University of Strathclyde

Ali Jadali

Effective Planning of end-of-life scenarios for offshore wind farm

Department of Naval Architecture Ocean and Marine Engineering

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Engineering

Academic Year: 2023

Supervisors:

Professor Feargal Brennan

Professor Athanasios Kolios

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(NB. This section can be removed if the award of the degree is based solely on examination of the thesis)

ABSTRACT

Many offshore wind turbines (OWTs) are approaching the end of their estimated operational life soon. It is challenging to develop a general decommissioning procedure for all OW farms. Therefore, this research aims to comprehend the available end-of-life (EoL) scenario for OWTs to decide on their application procedures and propose an innovative systematic framework for considering the EoL scenario.

The first part of the research critically reviewed the various end-of-life strategies for offshore wind farms, available technological options and the influencing factors that can inform such decisions. The study proposed a multi-attribute framework for supporting optimum choices in terms of main constraints, such as the possibility of end-of-life strategies based on unique characteristics and influencing factors.

In the selection of techno-economic, the primary procedure parameters influencing the three major end-life strategies, i.e. life extension, repowering, and decommissioning, are discussed, and the benefits and issues related to the influencing variables are also identified. In the next part, an initial comparative assessment between two of these scenarios, repowering and decommissioning, through a purpose-developed techno-economic analysis model calculates relevant key performance indicators.

With numerous OW farms approaching the end of service life, the discussion on planning the most appropriate EoL scenario has become popular. Planning and scheduling those main activities of EoL scenarios depends on forecasting leading environmental indicators such as significant wave height. This research proposes a novel probabilistic methodology based on multivariate and univariate time series forecasting of machine learning (ML) models, including LSTM, BiLSTM, and GRU.

In the end, the role of optimum selection of end-of-life scenarios is investigated to achieve the highest profitability of offshore wind farms. Various end-of-life scenarios have been evaluated through a TOPSIS technique as a multi-criteria decision-making procedure to determine an appropriate way according to environmental, financial, safety Criteria, Schedule impact, and Legislation and guidelines.

Keywords: Offshore Wind Turbine; Decommissioning; End-of-life scenarios; Decision making; Levelized Cost of Energy; Machine learning, Forecasting

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Preface/Acknowledgements

I would like to express my deep gratitude to my parents, Tahmin and Hushang Jadali, for their unwavering love and support throughout my journey. Their guidance and encouragement have been invaluable to me.

I also want to extend my thanks to my brothers, sister, and my late Great Uncle and Aunt, who hold a special place in my heart. The passing of my dear Aunt has left a void that I deeply feel and miss her greatly.

In addition, I am grateful to my supervisors who have provided me with guidance, mentorship, and opportunities for growth. I would also like to acknowledge the countless individuals I have encountered along the way, whether they became lifelong friends, trusted colleagues, or even brief acquaintances. Each interaction has contributed to my knowledge and shaped my thoughts in some way.

Lastly, I humbly recognize the importance of acknowledging myself. I appreciate my own dedication, hard work, and perseverance that have brought me to this point. It is through my own efforts that I have been able to overcome challenges and reach my goals.

CHAPTER 1

1.1 Background

Offshore wind power is a relatively new technology compared to onshore wind power, and its development was mainly motivated. The first offshore wind (OW) farm was installed in 1991 in Denmark [1]. Although the estimated lifetime of the offshore wind turbine (OWT) is about 20-25 years, the significance of decommissioning is often ignored by the owners [1], [2]. Current research around OWTs is majorly focused on offshore wind power's development, construction, maintenance, and operational aspects. This is even though about 70,000 MW of Europe’s installed wind power will reach its estimated end of life by 2030, as seen in Figure 1. This translates to an increase of more than 460% in demand for decommissioning activities within the next ten years. It is, therefore, imperative to consider the end-life scenarios in the design and development stages of the OW farms to avoid unexpectedly higher costs and associated environmental impacts of offshore wind power [3].

