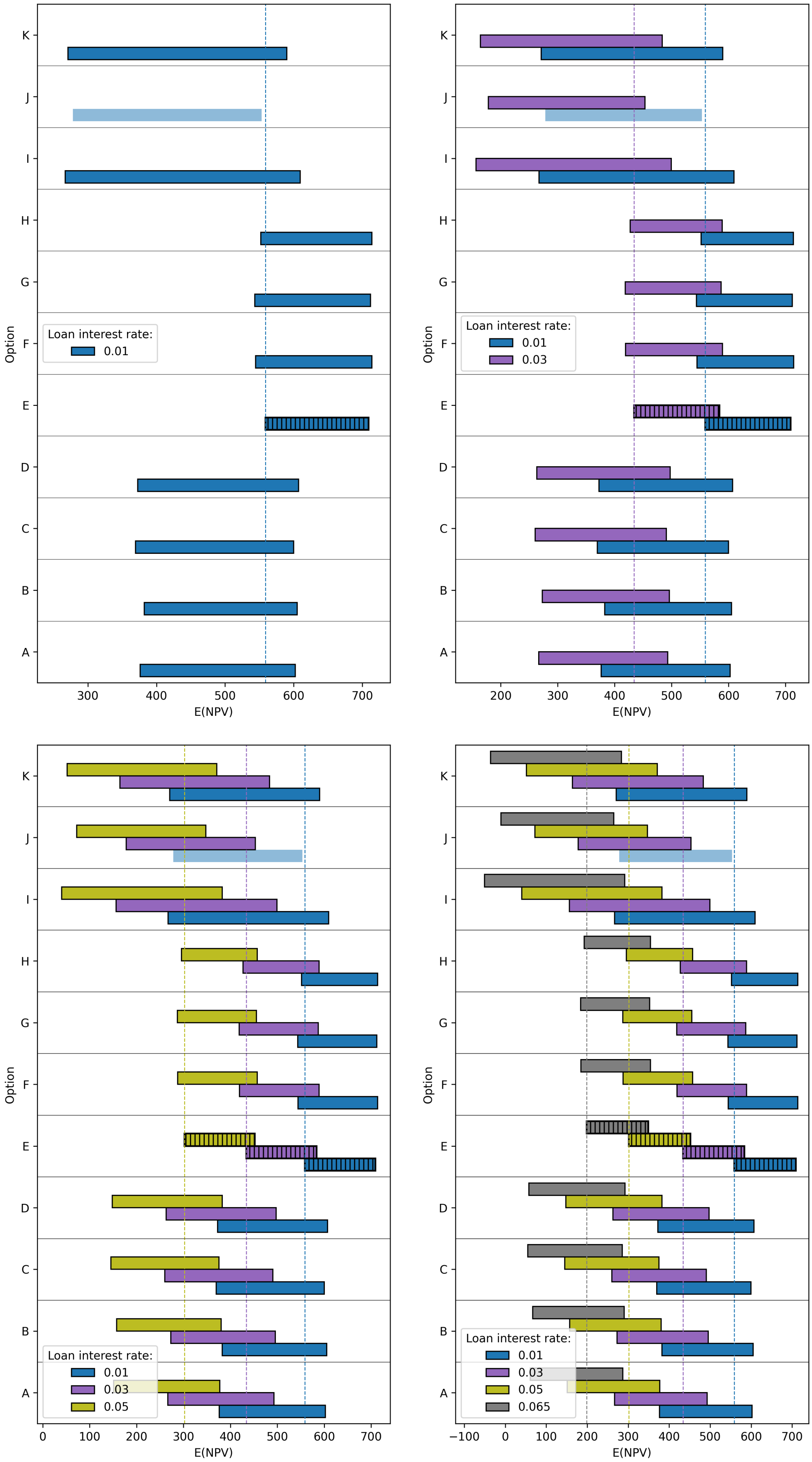


Figure 8.9: Shows the construction of the sensitivity analysis results plot and accompanies the explanation in this section.

NPV when the loan interest rate is changed to 5%. Using the Γ-maximin decision criterion, we again select option E. The plot shows that, again, no options remain below the Γ-maximin. Therefore, the decision made using interval dominance is unchanged (from 3% to 5%).

Finally, the fourth plot (shown in the bottom-right of Fig. 8.9) includes the bounds on the expected NPV when the loan interest rate is 6.5%. The Γ-maximin decision criterion selects option E. We see that, again, no options fall below the Γ-maximin line. Therefore, the set of options selected using the interval dominance decision criterion includes all options.

When reporting the results of investigating how the decision changes as a function of fixed values of the act-state independent variables, we present only the final plot. The sensitivity analysis, for each act-state independent variable, will be displayed on a single plot.

There exist some limitations in this sensitivity analysis approach to uncertainty handling. Firstly, we do not investigate aleatory uncertainty (the uncertainty due to variability). Modelling the failure and repair of components by the exponential distribution on the bounds introduces uncertainty due to the random process, and consequently, there will be differences between the realisations of the process. The analysis in Fig. 8.9 does not visualise this type of uncertainty primarily as we aim to maximise (or minimise if appropriate) the expectation of the metric of interest.

Instead, we focus on handling uncertainty in the input modelling parameters on account of the previously discussed severe epistemic uncertainty. Therefore, it is necessary to note that in the resulting plots, the intervals are due to epistemic uncertainty in the input parameters. Importantly, the ranges are not to be confused with confidence bounds which represent the uncertainty due to variability in the modelling process. Secondly, this analysis only handles uncertainty in one act-state independent variable at a time. Visualising the analysis in a way that is clear to interpret becomes challenging beyond one variable. Therefore, we restrict the analysis to one variable at a time.

8.3.5 Aleatory Uncertainty

So far, we have described a methodology that models aleatory uncertainty; however, we have not visualised this. Instead, we focused on expectations. In this section, we turn to visualise aleatory uncertainty, as some decision makers may be interested in the variability. Assessing the variability could be a secondary consideration in the decision making process, as it provides extra information and could narrow down the set of optimal options. For example, a decision maker may disregard an option if the variability is large and unfavourable.

In this example, we implemented the methodology of this chapter to design an offshore transmission system (OTS) for a 1200 MW project located one hundred kilometres offshore. We first designed forty-four possible topologies and then to select the economically preferable topology, we calculated bounds on the expected NPV. In Fig. 8.10, we present the distributions of the NPV realisations for one topology option. Ideally, it would be useful to have this information about variability when making investment decisions. Furthermore, it would be useful to have this information visualised for all options to allow the decision maker to understand the variability about the expectation.

Fig. 8.11 shows the aleatory uncertainty for all of the options in this example. A black outlined box shows the bounds on the expected value of the NPV. The box is filled in grey for interval dominant options, and black for Γ-maximin options. The vertical dotted line shows the Γ-maximin value to aid interpretation. The blue histograms show the worst-case scenario, and the red histograms show the best-case scenario. This is similar to Fig. 8.10, however Fig. 8.11 shows the information for all options. The blue dots show one standard deviation either side of the mean for the worst-case scenario. Similarly, the red dots are for the best-case scenario. For the input data used, Fig. 8.11 suggests that there is more significant variability for options seventeen onward (corresponding to the HVAC systems). Based on this extra information, a decision maker may choose to disregard options with considerable variability, especially if the economic metric is unfavourable.

8.3.6 Adapting to Other Markets

So far, this analysis has focused on the UK market and analysed from the perspective of an OFTO. This section details how this methodology could be adapted to other markets. Each country adopts an ownership structure for an offshore wind power plant. Moreover, in Chapter 2 we noted that the different approaches fall into three broad categories: a separate entity owning the offshore transmission system (OTS), the wind farm developer extending their ownership to include the OTS, and the onshore transmission system operator (TSO) extending their responsibilities offshore to include the OTS.

Firstly, we discuss how the methodology could be adapted for the scenario where the offshore wind developer also owns the OTS. The main difference between the various ownership structures is the revenue stream formulation in the economic model. The revenue stream for the wind farm developer is determined by the amount of energy they sell to the onshore grid and the market price. Furthermore, the amount of energy sold to the grid depends on the availability of the OTS.

With regard to OPEX and CAPEX, in a full economic analysis from a wind farm

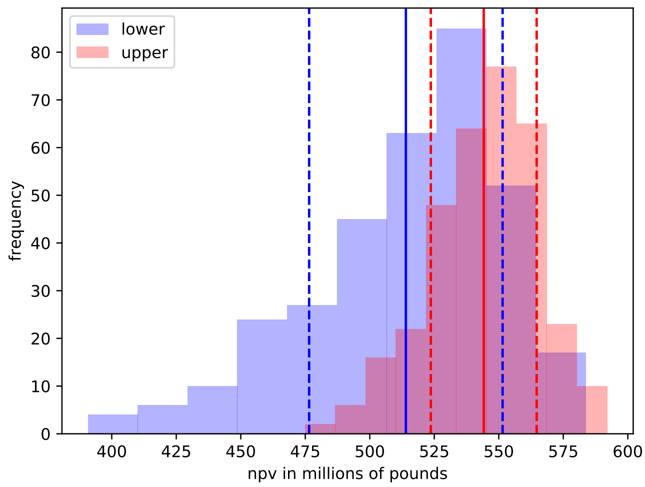


Figure 8.10: For one option, a histogram of the worst-case realisations of net present value (NPV) shown in blue and a histogram of the best-case realisations of NPV shown in red. The solid vertical lines show the corresponding mean values (blue for worst-case and red for best-case). Similarly, the dashed lines show one standard deviation either side of the mean.

developer's perspective, these values will be much higher as they also include the offshore generating assets (including turbines and array cables). However, the OPEX and CAPEX associated with the offshore transmission assets could be different, as perhaps there is some scope for cost savings due to coordinated maintenance strategies (between the offshore wind farm and the OTS).

With these variables in mind, a wind developer could use the analysis in the following ways. The availability of the OTS is critical to their profit, and therefore bounds on availability could form part of the decision making process. Furthermore, the availability bounds could be coupled with CAPEX and OPEX values relating to each option to assess the balance between availability and investment costs. Additionally, an offshore wind farm owner could conduct an economic assessment for the entire offshore wind farm, including their revenue structure, and implement the methods described in this chapter to handle epistemic uncertainty in the model inputs.

Secondly, we turn to the case of the onshore TSOs extending their assets offshore. It is important to note that an onshore TSO may not have the same freedom and therefore, may have limited technology choices to choose from if they are tightly regulated. Further details on onshore TSO ownership are difficult to obtain. In particular, information on the revenue streams. Therefore, to adapt the methodology described here, an onshore TSO could substitute in their revenue stream model. Another option, similar to the wind

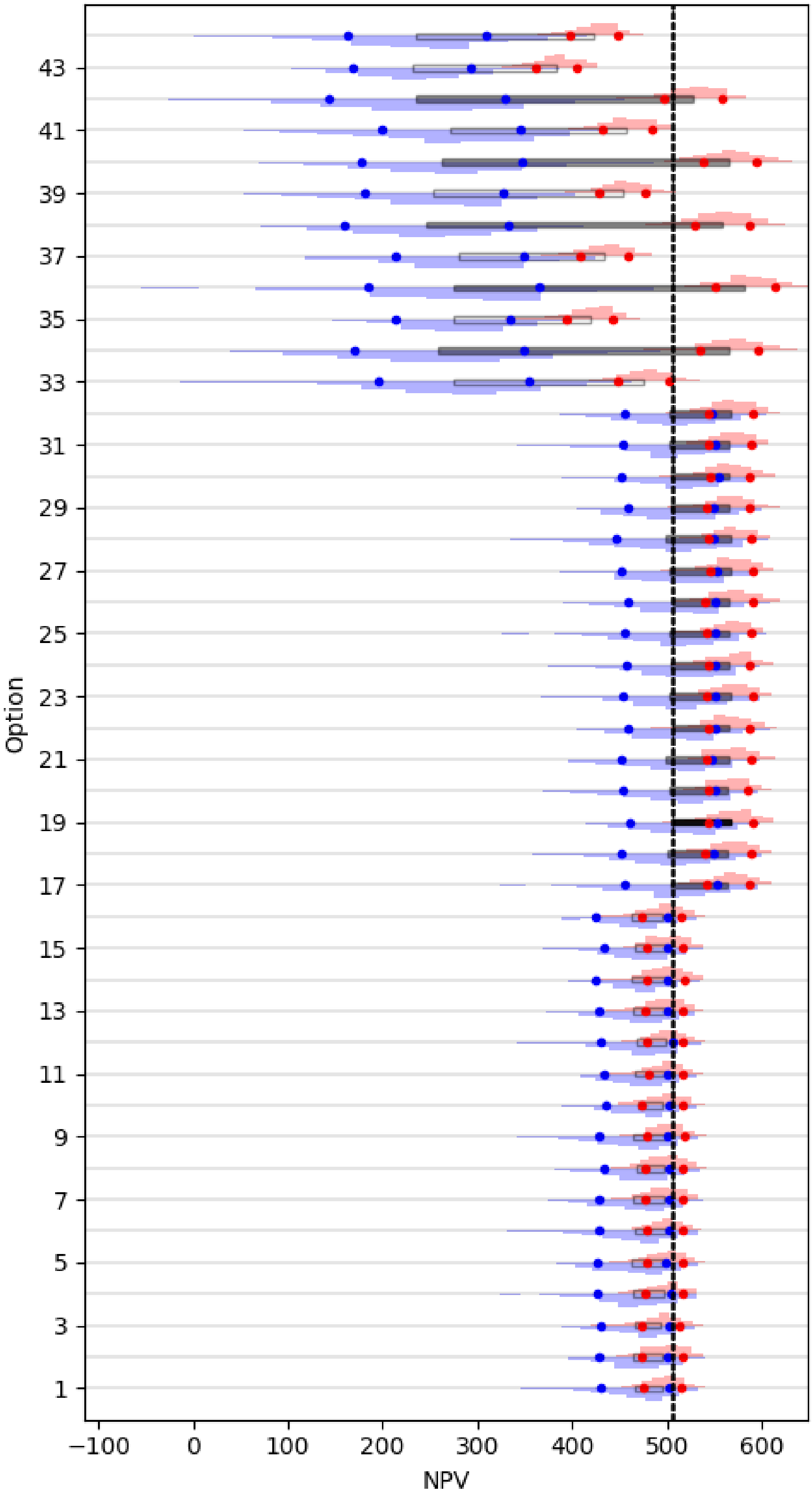


Figure 8.11: Shows the variability around the expectation of NPV for all options. The horizontal boxes show bounds on the expected value of NPV. The box is filled grey for interval dominant options, and black for Γ-maximin options. The vertical dotted line shows the Γ-maximin value. The blue dots show one standard deviation either side of the mean for the worst-case scenario. Similarly, the red dots are for the best-case scenario.

Component	Failure rate	Repair rate	Cost per failure	Daily downtime cost
Component	(fails/year)	(repairs/hour)	(£million)	(£million)
Offshore transformer	0.0105	0.0007	3.75	0.0035
Onshore transformer	0.0105	0.001	2.25	0
Offshore VSC	0.14016	0.005	3.23	0.0035
Onshore VSC	0.14016	0.0417	0.93	0
HVAC offshore cable	-	-	0.0042	0.1426
HVDC offshore cable	-	-	0.0042	0.1426
HVAC onshore cable	-	-	0.0841	0
HVDC onshore cable	-	-	0.0841	0

Table 8.7: Component failure and repair rates used in this analysis [99, 142]. The repair and failure rates for the cables are left empty in this table as they are uncertain due to limited data; these inputs are discussed and presented in Section 8.3.2. Costings are interpreted from [33, 36, 37, 93, 155].

farm developer case, is to use the proposed analysis to obtain CAPEX values and compare these to availability and OPEX bounds. The decision maker could then use these bounds on individual variables in a way that best suits their needs.

8.4 Results

In this section, we present the results of this chapter. The methodology described throughout this work facilitates the design of economically preferable offshore transmission systems (OTSs), for a given generation capacity and distance offshore. Using these design parameters, we identify several possible topologies using the methods described in Section 8.2. Following on from this modelling step, we aim to find optimal topologies from this set of possible topologies by selecting the economically favourable options. On account of the uncertainties described above, we implement techniques based on imprecise probability to find optimal topologies (see Section 8.3).

The analysis requires several input values that are discussed in this paragraph. We evaluate the CAPEX from individual component costs from [33, 36, 37, 146, 38], and using the approach detailed in Chapter 4. For each of the major components, we also require the failure rate, repair rate, one-off repair cost, and cost per day of downtime; these values are shown in Table 8.7. Furthermore, we take the number of operational years to be thirty years, distance onshore (from the landfall to the onshore substation) to be forty

Results case study brief description	Location in chapter
Case study one (700 MW, 30 km offshore)	Section 8.4.1
Case study two (700 MW, 100 km offshore)	Section 8.4.2
Case study three (1200 MW, 100 km offshore)	Section 8.4.3
Impact of cable failure rate scenarios for a 1200 MW project	Section 8.4.4

Table 8.8: A brief description of the studies considered in the results section.

kilometres, the loan duration to be twelve years and the number of loan instalments per year to be four.

In this section, we present the results of the analysis described above applied to four studies which are summarised in Table 8.8. We investigate three case studies: case study one is a 700 MW project located thirty kilometres offshore, case study two is a 700 MW project located one hundred kilometres offshore, and case study three is a 1200 MW project located one hundred kilometres offshore. We use the components given in Tables 8.2 and 8.3 to design OTSs. In practice, a decision maker can input a set of components available to them. The results for case study one, two and three are shown in Figs. 8.12 to 8.18, Fig. 8.19, and Figs. 8.20 to 8.24, respectively.

In the results figures, we show bounds on the expectation of the metrics of interest (conditionally on the act-state independent variables). We initially fix the daily vessel hire rate at £0.1 million, the loan interest rate at 3% and the planned OPEX factor at 0.5%. Then, for each case study and each metric of interest, we investigate how the decision changes as a function of fixed values of these act-state independent variables (displaying one variable at a time for clarity).

Additionally, in Section 8.4.4, we investigate the impact of different cable failure rate scenarios for a 1200 MW project located one hundred kilometres offshore. The description of this study is not exhaustive; nevertheless, it serves as an illustration as to how a decision maker could use the methods to investigate other decision problems of interest. Furthermore, these scenarios demonstrate the applicability of these methods beyond the three case studies considered.

8.4.1 Case Study 1: 700 MW Located 30 km Offshore

The first case study we examine is a 700 MW project located thirty kilometres offshore. To find an optimal OTS for this project, we first design a set of possible topologies by inputting the project design parameters into the modelling step. Tables 8.9 and 8.10 show all the OTSs that are designed in the modelling step. Next, we aim to find which of these topologies is economically preferable, and this is achieved in the inference step of the decision making analysis. The results of the inference step are shown in Figs. 8.12 to 8.18.

Fig. 8.12 shows the results for the metric NPV. Initially, for fixed values of the act-state independent variables, Γ-maximin selects option thirty-one, and interval dominance selects all of the HVDC bipole options. Option thirty-one is a HVDC system with one offshore platform and one branch to the onshore substation. We also note that the NPV tends to be greater for options one to thirty-two (the HVDC systems) than the HVAC systems.

Figs. 8.13 to 8.15 show the results of investigating the impact of the act-state independent variables. While investigating how the decision changes as we consider different fixed values of the loan interest rate, we observe that varying this input has a significant impact on the NPV; nonetheless, the optimal decision is almost unchanged. Whereas, varying the input vessel hire rate has a reasonably small impact on the NPV of the options. Again, the optimal decision remains largely unchanged. We find that, once more, interval dominance selects all HVDC bipole options. However, using Γ-maximin and depending on the value for the vessel hire chosen, the optimal topology varies.

The final act-state independent variable we consider is the planned OPEX factor, and the results suggest that this input has a similar impact to loan interest rate. Varying planned OPEX factor has a significant impact on the NPV; however, the optimal decision remains almost the same. In practice, we note that increased planned operations and maintenance should, in theory, reduce the unplanned OPEX. However, this is not captured by our model.

Secondly, for case study one, we consider the metric annual ROI, and the results are shown in Fig. 8.16. We notice that the results for ROI are considerably different from NPV; and therefore, we observe that the choice of utility function affects the decision (for more detail see the discussion in Section 6.4.2). Notably, for fixed initial values of the act-state independent variables, Γ-maximin selects options thirty-seven, and interval dominance selects several of the topologies (including both HVAC and HVDC technologies). Option thirty-seven is a HVAC topology with one offshore platform, and one branch connecting to the onshore substation. We find that the ROI only differs slightly across all case studies.

Furthermore, we investigate how the decision changes as a function of fixed values of the act-state independent variables. These results are shown in Figs. 8.17 and 8.18. Starting with Fig. 8.17, we observe that the annual ROI remains mostly unchanged for the different vessel hire rates considered, and interval dominance still cannot select between the options. However, for the different vessel hire rates investigated, Γ-maximin selects several options, including both HVAC and HVDC topologies. Another act-state independent variable we investigate is the planned OPEX factor, and these results are shown in Fig. 8.18. We find that the input value impacts the annual ROI of each option; however, the optimal decision is unchanged (Γ-maximin still selects option thirty-seven).

Option	Offshore platform	Offshore transformer*	Offshore cable**	Onshore cable**	Onshore transformer
Option 33	[2, 400]	[1, 350]	[1, 350]	[1.0, 350]	[2, 350]
Option 34	[2, 500]	[1, 350]	[1, 350]	[1.0, 350]	[2, 350]
Option 35	[2, 600]	[1, 350]	[1, 350]	[1.0, 350]	[2, 350]
Option 36	[1, 700]	[2, 350]	[1, 350]	[1.0, 350]	[2, 350]
Option 37	[1, 1200]	[2, 350]	[1, 350]	[1.0, 350]	[2, 350]

Table 8.10: Feasible HVAC topology options for case study one (and case study two) identified using the methods described. Here, * denotes when the quantity is given per platform and ** denotes when the quantity is given per transformer.

8.4.2 Case Study 2: 700 MW Located 100 km Offshore

The second case study we consider is a 700 MW project located one hundred kilometres offshore. To obtain optimal OTSs for this project, we first design a set of possible topologies by inputting the project design parameters into the modelling step. We note that the set of topologies designed for case study one and two are identical in terms of the major components and their quantities because the project capacities are the same. Therefore, Tables 8.9 and 8.10 also shows the topologies designed for case study two. However, since case study two is located 100 kilometres offshore, the cables will be longer, and the HVAC topologies will include a reactive compensation unit. The key differences between the two case studies will be considered in the economic analysis, for example, in project costs and system availability. Next, we aim to find which of the topologies is economically preferable, and this is investigated in the inference step of the decision making analysis. The results of the inference step are given in Fig. 8.19.

The left-hand side of Fig. 8.19 shows the results of evaluating the metric NPV for case study two. The optimal decision, when the act-state independent variables are initially fixed and using Γ-maximin as the decision criterion, is option twenty-four: a HVDC topology with one offshore platform connected to the onshore substation by one branch. We also notice that interval dominance selects all options except for the HVAC connections. The next stage of the decision analysis is to investigate how the decision changes as a

Option		Offshore VSC	Offshore platform	Offshore transformer*	Offshore cable	Onshore cable	Onshore VSC	Onshore transformer
Monopole	Bipole							
Option 1	Option 17	[1, 800]	[1, 1000]	[4, 200]	[1, 800]	[1, 800]	[1, 800]	[4, 200]
Option 2	Option 18	[1, 800]	[1, 1000]	[4, 200]	[1, 800]	[1, 800]	[1, 800]	[3, 250]
Option 3	Option 19	[1, 800]	[1, 1000]	[4, 200]	[1, 800]	[1, 800]	[1, 800]	[3, 300]
Option 4	Option 20	[1, 800]	[1, 1000]	[4, 200]	[1, 800]	[1, 800]	[1, 800]	[2, 350]
Option 5	Option 21	[1, 800]	[1, 1000]	[3, 250]	[1, 800]	[1, 800]	[1, 800]	[4, 200]
Option 6	Option 22	[1, 800]	[1, 1000]	[3, 250]	[1, 800]	[1, 800]	[1, 800]	[3, 250]
Option 7	Option 23	[1, 800]	[1, 1000]	[3, 250]	[1, 800]	[1, 800]	[1, 800]	[3, 300]
Option 8	Option 24	[1, 800]	[1, 1000]	[3, 250]	[1, 800]	[1, 800]	[1, 800]	[2, 350]
Option 9	Option 25	[1, 800]	[1, 1000]	[3, 300]	[1, 800]	[1, 800]	[1, 800]	[4, 200]
Option 10	Option 26	[1, 800]	[1, 1000]	[3, 300]	[1, 800]	[1, 800]	[1, 800]	[3, 250]
Option 11	Option 27	[1, 800]	[1, 1000]	[3, 300]	[1, 800]	[1, 800]	[1, 800]	[3, 300]
Option 12	Option 28	[1, 800]	[1, 1000]	[3, 300]	[1, 800]	[1, 800]	[1, 800]	[2, 350]
Option 13	Option 29	[1, 800]	[1, 1000]	[2, 350]	[1, 800]	[1, 800]	[1, 800]	[4, 200]
Option 14	Option 30	[1, 800]	[1, 1000]	[2, 350]	[1, 800]	[1, 800]	[1, 800]	[3, 250]
Option 15	Option 31	[1, 800]	[1, 1000]	[2, 350]	[1, 800]	[1, 800]	[1, 800]	[3, 300]
Option 16	Option 32	[1, 800]	[1, 1000]	[2, 350]	[1, 800]	[1, 800]	[1, 800]	[2, 350]

Table 8.9: Feasible HVDC topology options for case study one (and case study two) identified using the methods described. Here, * denotes when the quantity is given per platform.

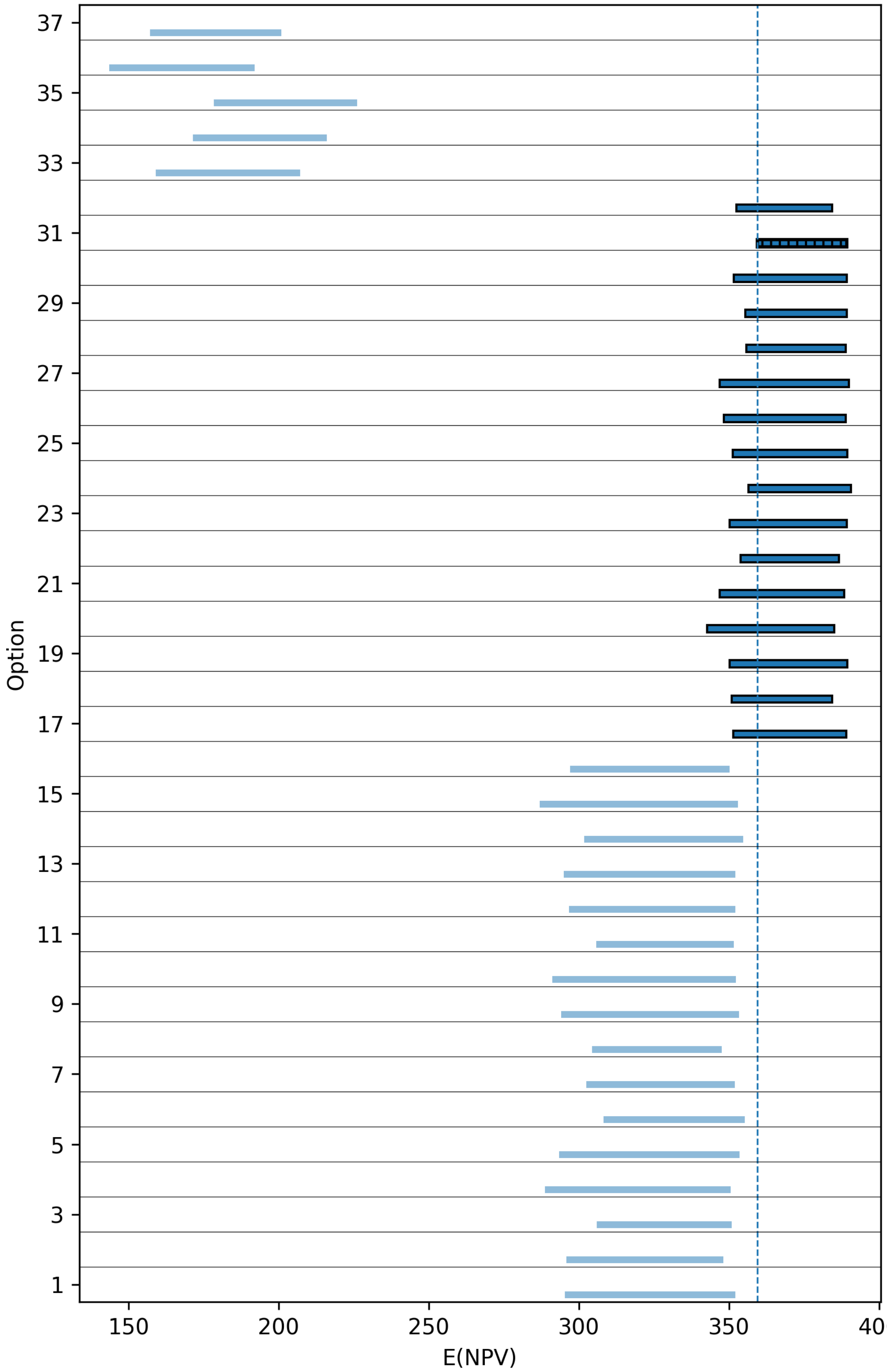


Figure 8.12: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We show the initial analysis for fixed values of the act-state independent variables. The dotted vertical line represents the Γ-maximin line.