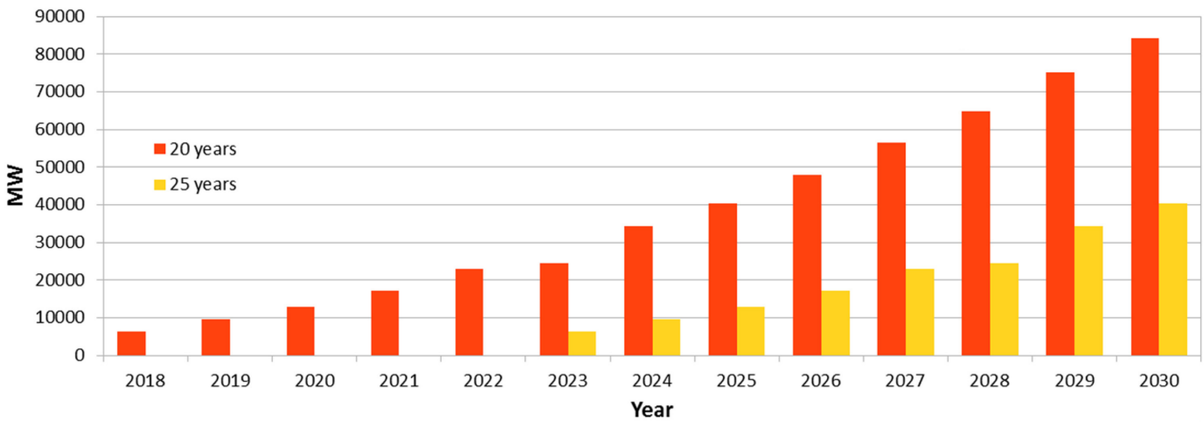


Figure 1.European wind power reaching the end of life[4].

Decommissioning is defined as disassembling the wind turbine farm to return the site to its pre-installation phase as much as possible [1], [2], [5]. The first decommissioning of an OW farm was done in 2016 due to the difficulty of finding spare parts and the enormous costs associated with repairs and upgrades after 15 years of its operation. Due to the commercialisation of many offshore projects in the early 2000s [2] and the upcoming end-life dates for the installed OWTs [6], many decommissioning projects are expected in the coming years.

The decommissioning process is influenced by several factors, such as the number and types of wind turbines, types of foundations, weather, and seabed conditions [1], [2], [7]. This presents a difficulty with developing a generic procedure for OW farms' decommissioning. It translates to the fact that each OW farm will have an exclusive and unique decommissioning scheme [2]. Decommissioning is divided into three main stages, i.e. planning, permitting, and implementation. Decommissioning can presumably be done in a few months; however, the whole process would most likely be completed in up to three years [8].

Decommissioning is a technology- and energy-intensive process. There are significant emissions of greenhouse gases as well as huge amounts of waste that cannot be recycled. Reusing an existing platform is recommended to reduce environmental pollution and high decommissioning expenses, which have potential effects on the deep draught vessels [8], [9], [10]. This highlights the importance of designing and selecting appropriate strategies for decommissioning an OW farm.

1.2 Problem statement

The selection of the most appropriate end-of-life strategy for an offshore wind farm is influenced by several factors, such as the number and types of wind turbines, types of foundations, weather, and seabed conditions as well as available technologies and environmental requirements. This presents a challenge when developing generic decision-making frameworks, meaning that each OW farm and even different wind turbines across the farm should be assigned a unique strategy to ensure the maximisation of profit while fulfilling technological, cost and environmental constraints. Previous research in this domain has not simultaneously considered the service life extension with other end-life scenarios.

This research focuses on the techno-economic comparison of decommissioning and repowering with the latter option depending on a higher level assessment of the technology rather than a detailed integrity assessment, even at a unit level, which is required for the service life extension option. Consideration of service life extension requires evaluation of failure rates of maintenance-significant components, e.g. drive train components, along with their variance throughout the asset's service life, which are difficult to retrieve considering the lack of data from operational OW farms. This information is not generally required to the same extent for a repowering strategy, and also, considering that technology has significantly advanced since the first generation of wind farms, this paper focuses on repowering as a competitive EoL scenario.

1.3 Aim and objectives

This research aims to review the end-life strategies for wind turbines, their merits, and demerits, then categorise the appropriate methods. The study determines the optimum EoL strategy regarding the condition of the farm based on the complexity of asset life due to several uncertainties such as cost and environment. The optimum EoL plan can be achieved by accurate forecasting of cost and environmental elements such as significant wave height. The result of accurate significant wave height forecasts helps decide whether to launch service vessels for offshore wind turbines farm.