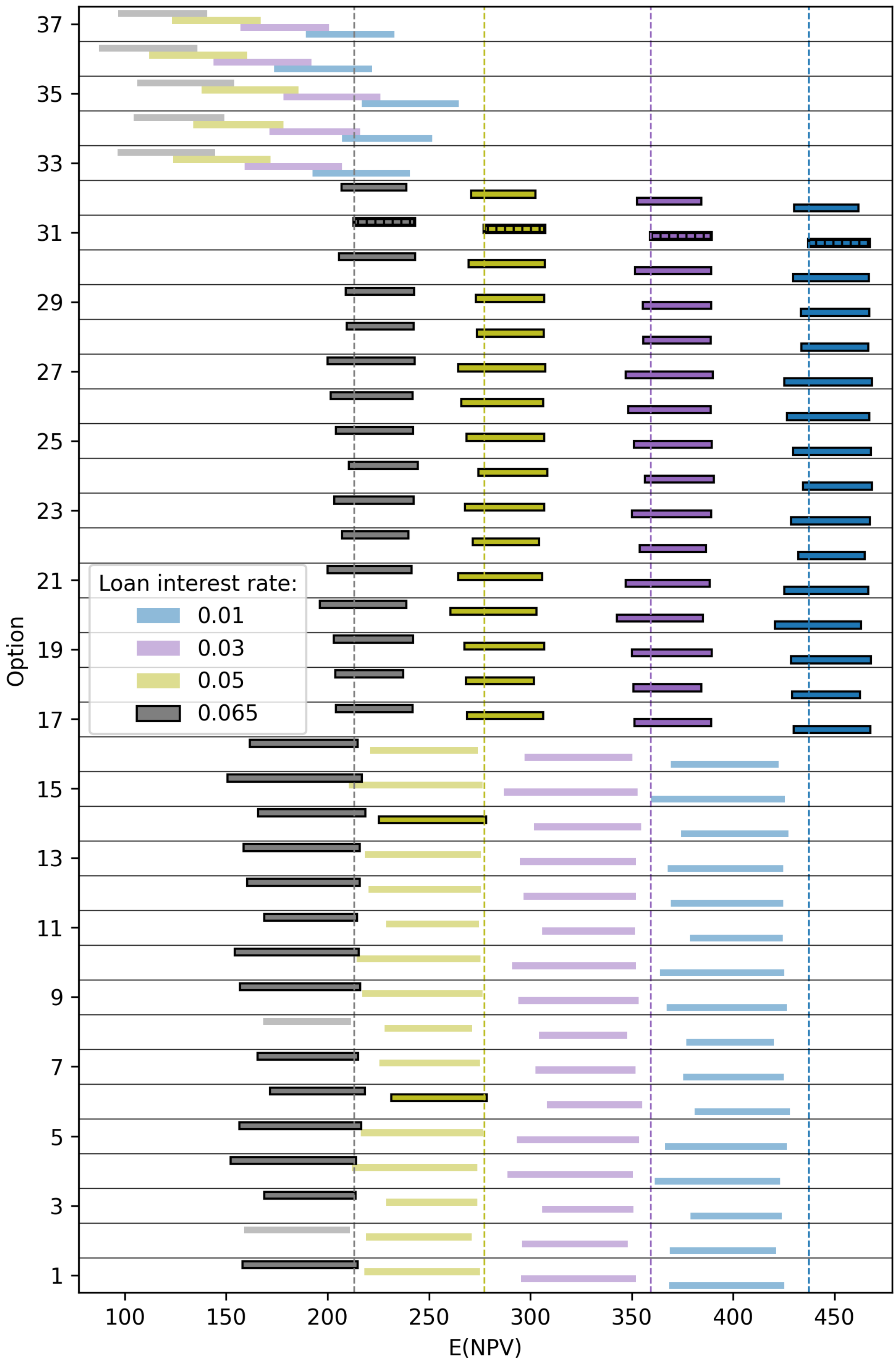


Figure 8.13: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We investigate how the decision changes as a function of fixed values of the input loan interest rate. The dotted vertical lines represent the Γ-maximin lines.

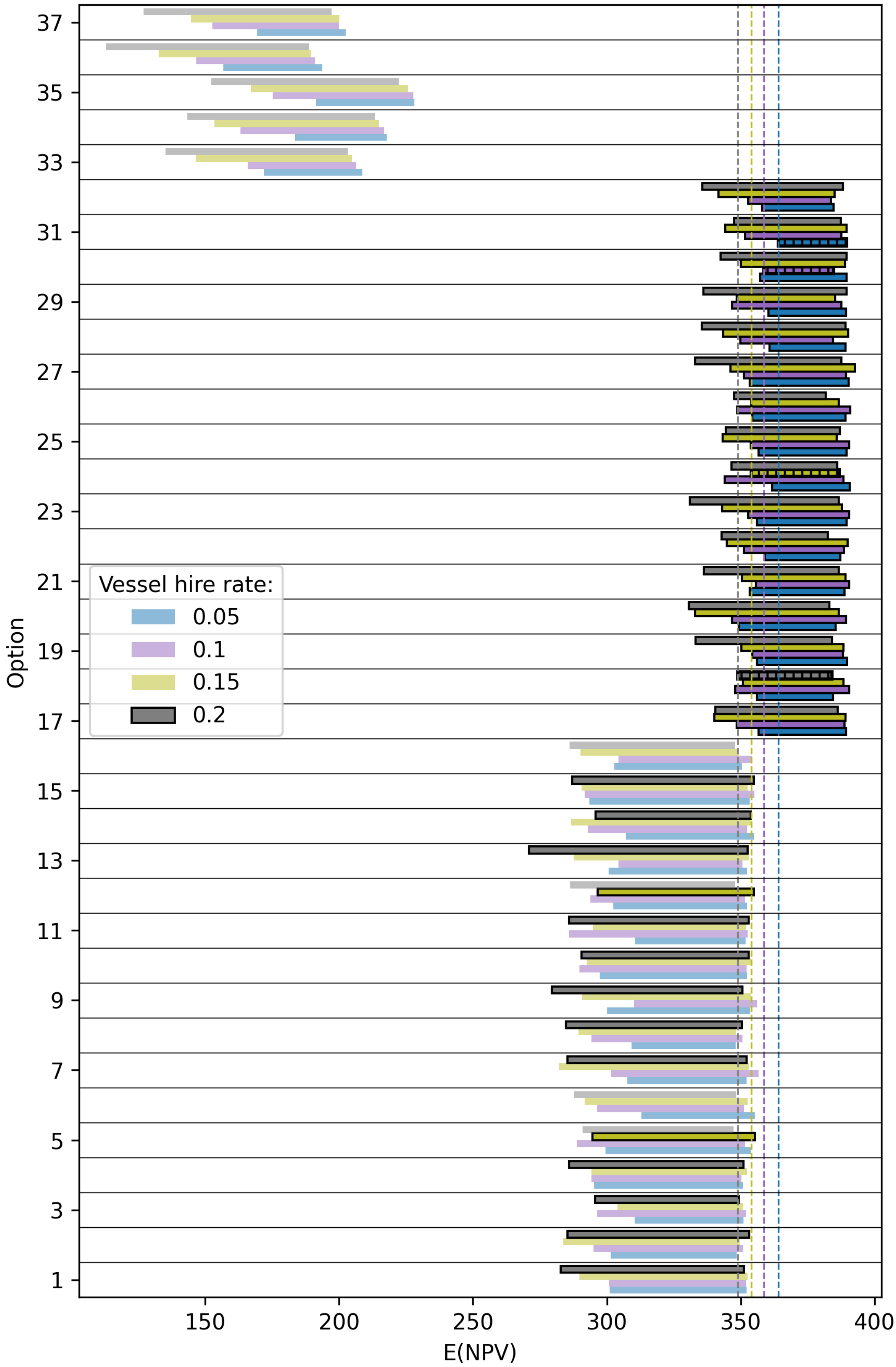


Figure 8.14: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We investigate how the decision changes as a function of fixed values of the vessel hire rate. The dotted vertical lines represent the Γ-maximin lines.

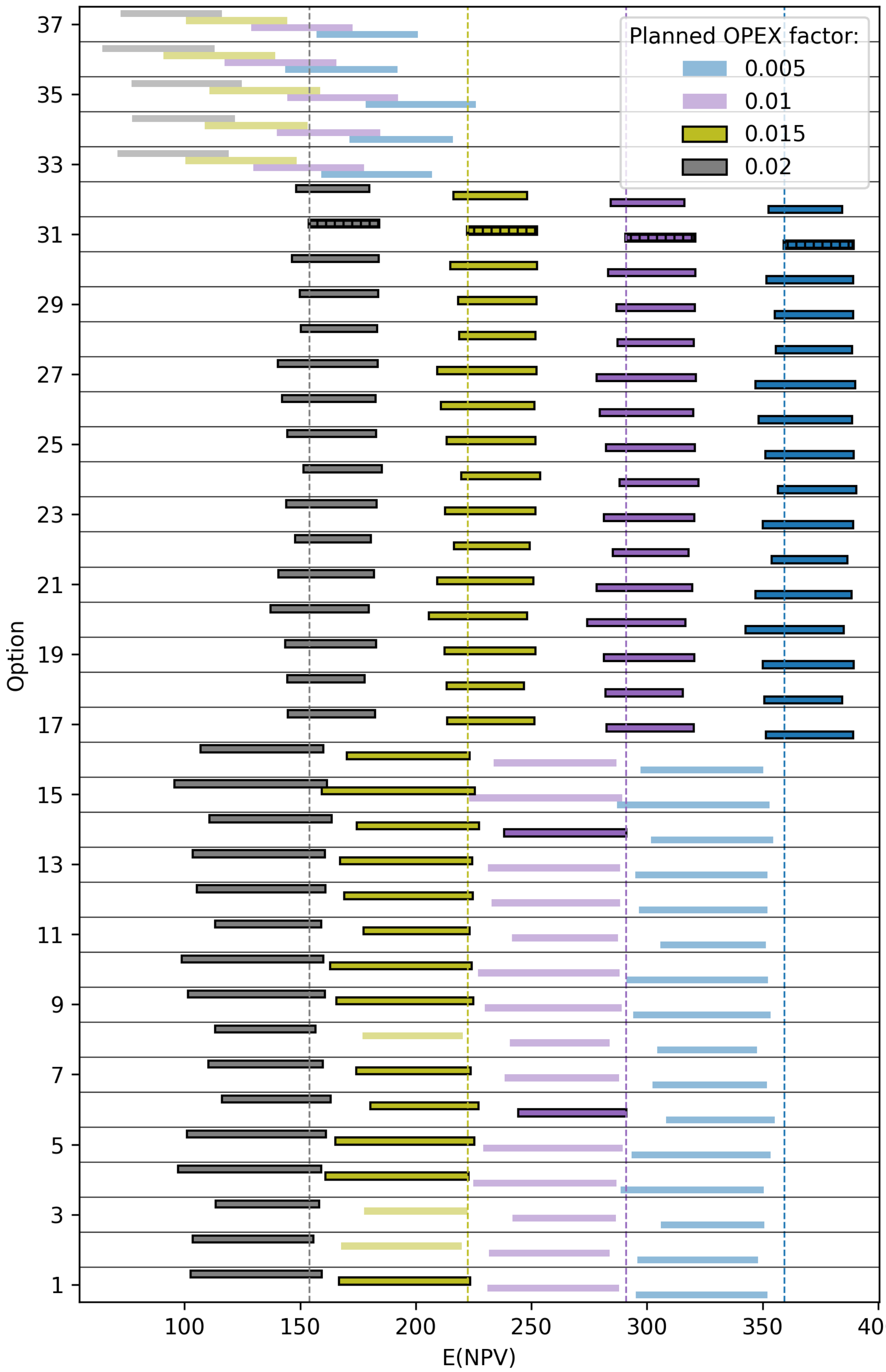


Figure 8.15: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We investigate how the decision changes as a function of fixed values of the planned OPEX factor. The dotted vertical lines represent the Γ-maximin lines.

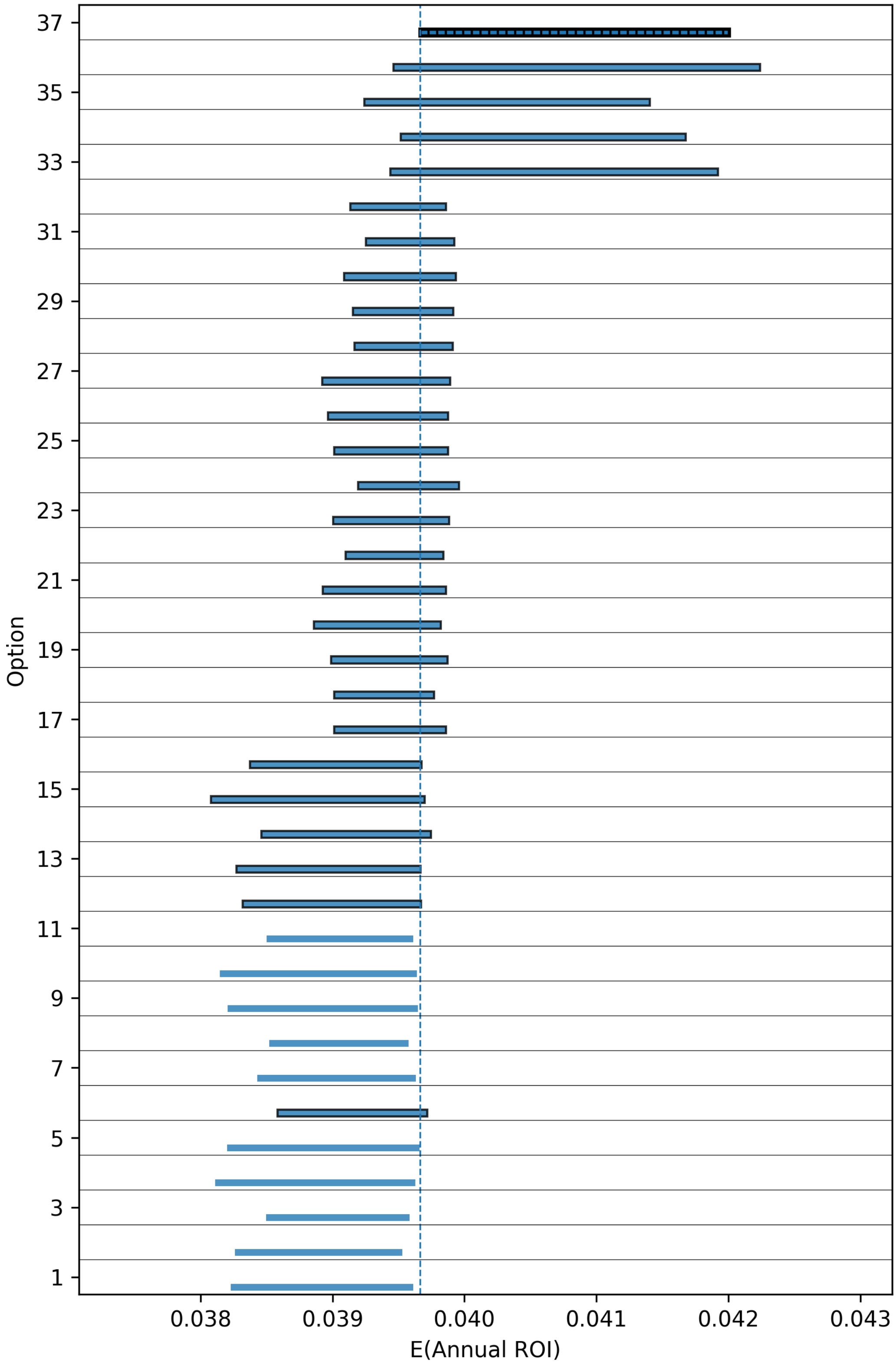


Figure 8.16: Bounds on the expected annual return on investment (ROI) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We show the initial analysis for fixed values of the act-state independent variables. The dotted vertical line represents the Γ-maximin line.

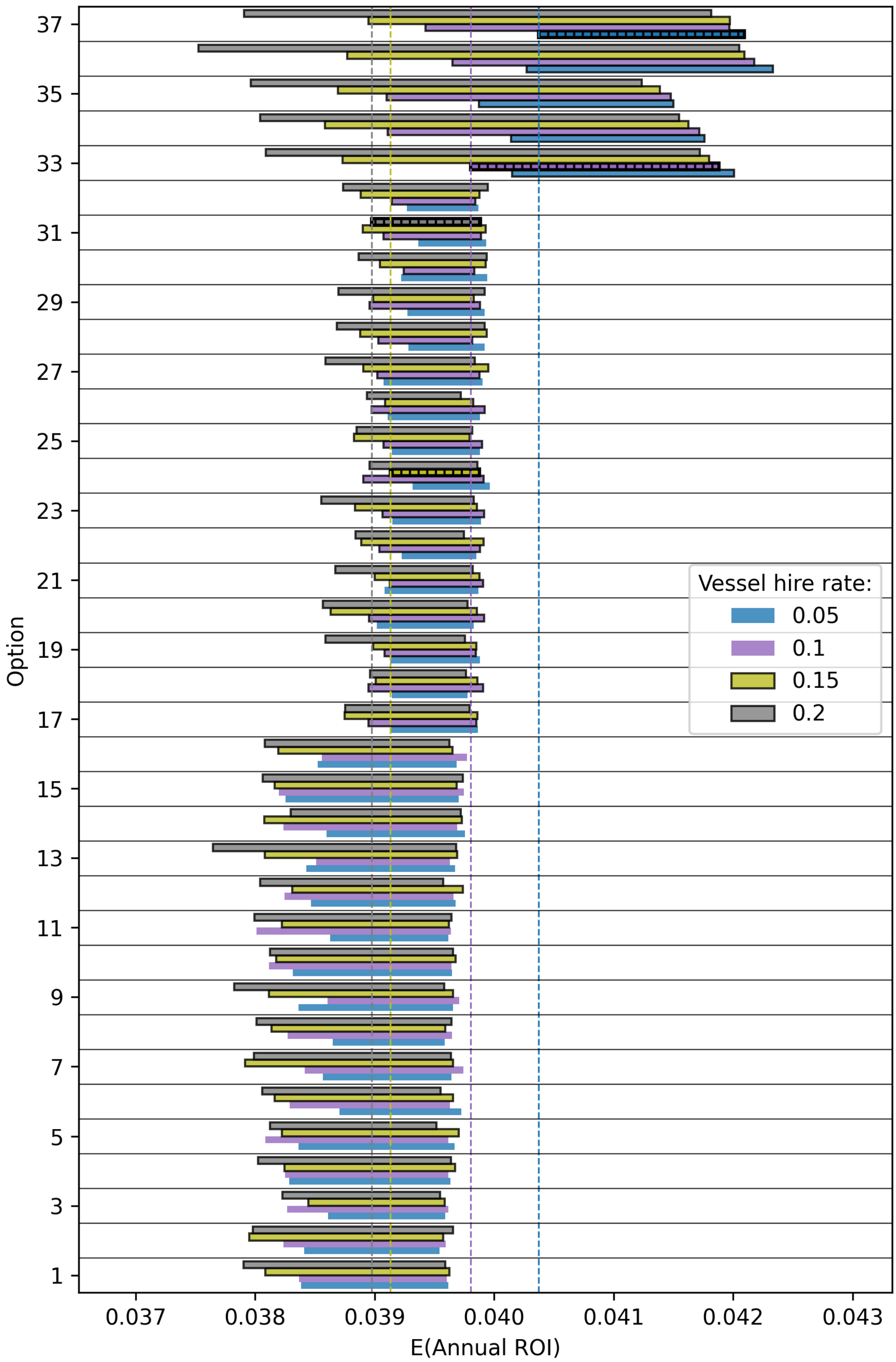


Figure 8.17: Bounds on the expected annual return on investment (ROI) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We investigate how the decision changes as a function of fixed values of the vessel hire rate. The dotted vertical lines represent the Γ-maximin lines.

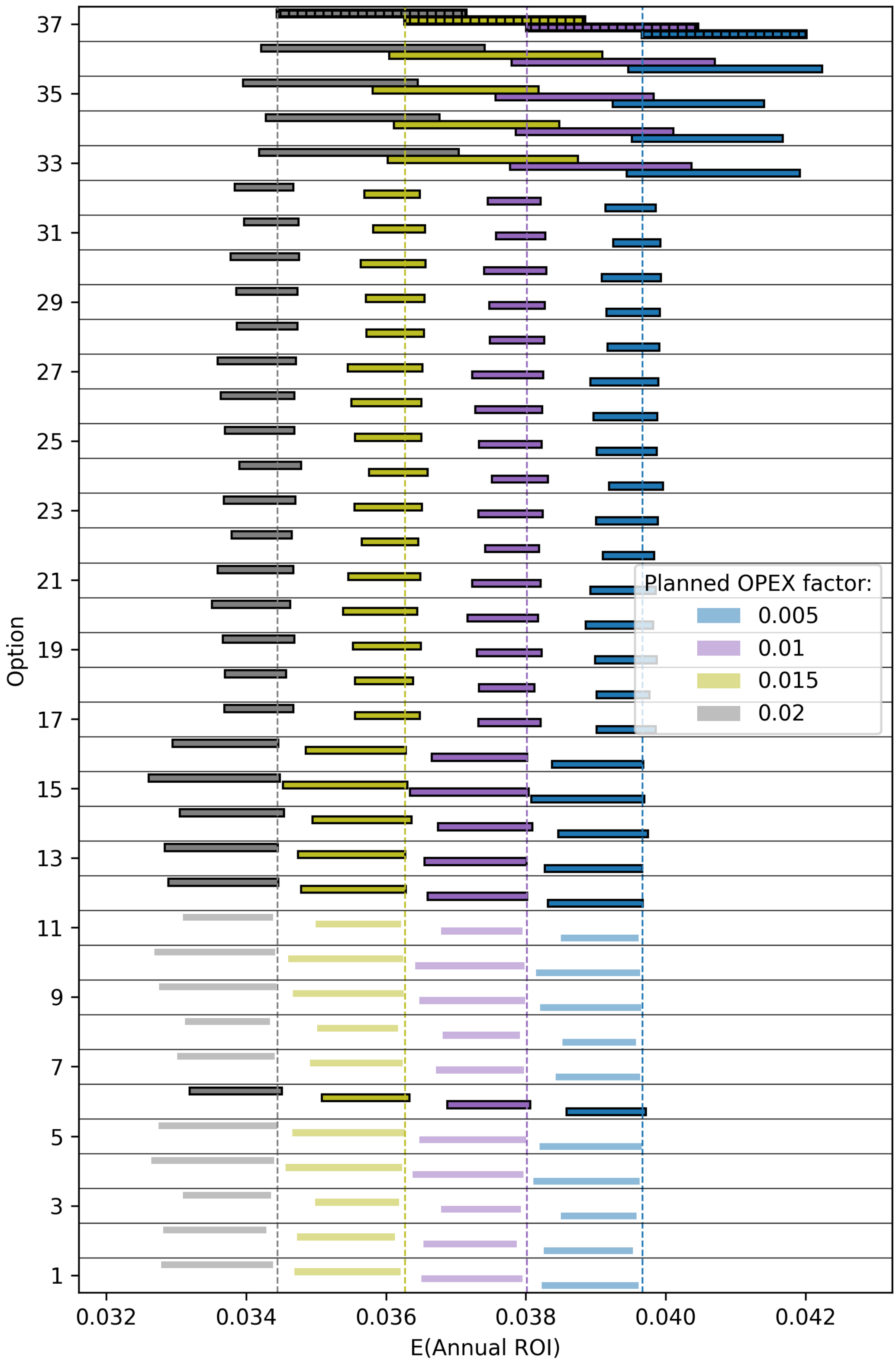


Figure 8.18: Bounds on the expected annual return on investment (ROI) for each option. Here, an option is a possible offshore transmission topology for case study one (a 700 MW project located 30 km offshore). We investigate how the decision changes as a function of fixed values of the planned OPEX factor. The dotted vertical lines represent the Γ-maximin lines.

function of fixed values of the act-state independent variables.

We find that many of the trends observed in the equivalent sensitivity analysis of case study one are also seen in case study two. Therefore, we do not include the resulting figures, but instead, discuss the findings. Varying the planned OPEX factor and loan interest rate significantly impacts the NPV of an option but does not change the optimal decision. Accordingly, option twenty-four is selected using Γ-maximin for all input values considered. Considering different values for the vessel hire rate does not appear to impact the NPV significantly; however, the Γ-maximin option does change. Overall we find that the optimal options using interval dominance are the HVDC topologies; though, occasionally, some HVAC connections are included in the interval dominant set.

The right-hand side of Fig. 8.19 shows the results for case study two considering the metric annual ROI. For the initial scenario, when the act-state independent variables are fixed, Γ-maximin selects options twenty-four, again. Alternatively, we find that the interval dominance criterion selects all options. The sensitivity analysis, which investigates the impact of uncertainty in act-state independent variables, showed similar patterns in the results to the analysis using the metric NPV. Therefore, the visualisation of this analysis is omitted.

8.4.3 Case Study 3: 1200 MW Located 100 km Offshore

In the third case study we consider a 1200 MW project located one hundred kilometres offshore. First, we input these project design parameters into the modelling step to design a set of possible topologies. We recall that this case study was used in Section 8.2.5, and that Tables 8.4 and 8.5 show the topologies that are designed in the modelling step. We note that these topologies are different from those designed in case study one and two as we are considering a larger project capacity. We also note that we have designed more topologies in case study three than the previous case studies. Next, we find which of these topologies is economically preferable by carrying out the inference step of the decision making analysis. The results of the inference step are given in Figs. 8.20 to 8.24.

Fig. 8.20 shows the bounds on the metric NPV for all of the OTSs that have been designed for case study three. We initially fixed the act-state independent variables and found that using Γ-maximin, the optimal topology is option twenty-eight (a HVDC system). We then investigated the impact of uncertainty in the act-state independent variables. These results are shown in Figs. 8.21 to 8.23. Again, we see many of the trends for the previous case studies (changing the loan interest rate and planned OPEX impacts the NPV but not the decision). In many of the scenarios considered, all but option forty-three falls into the optimal set when the interval dominance decision criterion is applied. Importantly,

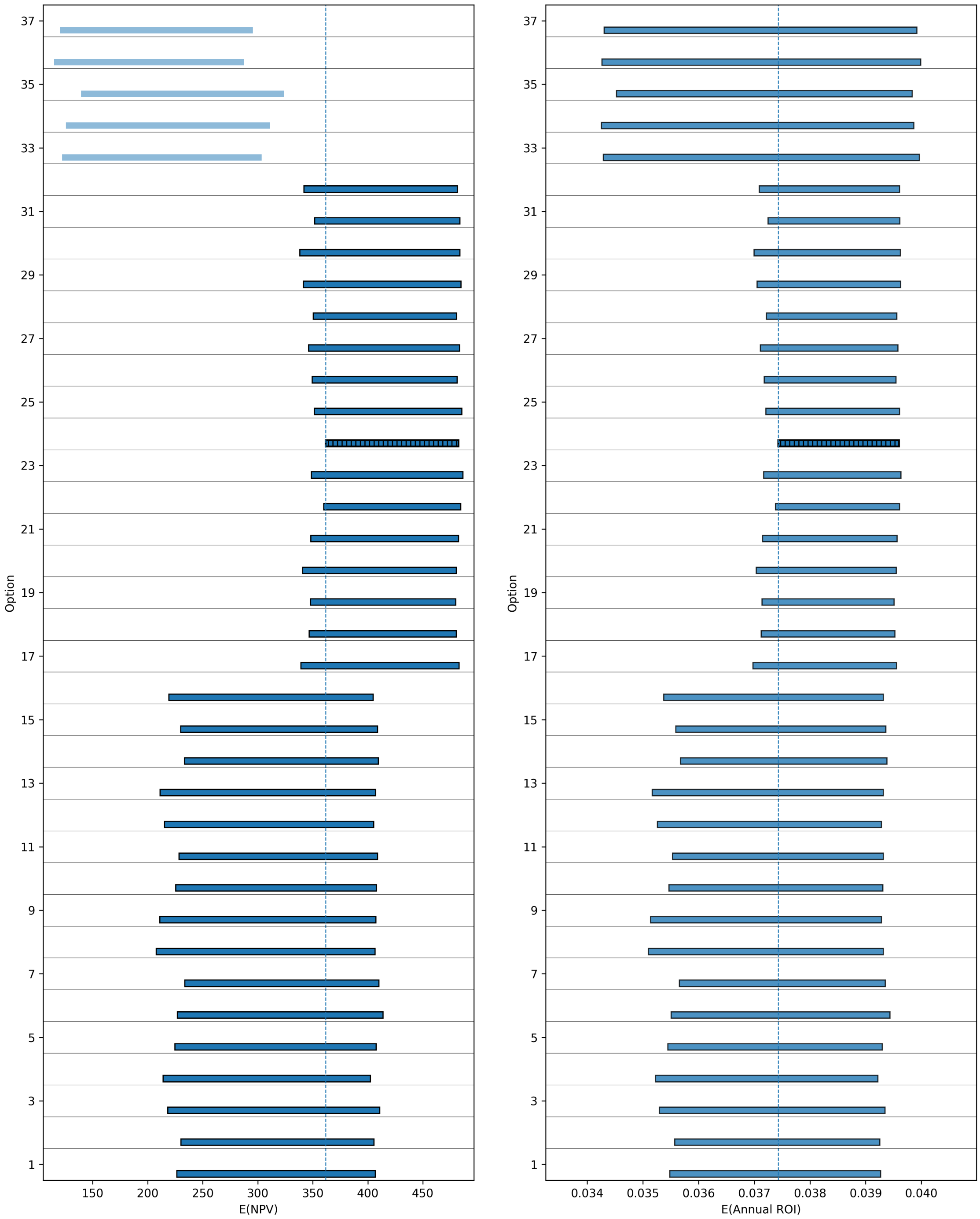


Figure 8.19: Bounds on the expected net present value (NPV) (left) and annual return on investment (ROI) (right) for each option. Here, an option is a possible offshore transmission topology for case study two (a 700 MW project located 100 km offshore). We show the initial analysis for fixed values of the act-state independent variables. The dotted vertical lines represent the Γ-maximin lines.

	HVAC offshore cable failure rate (fails/year/km)	HVDC offshore cable failure rate (fails/year/km)
Scenario 1	0.000705 - 0.0016	0.0001- 0.0007
Scenario 2	0.000705 - 0.0016	0.00021 - 0.0007
Scenario 3	0.0001 - 0.000705	0.00021 - 0.0007

Table 8.11: Scenario description where different ranges for the offshore cable failure rate are considered.

we note that for some HVAC topologies, the lower bound is negative. A negative NPV suggest that a project is not desirable to invest.

Similarly, Fig. 8.24 shows the bounds on the metric annual ROI. We also investigated the impact of uncertainty in the act-state independent variables on the annual ROI and found a similar pattern to the analysis that considered the metric NPV. For this reason, we do not include the visualisation of these results. Notably, option twenty-eight seems preferable in almost all scenarios considered. Additionally, we observe that the HVAC options have wider intervals than the HVDC options. This observation is a consequence of the ranges of the input values used, within which we consider all distributions.

8.4.4 Investigating the Impact of Different Failure Rates

This section focuses on case study three (a 1200 MW project located one hundred kilometres offshore). Here, we now consider different bounds on the offshore cable failure rates within which we consider all distributions. In practice, these bounds are determined by the decision maker and are based on the information they have available to them. The three scenarios investigated are summarised by Table 8.11 and the results are shown in Fig. 8.25.

Fig. 8.25 suggests that using the inputs of scenario one and scenario two result in similar bounds on the expected annual ROI. In contrast, scenario three results in different bounds on the expected annual ROI, in particular, for the HVAC systems. In terms of the optimal decision, interval dominance, for all three scenarios, cannot select between any of the options. Using the decision criterion called Γ-maximin, we select option twenty-seven for scenario one, and option thirty for scenario two and three. The explanation of this study is not exhaustive; but it serves as a demonstration of how a decision maker could use the methods to investigate another decision problem under severe uncertainty.