The thesis aims to deliver the following objectives:

- Perform a detailed review and develop a framework that will consider multiple criteria in the decision-making process, presenting and discussing available technologies and strategies, as well as influencing factors such as schedule, cost and environmental impact.

- Performs an initial comparative assessment between two of these scenarios, repowering and decommissioning, through a techno-economic analysis model which calculates relevant key performance indicators. The economic model of risk aversion is further adapted to calculate the certainty equivalent of LCoE (levelized cost of energy) based on each of the examined end-of-life scenarios and a stochastic expansion of the deterministic model.

- Forecasting leading environmental parameters such as significant wave height is critical in scheduling and preparing those main activities involved in planning EoL scenarios. This research studies the role of ML algorithms in significant wave height forecasting to predict accurately. It demonstrates the importance of feature selection in proposed multivariate or univariate time series forecasting and argues that a strong correlation does not necessarily have a strong causality of results accuracy.

- Investigate the various end-of-life strategies for offshore wind farms and the influencing criteria for optimised decisions. Different end-of-life scenarios have been evaluated through a TOPSIS technique as a multi-criteria decision-making procedure to determine an appropriate way according to environmental, financial, and safety criteria, schedule impact, and legislation and guidelines.

1.4 **Structure of thesis**

A general overview of the thesis structure is presented in Figure 2 and outlined in some more detail in the following:

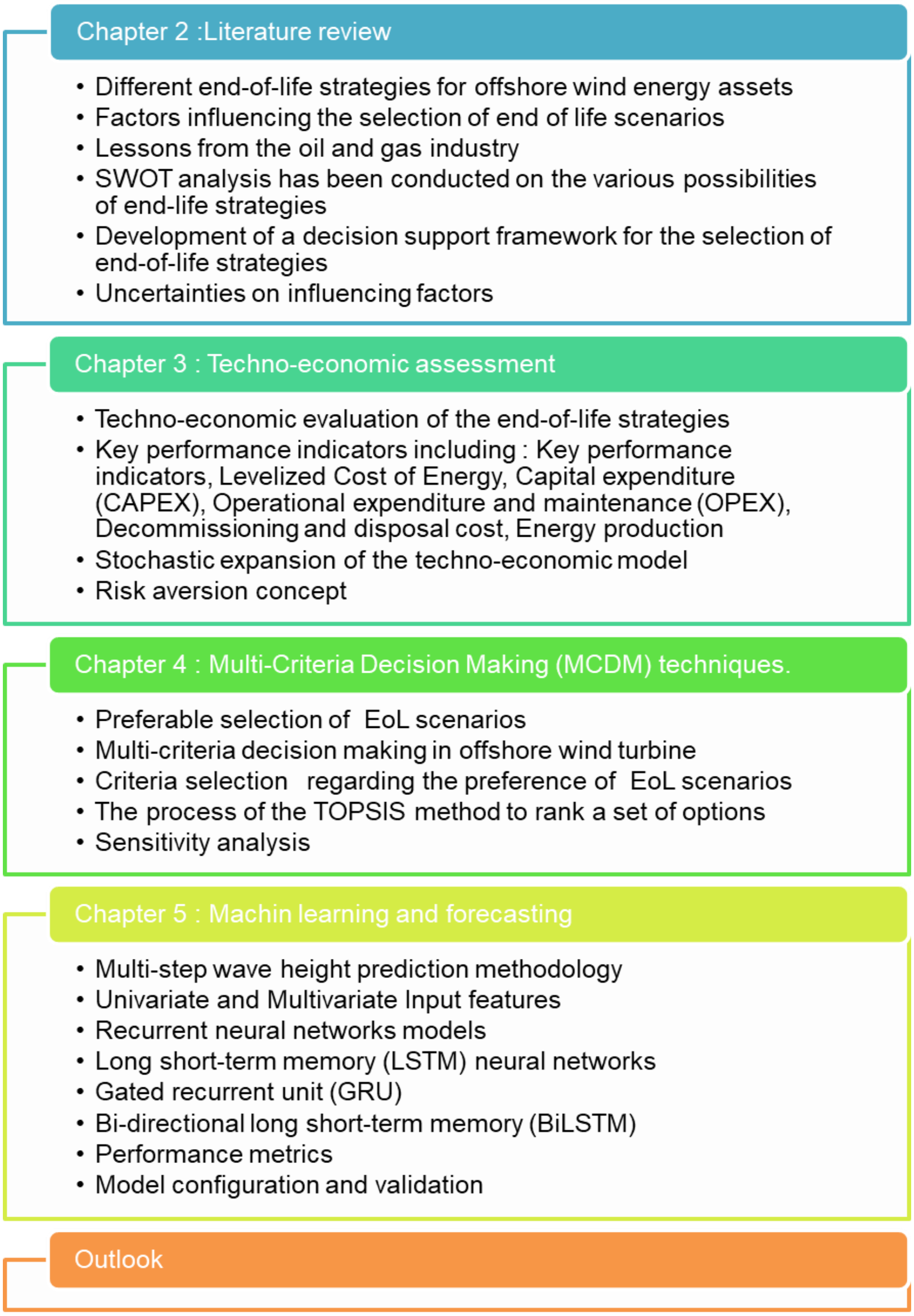


Figure 2.Flowchart of the thesis structure.

The insufficiency of systematic research on end-of-life strategies of offshore wind farms has been the main challenge regarding the decision-making process. A detailed study of the literature has revealed a lack of appropriate frameworks which can oversee decisions on available strategies based on the particular characteristics and influencing factors such as the number and types of WTs, types of foundations, and weather. The study assessed the different end-of-life strategies for offshore wind farms, known technical possibilities, and the influencing factors that declare such findings to deal with this issue. In addition, various alternatives have been qualitatively evaluated through SWOT analysis. In the second part, this research suggested a multi-attribute framework for allowing optimum decisions regarding significant conditions, such as the possibility of end-of-life strategies based on the unique features and influencing elements. The framework provides the opportunity to internal and external stakeholders to maximize the profitability of asset farms while reducing those main risks involved in the safety, technical, and environmental factors.

The third chapter investigated repowering and decommissioning as possible EoL scenarios as OFWs approach the end of their nominal service life. The chapter provides a framework for preliminary analysis on the extension of a techno-economic model that accounts for the typical actions and costs related to each option. LCoE has been used to consider the consequential cost of each alternative. The model developed stochastically to account for uncertain inputs, and the concept of RP was employed to quantitatively evaluate the impact of the results on the decision maker.

It is challenging to determine the optimum EoL strategy regarding the condition of the farm. The owner found it difficult to decide whether the repowering or decommissioning strategy for the end of the farm or beneficial to have a specified period as service life extension before any decision. The process was complex due to several uncertainties involved in the decision-making. This chapter introduces a methodological framework to guide decision-makers based on a comparative study of widely-applied Multi-Criteria Decision Making (MCDM) techniques to solve the complexity issue. The TOPSIS analysis as the MCDM method applies to select the EoL strategy. Attempts to find the most influential criteria should be defined for TOPSIS analysis by a literature review and brainstorming with experts. This provides an integrated evaluation of several economic, social, environmental, and technical criteria.

The planning method of EoL scenarios depends on supporters such as previous project experience, vessel selection, availability of trained crew and experts, weather and wave conditions, and distance to the port. The harsh environment can limit the operability of vessels during marine construction work. A harsh environment can restrict the accessibility of infrastructure in offshore farm zones, cause economic damage, and threaten human life. The enormous growth in the cost of any decision-related EOL operation might result from an inaccurate forecast of significant wave height. The accuracy of this forecasting provides the opportunity to mitigate those uncertainties involved in planning the EoL scenarios. This chapter proposed a novel probabilistic methodology based on multivariate and univariate time series forecasting of machine learning (ML) models, including LSTM, BiLSTM, and GRU, regarding significant wave height forecasting.

1.5 Publications in connection with the thesis

The following papers are submitted and published or under review throughout the research in scientific journals:

A. Jadali, A. Ioannou, K. Salonitis, and A. Kolios, “Decommissioning vs. repowering of offshore wind farms—a techno-economic assessment,” Int. J. Adv. Manuf. Technol. 2021 1129, vol. 112, no. 9, pp. 2519–2532, Jan. 2021, doi: 10.1007/S00170-020-06349-9.