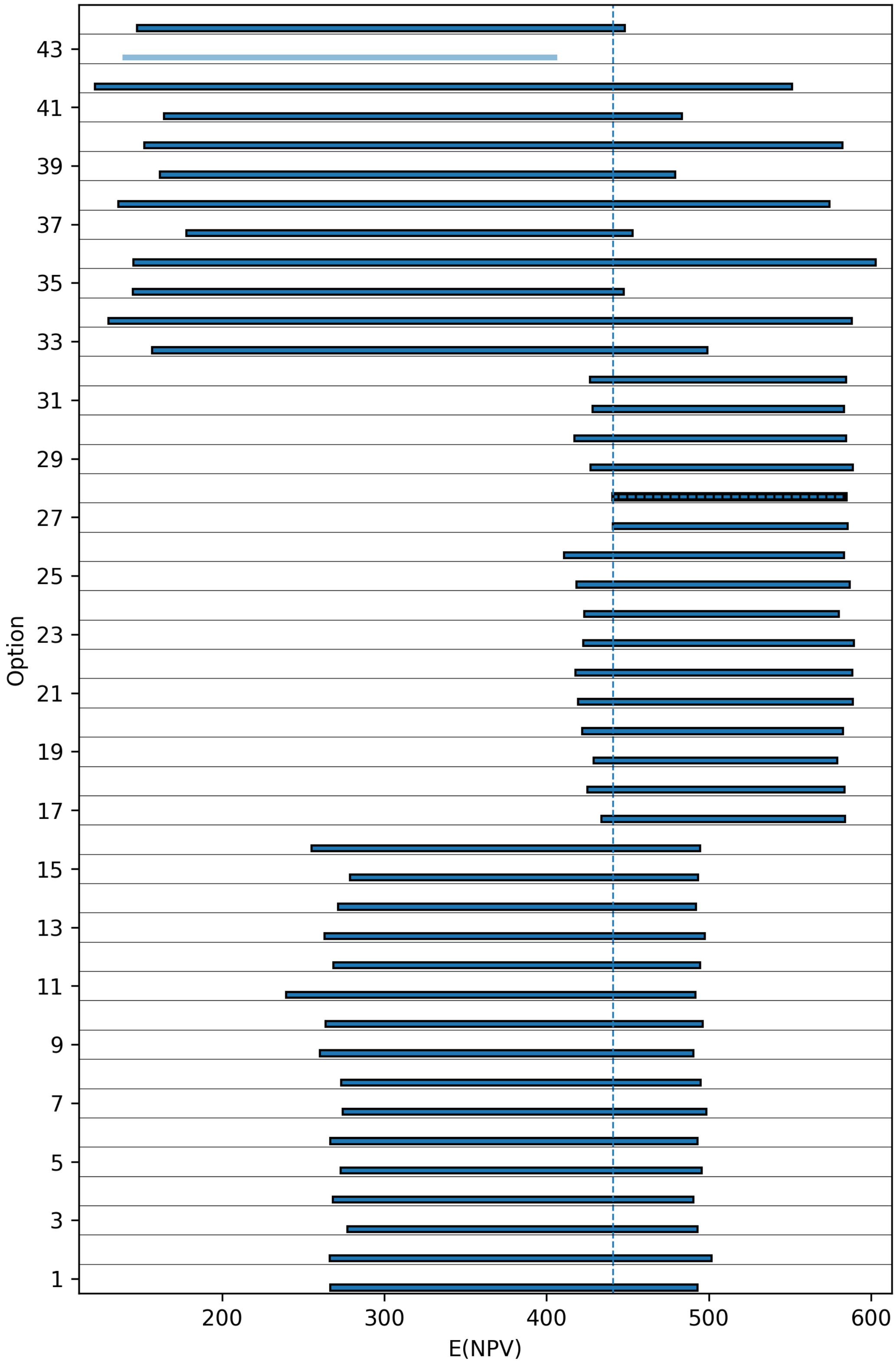


Figure 8.20: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study three (a 1200 MW project located 100 km offshore). We show the initial analysis for fixed values of the act-state independent variables. The dotted vertical line represents the Γ-maximin line.

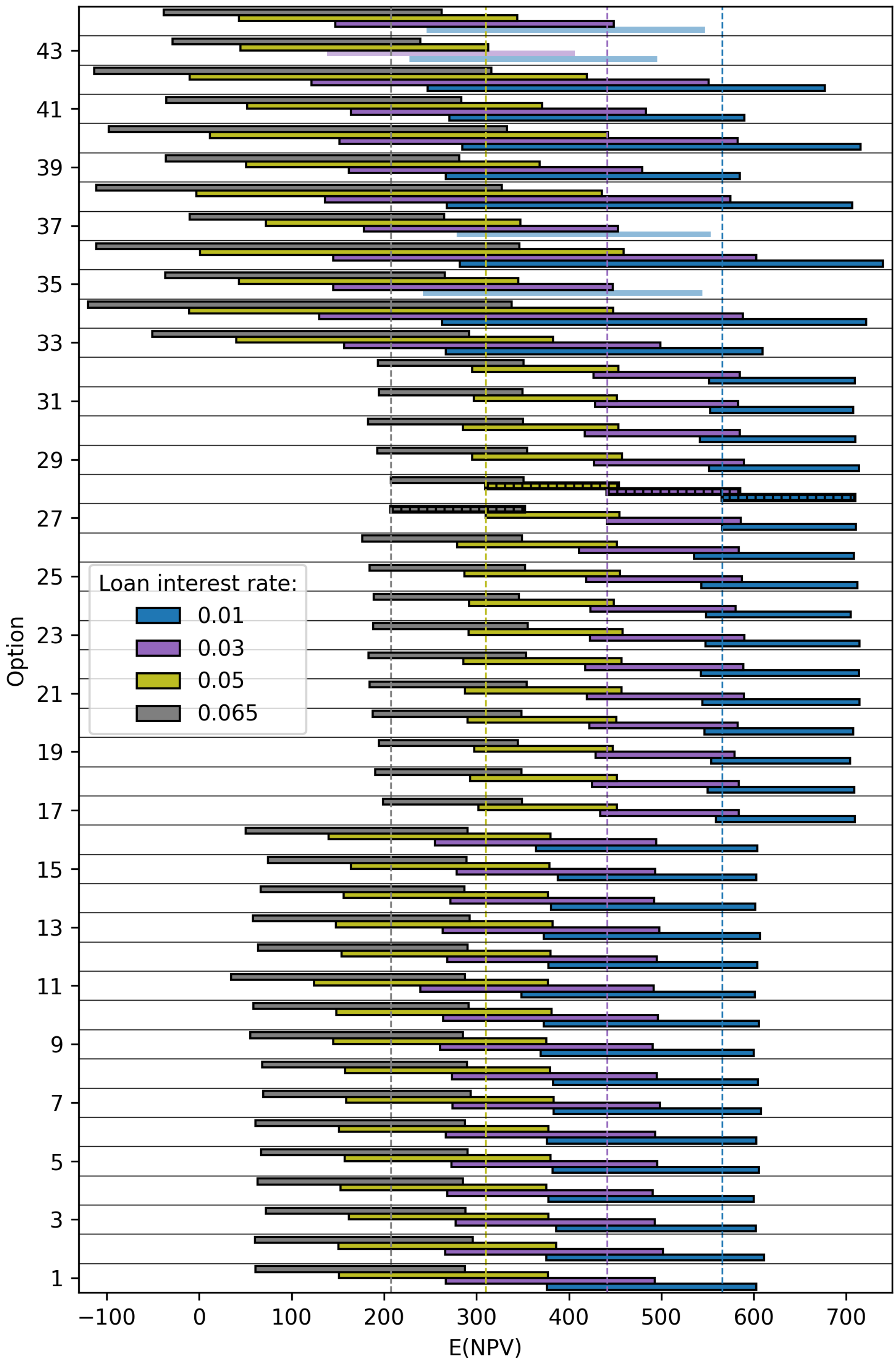


Figure 8.21: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study three (a 1200 MW project located 100 km offshore). We investigate how the decision changes as a function of fixed values of the loan interest rate. The dotted vertical lines represent the Γ-maximin lines.

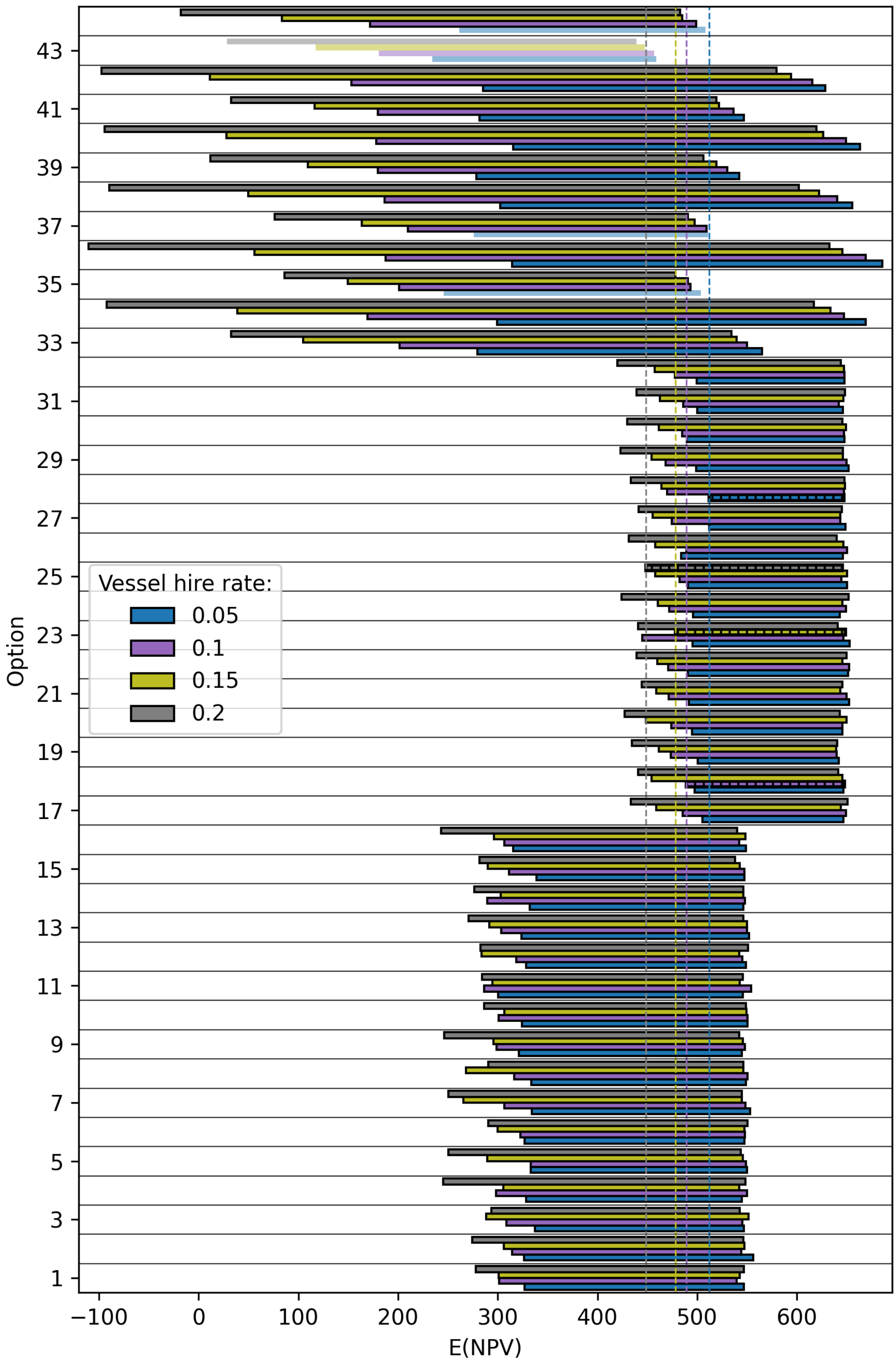


Figure 8.22: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study three (a 1200 MW project located 100 km offshore). We investigate how the decision changes as a function of fixed values of the vessel hire rate. The dotted vertical lines represent the Γ-maximin lines.

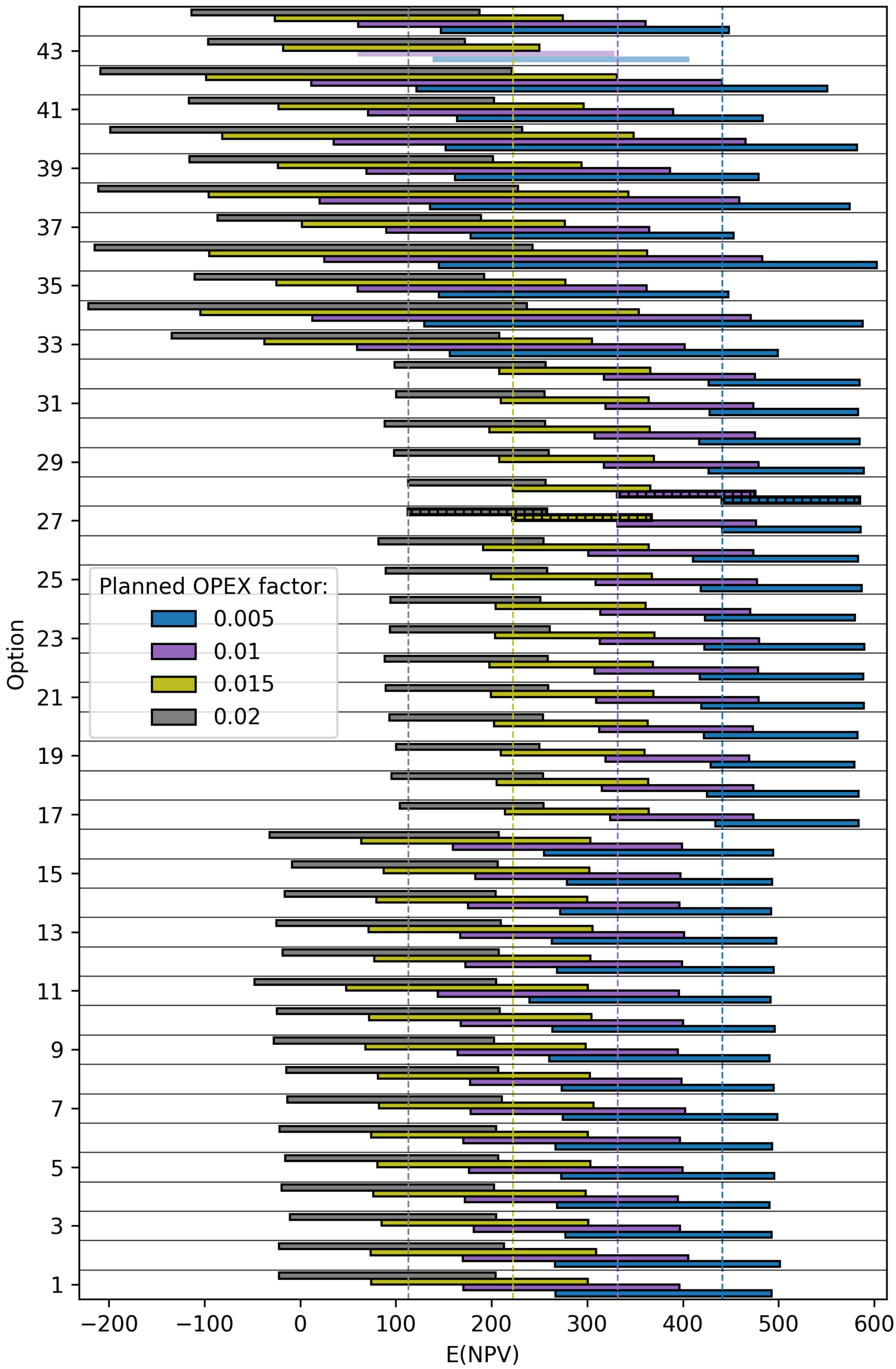


Figure 8.23: Bounds on the expected net present value (NPV) for each option. Here, an option is a possible offshore transmission topology for case study three (a 1200 MW project located 100 km offshore). We investigate how the decision changes as a function of fixed values of the planned OPEX factor. The dotted vertical lines represent the Γ-maximin lines.

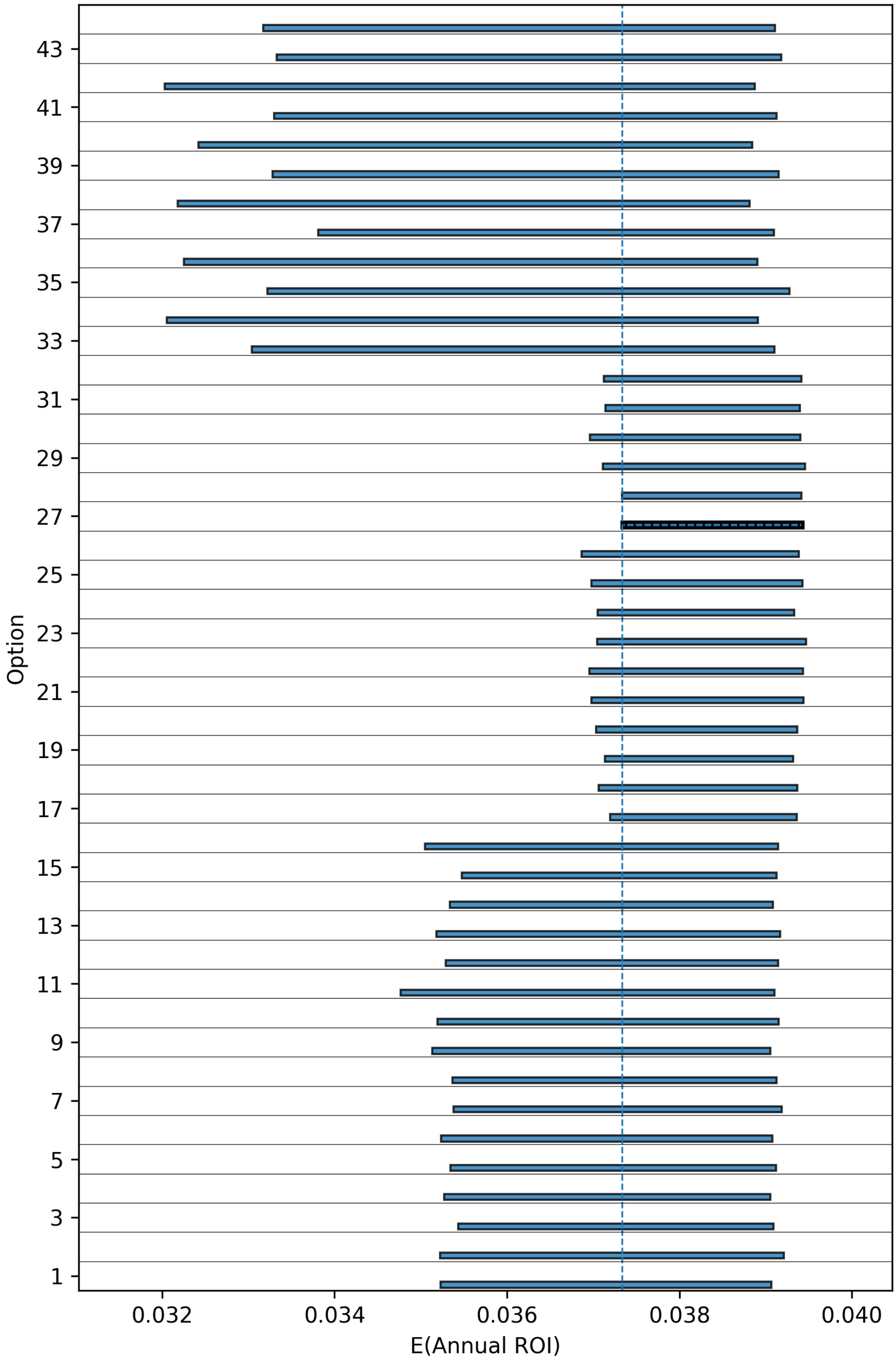


Figure 8.24: Bounds on the expected annual return on investment (ROI) for each option. Here, an option is a possible offshore transmission topology for case study three (a 1200 MW project located 100 km offshore). We show the initial analysis for fixed values of the act-state independent variables. The dotted vertical line represent the Γ-maximin line.

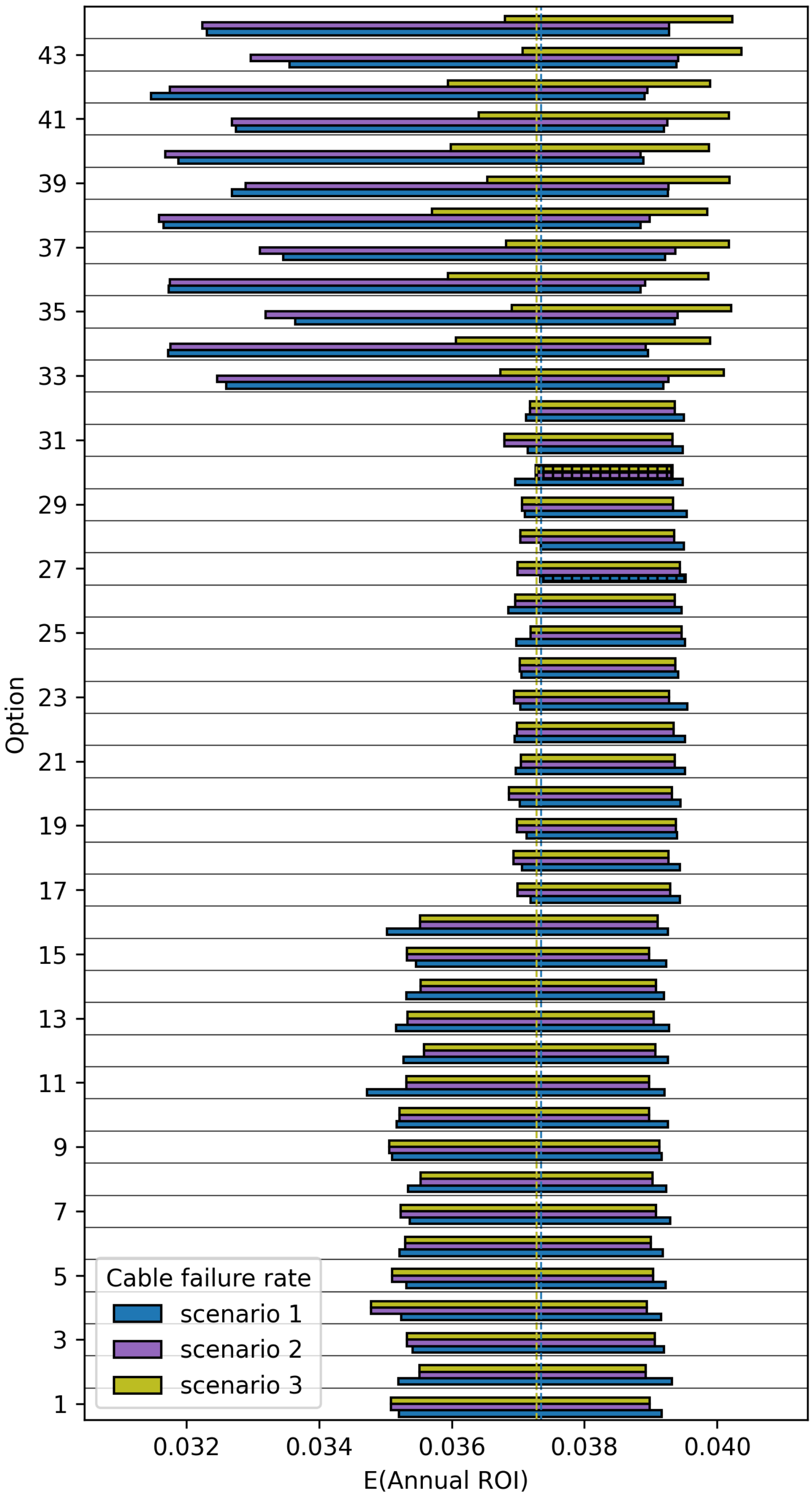


Figure 8.25: Bounds on the expected annual ROI for each option. Here, an option is a possible offshore transmission topology for a 1200 MW project located 100 km offshore. We investigate how the decision changes for the different scenarios investigated (see Table 8.11). The dotted vertical lines represent the Γ-maximin lines.

8.5 Conclusions

This chapter set out to demonstrate and investigate the implementation of imprecise probability to a more comprehensive offshore power transmission decision problem. Therefore, the purpose of this chapter was to present a novel investment planning tool that could be utilised under severe uncertainty. To develop this tool, we set out to design feasible offshore transmission systems (OTSs) from components available in the market, and then evaluate the economic benefit of each topology to select the optimal system. Furthermore, we investigated methods that enable this analysis to handle severe uncertainty appropriately. These research aims culminate to one overarching aim, which was to illustrate how techniques based on imprecise probability could be beneficial to decision makers who make critical investment decisions, regarding offshore transmission assets, under severe uncertainty.

As part of the developed investment planning tool, this study showed how to design the decision space this is a key difference between this chapter and the previous applications. In Section 8.2, we showed how to design HVAC and HVDC topologies from individual components using logical and physical constraints. This modelling step allows us to show, in a more direct way, how the proposed inference techniques introduced in Chapter 5 can be used to aid project planning for a range of projects. Furthermore, this step allows the work to be a more comprehensive investment planning tool.

Additionally, in Section 8.3 we demonstrated how to implement imprecise probability, to enable this investment planning tool to be robust under severe uncertainty. Firstly, we utilised the methods to evaluate bounds on the metrics of interest presented in Chapters 6 and 7. We also discussed the handling of uncertainty in several of the model inputs: offshore cable failure and repair rate, loan interest rate, vessel hire, and planned OPEX factor. Importantly, we show how we deal with uncertainty in act-state independent and act-state dependent variables. Once we obtained bounds for each option, we recalled the decision criteria introduced in Chapter 5, and implemented these techniques to find the optimal topology.

Most of the methodology focused on the expectation of a metric of interest; however, we did explore aleatory uncertainty and showed how the variability around the mean could be a secondary consideration in the decision making process. Before presenting the results, we discussed how the methodology could be adapted to suit the needs of other markets. Finally, we presented the results of the investment planning tool for three case studies.

A significant contribution to emerge from this study is the development of an investment planning decision tool that utilises imprecise probability to more appropriately handle severe uncertainty. The results suggest that: firstly, imprecise probability can be implemented to aid in the planning of OTSs; secondly, the results of the techniques can be visualised in a way that is clear to communicate and interpret; and finally, the proposed techniques advance the current handling of uncertainty in economic evaluations and should be implemented in the case where it is challenging to assign a probability distribution due to limited data.

Chapter 9

Chapter Summaries

In this chapter, we present summaries of each of the chapters in this thesis. Furthermore, we discuss how and where we address the research aims of this thesis. To recap, in Chapter 1 we introduced the thesis and the broader context in which the research of this thesis sits. In Chapter 1, we also outlined the research aims and questions that are addressed in this research, as well as detailing the original research contribution of this work. In Chapters 2 to 4 we motivated the research needs, in particular, the need for advanced statistical methods to support decision making in offshore power transmission. In Chapter 5, we presented the advanced statistical methods proposed to handle severe uncertainty, and in Chapters 6 to 8, we showed the application of the described techniques. In Chapter 10, we will summarise the conclusions of this thesis and discuss areas of further work.

9.1 Chapter 2 Summary

We began by reviewing the literature in Chapter 2 to gain a deeper understanding of the offshore transmission system (OTS) and its current situation. We defined what is meant by an OTS and studied the components that make up this system. We also examined the ownership structures of the OTS adopted by the leading nations in offshore wind. We remarked that the ownership structure usually falls into three broad categories: third-party entity ownership, offshore wind farm ownership and onshore transmission system operator (TSO) ownership.

Following this, we investigated challenges faced by the offshore wind industry, including cost reduction. We established that as offshore wind projects grow in capacity and move further offshore, the role of the OTS becomes even more crucial. From the literature, we identified that the main challenges to planning future OTSs centre around reliability, cost and uncertainty.

Furthermore, we noticed that a common theme amongst the literature reviewed is that there is limited data regarding the OTS, and there is considerable variation in the data that is available. Unfortunately, there is concern that this uncertainty can have substantial impacts on operational projects. Despite these challenges, we learnt that policy, planning and operational decisions would be made to support the development and installation of offshore electrical transmission infrastructure. Additionally, we investigated the types of decisions taken surrounding these assets to realise the relevant problems.

In particular, we gained a deeper understanding of uncertainty due to limited data regarding the failure and repair of offshore cables a key focus of this thesis. Unfortunately, we found that some offshore transmission projects have experienced costly cable failures, and these cable failures occurred more frequently than initially expected. This operational experience suggested that the failure rate of an offshore cable contains severe uncertainty. Using a lower than realistic failure rate in economic assessments that underpin investment decisions could significantly impact the companies involved. Therefore, to address these concerns, we planned to investigate methods that handle severe uncertainty in inputs required for economic assessments.

Chapter 2 motivated the need to conduct research that firstly, investigates suitable methods to handle severe uncertainty in decision making and secondly, explores applying these techniques to decisions made in offshore power transmission. This research attention is on account of the industry's challenge of uncertainty; the growing importance of OTSs; the need to take policy, planning and operational decisions concerning the OTS; and the limited amount of techniques applied in this area that adequately handles severe uncertainty.

9.2 Chapter 3 Summary

In Chapter 3, we collected and curated data that is relevant to the offshore transmission system (OTS). Although relevant data in this space is scarce, some data does exist. This data may be for older projects with previous technologies. Nonetheless, we suggested that this data can be useful as a starting point and to identify trends.

The data presented in Chapter 3 provided details of operational projects in the UK, including a breakdown of the assets involved, availability levels, projects costs and revenue streams. Additionally, we collected component costing data, failure and repair data, and operational costs from the literature. We presented some data for offshore interconnectors to supplement our knowledge of offshore power transmission. Furthermore, we discussed a tool to obtain historical wind speed data that can be used for energy modelling [160].

Finally, we detailed future technologies in the offshore transmission space, as it is vital to understand the direction the industry is expected to move when planning future projects.

The work of Chapter 3 contributes to our understanding of offshore transmission and provides a more in-depth insight into the operational costs and experiences of projects. As offshore power transmission is an area where data is scarce, presenting a collection of the data that is available may be valuable to the research community. With regards to the thesis, the work of Chapter 3 further motivates the need for techniques to handle uncertainty due to a limited amount of relevant data for some inputs parameters, and where data does exist, provides information to input into economic evaluations.

9.3 Chapter 4 Summary

In Chapter 4, we developed and presented a model to evaluate projects economically from an offshore transmission owner's (OFTO) perspective. The model was based on the economic metric net present value (NPV) and considered the revenue streams, capital costs, and operational expenditure. This economic framework could be used to base investment decisions regarding the offshore transmission system (OTS) and therefore, is used throughout the thesis.