A. Jadali, A. Ioannou, and A. Kolios, “A multi-attribute review toward effective planning of end-of-life strategies for offshore wind farms,” 2021, doi: 10.1080/15567249.2021.1941434.

A. Jadali and A. Kolios, "Selection of appropriate End-of-life scenarios for offshore wind farms" – In revision pending the final decision.

A. Jadali and A. Kolios, " Comparative performance of Multivariate time series forecasting based on various deep learning models to consider effective planning of end-of-life strategies for offshore wind farms"- In revision pending the final decision.

Chapter 2

2 A multi-attribute review toward effective planning of end-of-life strategies for offshore wind farms

2.1 Introduction

Offshore wind farms are probably the most rapidly developing technology, aiming to contribute actively to the net-zero targets that have been established for the next decades. This is due to the increased wind shear available offshore, the larger units and farms that can be deployed, and the reduced competition for alternative uses of the marine environments [2], [11]. Research since the first installation of offshore wind farms, which took place in 1991 in Denmark, mainly focused on qualifying technologies around the development, construction, operation and maintenance of offshore wind energy assets with a view to reducing costs (especially capital expenditure, CAPEX), while the fate of the assets after their nominal design lifetime which is about 20-25 years has received less attention, although it is expected that suboptimal decisions should reduce the value extracted and eventually may cost significantly to asset operators [1], [2].

Onshore wind energy has accumulated some experience during the past decades, with around 70,000 MW of Europe's installed wind power reaching its estimated end of life by the year 2030 [4]. This translates to more than 460% in demand for decommissioning activities within the next ten years. Although many lessons can be transferred to offshore wind energy assets, it should be noted that not all aspects have been resolved, particularly with the way that composite materials can be disposed of. The offshore environment involves a number of parameters and influencing factors that need to be considered in order to support decisions related to end-of-life strategies. In fact, it is imperative to consider the end-life scenarios in the design and development stages in order to avoid unexpectedly higher costs and associated environmental impacts of offshore wind power [3].

Decommissioning, which is the ultimate end of life strategy to be considered for an asset, is defined as the process of disassembling the wind turbine to return the site to its pre-installation phase, to the extent possible [1], [5]. The first decommissioning of an OWF was done in 2016 to the Vindeby wind farm in Denmark, due to the difficulty in finding spare parts, technology obsolesce, and the considerable costs associated with repairs and upgrades after 25 years of its operation. Due to the development of many offshore projects in the early 2000s and the approaching end-life dates for the installed OWTs [6], many decommissioning projects are expected in the coming years. Decommissioning is a technology- and energy-intensive process. There are significant emissions of greenhouse gases and vast amounts of waste that cannot be recycled. Reusing an existing platform is recommended to reduce environmental pollution and high decommissioning expenses, which have potential effects on the deep draught vessels [8], [9], [10]. This highlights the importance of designing and selecting appropriate strategies for decommissioning an OW farm.

Alternative strategies that can proceed with decommissioning can be repowering and service life extension. Service life extension accounts for evaluating the asset's current integrity state, intending to assess its residual service life and issue a certificate of fitness for purpose for an additional period. Repowering is the process of changing critical sub-systems/components of an asset, such as generator and blades, potentially with more technologically advanced parts which can harvest more energy potential while maintaining subsystems designed for longer nominal life, such as the tower and balance of plant (BOP). The confidence influences both processes in evaluating the integrity of the structure after 20-25 years of operation and, in the case of repowering, the capacity of the electrical infrastructure to handle the maximum load.

The selection of the most appropriate end-of-life strategy for an offshore wind farm is influenced by several factors, such as the number and types of wind turbines, types of foundations, weather, and seabed conditions, as well as available technologies and environmental requirements. This presents a challenge when developing generic decision-making frameworks, meaning that each wind farm and even different wind turbines across the farm should be assigned with a unique strategy that will ensure profit maximisation while fulfilling technological, safety and environmental constraints.