In Chapter 4, the methodology was implemented on a 1.2 GW project. Additionally, we used this framework to assess the impact of uncertain model variables on the expected NPV. We found that some variables, in particular, offshore cable failure rate, have a significant impact on a project's economic benefit. Since these economic assessments may be used in the decision making process, we identified a need for advanced statistical techniques when planning future OTSs under severe uncertainty. The results of Chapter 4 further motivated the research objectives of this thesis. Furthermore, the research of Chapter 4 contributes to a deeper understanding of the severe uncertainties involved in offshore transmission planning and their impact on a project's expected profit.

The first research aim of this thesis was primarily addressed in Chapter 4 (although, the work of Chapter 4 builds on Chapters 2 and 3). The first research aim centred around understanding what information and methodology are required to assess the economic benefit of an OTS effectively. To achieve this objective, data, regulatory information and expert knowledge have been collected, curated and, where necessary, combined with statistical techniques, to develop the required bottom-up methodology tailored to the UK market. In Chapter 4, we discussed the need to consider the perspective of a particular stakeholder, and in this case, we chose the OFTO in the UK. Nonetheless, throughout the thesis, we discussed how the model could be adapted to suit the needs of other markets. The developed methodology, and its ability to be applied to more realistically assess offshore transmission projects economically, required the collection and curation of useful data regarding CAPEX, availability, and OPEX from a variety of sources.

In addition, we visually displayed the developed economic model using a graphical representation. This visualisation included displaying all variables required in the model and showing the dependencies between model variables. Furthermore, this graphical representation aids in the communication of the model, and in particular, facilitates a way to convey how uncertainty impacts the analysis. This approach is one way we addressed the fifth research aim of this thesis.

The second research aim of this thesis focused on identifying areas of the economic model that contain severe uncertainty and have a significant impact on the results. In Chapter 4, during the quantification process, many areas were highlighted to contain severe uncertainty. We investigated six input parameters that are uncertain to a degree where it is difficult to assign a distribution. The six input parameters were the planned OPEX factor (α), daily vessel hire rate for offshore cable repairs, the loan interest rate, offshore cable failure rate, offshore cable repair time and CAPEX evaluation parameter (ε_2). We conducted interval analysis to quantify the economic impact of these uncertainties on project performance. The results of Chapter 4 showed that loan interest rate, planned operational expenditure and, especially, offshore cable failure rate are unknowns in offshore power transmission that are critical to the offshore transmission owner's profit.

9.4 Chapter 5 Summary

On account of the findings from Chapter 4, in Chapter 5 we explored more robust methods under severe uncertainty. We began by defining severe uncertainty; in summary, to be a scenario when we do not have enough information to assign a probability distribution accurately. Following this, we revisited statistical techniques currently implemented when making decisions in offshore power transmission. This included discussing the classical, frequency and subjective interpretations of probability. We went on to discuss the limitations of classical probability theory when applied to problems that involve severe uncertainty.

These shortcomings motivated the need for more suitable techniques when making decisions under severe uncertainty (which we identified to be often the case in offshore power transmission). This issue is encapsulated by the third research aim of this thesis. To achieve this aim, Chapter 5 explored advanced statistical techniques that handle severe uncertainty. We presented and explained a behavioural interpretation of probability that uses supremum buying and infimum selling prices, also known as lower and upper previsions. More generally, this approach is called imprecise probability [25].

Additionally, we discussed techniques within the theory of imprecise probability that are relevant to our application; these include, imprecise continuous-time Markov chains and decision making criteria. The second part of the third research aim is to understand how these techniques could be applied. In the final section of Chapter 5, we presented two small examples where these more robust techniques under severe uncertainty are utilised. In these examples, we assessed the benefits and limitations of taking this approach and thus contributes to addressing the third research aim of this thesis.

In Chapter 5, the techniques presented showed promising signs to be beneficial in the application to offshore power transmission. However, the application of theoretical methods to practical problems may bring challenges, and these are explored in detail in the application chapters of this thesis (Chapters 6 to 8). In Chapter 5, we introduced one of the main hurdles to implementing these techniques, namely the presence of act-state dependence. This challenge is the scope of the fourth research aim of this thesis and is addressed further in Chapters 6 to 8.

9.5 Chapter 6 Summary

Chapter 6 was the first of the application chapters presented in this thesis. In Chapter 6, we summarised and contrasted current regulatory regimes, before formulating two decision problems: firstly, which ownership structure to implement and secondly, which technology choice to install for a 1.2 GW project. Exploring these decision problems addressed research aim 7a of this thesis.

For the HVAC and HVDC case studies considered (and contingent on model choices), the study found third-party ownership to be optimal. These results were obtained using the described advanced statistical techniques to handle severe uncertainty. Furthermore, the work of Chapter 6 compared the techniques used to approaches based on the classical theory of probability. Overall, we presented a more in-depth insight into the benefits of using techniques based on imprecise probability for decision making in offshore power transmission, under severe uncertainty.

The fourth research aim of this thesis set out to understand and overcome challenges that arise during the application of advanced statistical methods to practical applications. This research aim was addressed in Chapter 6. When applying imprecise probability in Chapter 6, we encountered a problem in that we have act-state dependence (the set of distributions of the state of nature depends on the decision). In this chapter, to overcome the issue of act-state dependence, for the act-state dependent variable (which we identified as availability), we assigned a set of distributions for each input parameter and simulated the system to obtain best- and worst-case scenarios. Using these scenarios, we bounded expected return on investment (conditional on the act-state independent variables) and analysed these bounds, using interval dominance and Γ-maximin, to find economically preferable options. To handle uncertainty in the act-state independent variables (which we identified to be the capacity factor and the wholesale price of energy), we investigated how the decision changes as a function of fixed values of these inputs.

The fifth research aim of this thesis focuses on exploring how to communicate the handling of severe uncertainty effectively. In Chapter 6, we explored ways to present the results in a way that is clear to interpret and achieved this using a 2-D visualisation of the sensitivity analysis. Additionally, the visual output allows decision makers to use their expert knowledge to simply read off the optimal decision(s), rather than input their knowledge into the model.

Through the application presented in Chapter 6, we showed how to handle uncertainty in cable failure rates, cable repair times, wholesale energy prices and wind farm capacity factors. Therefore, this work contributed to addressing the sixth research aim of this thesis. The study improves our understanding of applying imprecise probability to offshore power decision problems and, confirms that by implementing these advanced statistical techniques, we can more suitably handle severe uncertainty. These findings suggest that the application of imprecise probability to offshore power transmission advances the current practice.

The eighth research aim of this thesis involved comparing the proposed techniques to conventional methods; especially, to identify the benefits and drawbacks of the advanced statistical techniques when applied to offshore power transmission. The work of Chapter 6 included a discussion that compared the advanced statistical methods to techniques based on the classical theory of probability. The advantages and disadvantages identified in Chapter 6 will be summarised in Chapter 10.

9.6 Chapter 7 Summary

In Chapter 7, we set out to demonstrate how to apply imprecise probability to handle severe uncertainty in a specific project design decision problem. This investigation assessed the benefit of investing in an interlink between two offshore substations from two perspectives: an offshore wind farm owner and an offshore transmission owner (OFTO). We formulated the decision problem from both perspectives by detailing the NPV from the offshore transmission owner's (OFTO) perspective and the energy generated and transmitted from the wind farm owner's perspective. We found that for the 800 MW case study and described modelling approach, the two stakeholders select different sets of optimal decisions. Therefore, the work of Chapter 7 addressed research aim 7b of this thesis.

In addition, we discussed that this investment decision, like others in offshore transmission, is taken under severe uncertainty due to a limited amount of relevant data. This severe uncertainty necessitated a suitable decision making approach, and therefore, we utilised imprecise probability. Again, while applying imprecise probability, we encountered a challenge due to act-state dependence (as the set of distributions for availability depends on the decision made). Therefore, in Chapter 7, we explained how act-state dependence impacts the handling of uncertainty in different variable types. In a similar way to Chapter 6, we described and demonstrated how to overcome the challenge of act-state dependence. Consequently, this work also contributes to addressing the fourth research aim of this thesis.

The fifth research aim of this thesis focuses on exploring how to communicate the handling of severe uncertainty effectively. In Chapter 7, the approach allows the decision maker to select wind speeds that are appropriate to their specific project and therefore, read off the results that are relevant to them. Furthermore, the decision maker can see if and how specific inputs affect the decisions made. In terms of visualisation, we plot the results for varied mean wind speeds for a fixed standard deviation. We then repeat this visualisation for different standard deviations. These visualisations contribute to addressing the fifth research aim of this thesis.

The application presented in Chapter 7 is another contribution to the sixth research aim of this thesis. In particular, we demonstrate how uncertainty in cable failure rates, cable repair times and wind speed can be handled in the decision making analysis. Furthermore, the work of this chapter illustrates how techniques based on imprecise probability compare to conventional techniques based on the classical theory of probability (therefore, addressing the eighth research aim of this thesis). We discussed how the approaches differ, in particular, how techniques based on the classical theory of probability require enough information to assign a probability distribution. In contrast, the techniques based on imprecise probability relax this requirement and instead consider a set of distributions. This relaxation provides a way to consider epistemic uncertainty in the input parameters. Therefore, we showed how techniques based on imprecise probability provide a more robust way to handle severe uncertainty than conventional techniques.

9.7 Chapter 8 Summary

The work of Chapter 8 set out to demonstrate the implementation of imprecise probability to a more comprehensive offshore power transmission decision problem. Furthermore, the purpose of Chapter 8 was to present a novel investment planning tool that could be utilised under severe uncertainty and illustrate the benefit of this approach. As part of the developed investment planning tool, we showed how to design the decision space this is a key difference between Chapter 8 and the previous application chapters. We designed feasible HVAC and HVDC topologies from individual components using logical and physical constraints. This modelling step allowed us to show, in a more direct way, how the proposed advanced statistical methods could support project planning for a range of projects.

Next, in the inference part of the decision making analysis, we evaluated the economic benefit of each topology. This step involved demonstrating how to implement imprecise probability to enable this investment planning tool to be robust under severe uncertainty. We discussed the handling of uncertainty in several of the model inputs: offshore cable failure and repair rate, loan interest rate, vessel hire, and planned OPEX factor. Importantly, we showed how we deal with uncertainty in act-state independent and act-state dependent variables (again, addressing the fourth research aim of this thesis).

Following the described methods, for each topology option, we evaluated bounds for the expectation of the metrics of interest (conditional on the act-state independent variables). Then, we utilised decision criteria, namely Γ-maximin and interval dominance, to find the optimal topology. Most of the methodology focused on the expectation of a metric of interest; however, we explored aleatory uncertainty and showed how the variability around the expectation could be a secondary consideration in the decision making process. We also discussed how the methodology could be adapted to suit the needs of other markets. Finally, we presented the results of the investment planning tool for three case studies, which addresses research aim 7c of this thesis.

A significant contribution to emerge from this study is the development of an investment planning decision tool that utilises imprecise probability to more appropriately handle severe uncertainty. Therefore, this work contributes to addressing the sixth research aim of this thesis. The results suggest that: firstly, imprecise probability can be implemented to aid in the planning of offshore transmission systems (OTSs); secondly, the results of the techniques can be visualised in a way that is clear to communicate and interpret (a contribution to the fifth research aim of this thesis); and finally, the proposed techniques advance the current handling of uncertainty in economic evaluations and should be implemented in the case where it is challenging to assign a probability distribution due to limited data. Additionally, this work contributes to the eighth research aim of this thesis by illustrating the benefits of taking this alternative approach and discussing limitations to the sensitivity analysis approach of handling uncertainty in the act-state independent variables.

Chapter 10

Conclusions and Further Work

10.1 Conclusions

The work of this thesis set out to, firstly, investigate techniques that handle severe uncertainty in the input parameters due to limited data, knowledge, and expertise. Secondly, upon identifying suitable methods, the main aim was to assess the application of these statistical methods for long-term decision making in offshore power transmission. In this thesis, as outlined in Chapter 1, these research aims are divided into three areas: motivating the need for the robust handling of severe uncertainty in decision making analysis to support offshore wind integration; understanding the advanced statistical methods that could be applied in this space; and finally, the application of these techniques to demonstrate how they may be beneficial to decision makers in offshore power transmission.

In Chapters 2 to 4 we motivated the need for advanced statistical methods. This was achieved through reviewing and summarising the literature in the field (Chapter 2), collating data associated with offshore transmission systems (OTSs) (Chapter 3), and through presenting an economic model which we used to assess the impact of severe uncertainty (Chapter 4). Furthermore, the research of Chapter 4 contributes to a deeper understanding of the severe uncertainties involved in offshore transmission planning, and their impact on a project's expected profit. We also gained a deeper understanding of uncertainty due to limited data regarding the failure and repair of offshore cables. Moreover, we identified that there was a research need to develop and implement suitable techniques to handle severe uncertainty when making decisions concerning the OTS. This work, in particular that of Chapter 4, addressed the first and second aims of this thesis which were outlined in Chapter 1.

In Chapter 5, we presented the advanced statistical methods proposed to handle severe uncertainty, namely imprecise probability. Additionally, we discussed techniques within the theory of imprecise probability that are relevant to our application; these include, imprecise continuous-time Markov chains and decision making criteria. We put forward the advantages of these methods as well as introduce hurdles to implementing these techniques, namely act-state dependence. The work of Chapter 5 addresses the third, fourth and fifth aims of this thesis which were outlined in Chapter 1.

Following this, in Chapters 6 to 8 we demonstrated applications of the described techniques. We applied the advanced statistical methods to three applications: two specific decision problems and one comprehensive decision problem that developed a novel investment planning tool. This tool could be used to support decision makers in offshore power transmission by designing and planning OTSs under severe uncertainty. The work of Chapters 6 to 8, addresses the rest of the research aims presented in Chapter 1.

To summarise, the main contribution of this work is the demonstration of how to apply advanced statistical techniques to handle severe uncertainty in long-term decision problems in offshore power transmission. We confirmed the ability of the methods to handle uncertainty in the input parameters required to make investment and planning decisions. Furthermore, the applications allowed us to prove the benefits of applying these methods to handle uncertainty, to discover the challenges of applying these techniques (in particular, regarding act-state dependence) and overcome them.

10.1.1 Advantages

The work of this thesis advances our knowledge of how advanced statistical methods can be beneficial to decision makers in offshore power transmission, and these advantages are identified and discussed throughout the thesis. Furthermore, the findings contribute to our understanding of handling severe uncertainty, and this could be utilised in both technical and policy decisions (within the context of offshore transmission or in other applications). The main advantages of the described advanced statistical methods can be summarised as:

- **Overcome the challenge of assigning probability distributions under severe uncertainty**

  The methods can be used when techniques based on the classical theory of probability are not suitable. In scenarios when we have insufficient data (which we identified to, often, be the case in offshore power transmission), it can be challenging to assign probability distributions. Methods based on classical probability theory usually require values or distributions to be assigned to model inputs. Assigning a distribution under severe uncertainty, may not adequately represent the data available, and this may impact the accuracy of the outputs. Therefore, it could be inadvisable to base investment decisions on these outputs. In contrast, the proposed advanced statistical methods do not require probability distributions to be assigned and, instead, work with sets of distributions.

- **A framework to model epistemic uncertainty**

  The presented framework, which utilises imprecise probability, allows epistemic uncertainty (uncertainty due to limited knowledge) in the input parameters to be modelled. We noticed that this uncertainty in the input modelling parameters is due to a limited amount of useful data. Consequently, decision makers can make their decision based on outputs that reflect the epistemic uncertainties involved. Additionally, we explored aleatory uncertainty and showed how variability around the mean could be a secondary consideration in the decision making process.

- **An alternative approach when modelling assumptions cannot be verified**

  Conventional techniques used to evaluate the yearly availability of a component assume that the failure and repair of components are exponentially distributed. We discussed that these assumptions might be too strong in offshore transmission; for example, we discussed that cable repairs might be quick or slow depending on the type of repair required. Therefore, we suggested techniques that allow this assumption to be relaxed, and we utilised imprecise continuous-time Markov chains to achieve this. In this approach, the modelling assumptions of a Markov process are relaxed to allow the handling of epistemic uncertainty. Specifically, we consider a set of transition matrices by considering inputs within more suitable ranges and therefore, we work with a set of processes. We showed how these techniques, for the two-state imprecise Markov chain, resulted in closed expressions to evaluate bounds for many quantities of interest (including availability).

- **An approach that allows for indecision**

  We discussed and showed that the methods allow for indecision when there is insufficient data to draw conclusions. This aspect is in contrast to techniques based on the classical theory of probability.

- **Communication of uncertainty handling**

  This study has shown ways to communicate the handling of uncertainty effectively. Advancements in clearly communicating results support the ability of advanced statistical methods to be implemented more widely the uptake of unconventional techniques is a considerable challenge to overcome. These findings extend our knowledge of how to communicate advanced statistical modelling and the results of these methods.

In this thesis, one way to aid the communication of uncertainty handling is introduced in Chapter 4. Here, we visually displayed the developed economic model, including all model variables and dependencies between model variables. This graphical representation combined with a detailed explanation aids in the communication of the economic model, and in particular, facilitates a way to convey how uncertainty impacts the analysis.

Another example, but focused on communication of the results is shown in Chapter 6. We explored ways to present the results in a way that is clear to interpret and achieved this using a 2-D visualisation of the sensitivity analysis. We showed that taking this sensitivity analysis approach facilitates effective communication of the results. Additionally, the visual output allows decision makers to use their expert knowledge to simply read off the optimal decision(s), rather than input their knowledge into the model.

- **Gained an understanding of how to implement the proposed techniques**

  The work of this thesis contributes to our understanding of how these techniques could be applied to decision problems in offshore power transmission. Specifically, in Chapters 6 to 8, we demonstrated how to implement these methods to handle severe uncertainty present in three different, but relevant, decision problems. These applications provide more in-depth insights into the benefits of using imprecise probability for decision making in OTS.

- **Advances current practice**

  The findings of this thesis suggest that the application of imprecise probability to offshore power transmission advances current practice by providing a framework to handle severe uncertainty when making decisions. In particular, the work of Chapters 6 to 8 supports this. Although this study focuses on the applications in offshore power transmission, the impacts of this thesis may extend beyond this field.

- **Development of an investment planning tool under severe uncertainty**

  A significant contribution to emerge from this study is the development of an investment planning decision tool that utilises imprecise probability to more appropriately handle severe uncertainty. The work of Chapter 8 presented a more comprehensive application of advanced statistical techniques to offshore power transmission, by extending the decision problem to include a framework that constructs the decision space. Specifically, for given design parameters specified by the decision maker, we designed feasible OTSs from components available in the market.

Additionally, we demonstrated how to implement imprecise probability to enable this investment planning tool to be robust under severe uncertainty. The results of this study suggest that: firstly, imprecise probability can be implemented to aid in the planning of OTSs; secondly, the results of the techniques can be visualised in a way that is clear to communicate and interpret; and finally, the proposed techniques should be implemented in the case where it is challenging to assign a probability distribution due to limited data.

10.1.2 Limitations

So far, we have discussed the main advantages that were identified throughout this thesis. However, it is important to note the limitations of these methods, and again, these were discussed throughout this thesis. Here, we provide a summary of these drawbacks.

One limitation is that the method requires a set of distributions to be assigned to the input parameters. Therefore, the methods require expert knowledge. Although this is not as restrictive as assigning a probability distribution (as is the case for techniques based on the classical theory of probability), this may still be a challenge. Therefore, the decision maker must be able to assign these sets or, as we discussed in Chapter 6, know which regions to consider on the resulting sensitivity analysis plot. In the case where a set of distributions is challenging to identify, we may end up considering a wide range of values. Ultimately, we could obtain large sets of distributions for the outputs that may not be informative. However, if the primary purpose is to compare different options to make a decision, these large intervals may not be so much of a limitation.

There exist some limitations in the sensitivity analysis approach to uncertainty handling, and we described these in the application chapters. Usually, although it was discussed in Chapter 8, we did not investigate aleatory uncertainty (the uncertainty due to variability). We explained that modelling the failure and repair of components by the exponential distribution on the bounds introduces uncertainty due to the random process, and consequently, there will be differences between the realisations of the process. In the presented decision making process, we did not (usually) consider aleatory uncertainty as we primarily aimed to maximise the expectation of the metric of interest. Instead, we concentrated on handling uncertainty in the input modelling parameters on account of severe epistemic uncertainty. Therefore, in the resulting plots, the intervals were due to epistemic uncertainty in the input parameters. In Chapter 8, we did discuss how investigating aleatory uncertainty could be a secondary consideration in the decision making analysis, but it was not the focus for most of the methodology presented.

Another limitation to the described approach in Chapter 8 is that the analysis only handles uncertainty in one act-state independent variable at a time. Visualising the analysis in a way that is clear to interpret becomes challenging beyond one variable. Therefore, we restricted the analysis to one variable at a time. In Chapter 6, we considered two variables at a time by visualising the decision made (rather than bounds on the metric of interest).

10.2 Further Work

The research of this thesis raises a number of areas of further work, and these are discussed below.

Commercialisation

A natural progression of the work of this thesis is to understand how to take the presented methods closer to the industry. This activity could involve firstly, understanding, in more detail, the specific needs of the industry and secondly, making a commercially available tool.

To support the commercialisation of this research, we must ensure that the outcome is useful and relevant to those in the industry. Additional work could be done to comprehend the market requirements and gain valuable insights into the needs of the industry. This could also be achieved by engaging with stakeholders to understand the demands of end-users (regarding a new solution to handling severe uncertainty), finding out precisely where these methods could be implemented, and learning more about how the methods improve their current practice. Ultimately, further work in this direction would help ensure a developed tool meets the industry's needs.

Further work could also extend the methods and tool into a product that could be used by an end-user. This process could involve developing a user-friendly demonstration tool, that could support our understanding of how to move this research closer to the market. The end goal of this additional research would be the development of a competitive tool that is available to the industry.

Investigate a broader range of applications

The findings of this work have shown, through three applications, the benefits of applying advanced statistical methods to handle uncertainty, when making long-term decisions in offshore power transmission. These applications gave us insight into the advantages of these approaches, and, consequently, indicated that they could be implemented in other applications. Moreover, through conducting this work, we gained a better understanding of where these methods may be appropriate.

Closely linked to the decision problems presented in this thesis, we believe these methods could be useful when applied to decision problems concerning the selection of an offshore grid layout. This issue was addressed somewhat in the thesis. However, additional work could go further and investigate a more coordinated approach for offshore wind connections such as meshed systems. Studies into meshed grids already exist, but analysis using the methods of this thesis could be adopted to handle the severe uncertainty, and it would be interesting to see the implications of this. Furthermore, the move to meshed offshore grids, especially where multiple nations are connected may require regulatory and economic frameworks to be developed. This task in itself raises many research questions that are currently being addressed by the research community and industry.

In the work of this thesis, we focused on long-term planning decision problems. By conducting this work, we were able to understand better the applicability of these methods to short-term operational decisions. We also gained awareness of the uncertainties present in these operational decisions. Given the benefits of advanced statistical methods to long-term planning, we recommend that further work: investigates how these techniques could be applied to short-term operational decision problems in offshore power transmission; finds and overcomes challenges that arise in this application; and assesses the benefits of implementing these techniques. Conducting a similar study to the one of this thesis, but focusing on operational decision problems could be a fruitful area of research, given the inherent uncertainty.

In this thesis, we gained an understanding of the research need to investigate and improve the operational maintenance strategy for offshore cables. This research was beyond the scope of this thesis, primarily as a result of not having access to the data that those who make operational decisions have. Nevertheless, we believe this is a place where these advanced statistical methods could be beneficial, and further research could explore this.

In addition, the techniques applied in this thesis could be applied elsewhere in offshore transmission and indeed, offshore wind. Further research could assess the impact of implementing these techniques to handle uncertainty in decision problems concerning the long-term planning of offshore wind farms (including the wind turbines and array cables). More broadly, these methods could be applied to other decision problems regarding power systems or to support investment decisions of other infrastructure projects, and further work could investigate the benefits of doing this.

Mathematical aspects

The research presented in this thesis raises questions of a more mathematical nature that require further investigation. In this work, we did not conduct a full uncertainty quantification, and therefore further work could address this. Additionally, a greater focus on assigning sets of distributions from small data samples (rather than literature values) could produce interesting findings that may move the work forward. Access to data is required to enable this investigation. With access to this data, further work could apply techniques that more robustly represent our knowledge, such as implementing a robust Bayesian model.

Appendix A

Data

A.1 UK Operational Cable Data

The Table A.1 provides information on the cable outages experienced by some UK offshore wind cable systems. This data is collected from [141] between 2013 and 2016. For more recent years, we refer to the more recent reports by [141].

Date	Fault	Downtime (Days)
	London Array	
04/10/2013	Export cable 2 and 4	0.02
04/10/2013	Export cable 2 and 4	0.02
16/12/2013	Export cable 2 and 4	0.04
16/12/2013	Export cable 2 and 4	0.02
06/09/2016	Export circuit 2	0.47
20/09/2016	Export circuit 4	0.47
26/09/2016	Export circuit 1	0.49
	Gwynt Y Mor	
01/04/2015	Export cable 1 primary system fault (continued from previous year)	76.86
02/03/2015	Export cable 1 primary system fault	29.25
13/09/2016	Export circuit 1 trip due to static var compensator (SVC) system fault	0.05
13/09/2016	Export circuit 1 trip due to SVC system fault	0.04
19/12/2016	Export circuit 2 trip due to SVC system fault	0.06
19/12/2016	Export circuit 1 trip due to SVC system fault	0.05
	Thanet	
23/02/2015	Export cable 1 primary system fault	36.46

01/04/2015	Export cable 1 primary system fault (continued from previous year)	97.48
05/03/2016	Export cable 2 primary system fault	28.48
01/04/2016	Export cable 2 primary system fault (continued from previous year)	27.6
	Lincs	
19/09/2015	A faulty component on the cable sealing end oil booster tank resulted in a circuit trip	0.13
	Walney 2	
06/11/2013	Land cable fault	17.7
04/12/2015	Export cable fault	105.28
25/09/2016	Export cable 2 primary system fault	153.64
	Robin Rigg	
01/03/2015	Export cable fault	13
	Gunfleet Sands	
12/06/2014	Outage to repair cable sealing end	1
	Sheringham Shoal	
05/08/2013	Circuit 1	0.5
06/08/2013	Circuit 2	0.48

Table A.1: Details of cable downtime reported in National Grid's performance reports [141].

Appendix B

Proofs

Theorem B.0.1. *Let O_0 and $\eta_1, \ldots, \eta_{n_1}$ be given, where O_0 is the final transfer value and η_ℓ is the interest rate in the ℓ^{th} instalment. We aim to find $P_1, ..., P_{n_1}$ such that:*

1. *The loan amount, O_0, is paid off in the loan period after n_1 instalments: $O_{n_1} = 0$, where $O_\ell = O_{\ell-1}(1 + \eta_\ell) - P_\ell$ for $i = 1, ..., n_1$ (see Lemma B.0.2).*

2. *The payments are constant for a fixed interest rate. If $\eta_1 = \eta_2 = \cdots = \eta_{n_1}$ then $P_1 = P_2 = \cdots = P_{n_1}$ (see Lemma B.0.3).*

The following equation is a standard repayment formula that satisfies the two conditions above.

$$P_\ell = \frac{O_{\ell-1}\eta_\ell}{1 - (1 + \eta_\ell)^{-(n_1+1-\ell)}} \tag{B.1}$$

Lemma B.0.2. *After n payments the outstanding loan is zero: $O_{n_1} = 0$.*

Proof.

$$O_{n_1} = O_{n_1-1}(1 + \eta_{n_1}) - P_{n_1} \tag{B.2}$$

$$\begin{aligned} P_{n_1} &= \frac{O_{n_1-1}\eta_{n_1}}{1 - (1 + \eta_{n_1})^{-(n_1+1-n_1)}} && \text{(B.3)} \\ &= \frac{O_{n_1-1}\eta_{n_1}}{1 - \frac{1}{1+\eta_{n_1}}} && \text{(B.4)} \\ &= \frac{O_{n_1-1}\eta_{n_1}}{\frac{1+\eta_{n_1}-1}{1+\eta_{n_1}}} && \text{(B.5)} \\ &= O_{n_1-1}(1 + \eta_{n_1}) && \text{(B.6)} \end{aligned}$$

Substituting Eq. (B.6) into Eq. (B.2) leads to:

$$O_{n_1} = O_{n_1-1}(1 + \eta_{n_1}) - O_{n_1-1}(1 + \eta_{n_1}) = 0 \tag{B.7}$$

□

Lemma B.0.3. *For a constant interest rate all payments are the same.*

Proof. Assumption: $\forall\ \ell \in (1, n_1),\ \eta_\ell = \eta$. The following proof shows that all P_ℓ are the same $\forall\ \ell \in (1, n_1)$. This can also be expressed as $P_{k-1} = P_k$ for a constant interest rate. For any $k \in \{2, \ldots, n_1\}$:

$$P_{k-1} = \frac{O_{k-2}\eta}{1 - (1+\eta)^{-(n_1+1-k+1)}} \tag{B.8}$$

$$= \frac{O_{k-2}\eta}{1 - (1+\eta)^{-(n_1+1-k)}(1+\eta)^{-1}} \tag{B.9}$$

$$= \frac{O_{k-2}\eta(1+\eta)}{1 + \eta - (1+\eta)^{-(n_1+1-k)}}. \tag{B.10}$$

Note, rearranging one has:

$$P_{k-1}(\eta + (1 - (1+\eta)^{-(n_1+1-k)})) = O_{k-2}\eta(1+\eta). \tag{B.11}$$

Also,

$$P_k = \frac{O_{k-1}\eta}{1 - (1+\eta)^{-(n_1+1-k)}} \tag{B.12}$$

$$= \frac{O_{k-2}(1+\eta)\eta - P_k\eta}{1 - (1+\eta)^{-(n_1+1-k)}}. \tag{B.13}$$

Combining Eq. (B.11) and Eq. (B.13) results in the following equation:

$$P_k = \frac{P_{k-1}(1 - (1+\eta)^{-(n_1+1-k)})}{1 - (1+\eta)^{-(n_1+1-k)}} + \frac{P_{k-1}\eta - P_k\eta}{1 - (1+\eta)^{-(n_1+1-k)}}. \tag{B.14}$$

Therefore,

$$P_k\left(1 + \frac{\eta}{1 - (1+\eta)^{-(n_1+1-k)}}\right) = P_{k-1}\left(1 + \frac{\eta}{1 - (1+\eta)^{-(n_1+1-k)}}\right). \tag{B.15}$$

So, $P_k = P_{k-1}$ as required. □

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