This chapter aims to perform a multi-attribute review toward effective planning of end-of-life strategies for offshore wind farms. For this, alternative strategies and associated technological options are presented, together with associated influencing factors to be considered, resulting in a decision support framework that can inform decisions. Previous research in this domain has not considered all of the available strategies considered; service life extension, repowering or decommissioning. Hence this research can provide the context for future studies that can quantify the technical and economic assessment of specific case studies and scenarios, which will subsequently facilitate planning and reduce the uncertainty of end-of-life operations.

2.2 End of Life Strategies

This section will present the different end-of-life strategies for offshore wind energy assets, starting from decommissioning and moving to service life extension and repowering, presenting other processes and decision alternatives that need to be considered.

2.2.1 Decommissioning

The decommissioning process can be defined as the reversal of the installation process, thus it is expected to have similar constraints [7], but with the additional complexity of the marginal value of the asset. The decommissioning process starts with disconnecting the wind turbine from the grid and de-energizing it followed by the blade, nacelle, and tower removal [12]. The foundation may either be partially or fully removed. Partial removal of the foundation leaves some parts in place, such as the scour protection, cables, or even a part of the actual foundation, while total removal is based on the idea of bringing back the site to its pre-installation state [13].

2.2.1.1 Turbine removal

Defining the stages of deconstruction process that typically occur in offshore wind farms is imperative. The different options for the disassembly process are generally similar to those for the installation process, with the size of turbines and the weight of modules standing as key influencing factors [14]. Typically, after isolating and de-energising the turbine from the grid, the turbine's disassembly involves removing lubricants, blades, hub nacelle, and the tower. Disassembling is presumably as costly as an installation because similar vessels (such as heavy lift or dynamic positioning vessel) are needed. The removal of a turbine can be done in 1 to 6 lifts and then all the components can be transported for reuse, recycling or disposal [15], [16]. A reduced number of lifting operations can reduce safety risks and expected duration but usually require larger vessels which come at a higher cost and lead time.

After removal of the rotor, any chemical liquid (such as gear or motor oil) should be collected and removed from the turbine or kept inside the nacelle to reduce the risk of spillage or dropped objects. The removal of bolts and apparatuses can then be done using standard practices or angle grinders and plasma cutters, followed by the cutting of interconnecting cables to adjacent structures. Furthermore, preparation for the removal of the foundation can be done when the tower is being lifted. Important factors to consider are risks to personnel involved, operating time exposure, costs and environmental conditions while deciding the removal options [2], [9].

2.2.1.2 Foundation

The operation selection depends on the type of foundations as specific vessels are needed due to lifting heavy foundations/modules. Initially, the J tubes, which are responsible for the output of cables from the foundation for connection to the inter-array cables, are removed, allowing internal access to the foundation (this is an optional step as, depending on the method, the J-tube can be removed together with the foundation). The foundation may either be partially or fully removed.

Partial removal accounts for cutting of the foundation no less than 2 m below the mud line while leaving the remaining parts on the ground. After removing the foundation, it is necessary to cover the hole by landfilling. This is based on the assumption that after 20-25 years since initially disturbing the local environment, a new natural ecosystem has been developed, and it is unnecessary to cause a new disturbance [1], [17]. This approach is becoming prevailing due to lower risks and costs involved as removing certain components, such as the pile and cables, can cause a significant environmental disturbance.

Several methods are implemented to remove the foundation, including but not limited to external cutting, internal cutting, and the use of explosives. Cutting of the monopile is carried out in various steps based on the cutting stage involved, i.e. external cutting or internal cutting. Internal cutting involves dredging or pumping away the mud to create an execution pit to enable the cutting and removal of the pile. After this step, it would be possible to cut the monopile and remove it. The pit should be filled with mud again after the execution of the job [13], [14].

The type of foundation plays a critical role in the removal operation. The decommissioning processes for various types of foundations are presented herewith:

2.2.1.2.1 Monopiles

An initial inspection of the piles at the site is recommended to determine the lifting equipment and attachments required. The inspection can be done by divers or remotely operated vehicles (ROVs). The vessels, such as a floating crane or a jack-up barge, can be mobilised and assembled for operation at the site [17]. The crane hooks are attached to the foundation, and the piles are cut under the seabed. The distance between the seabed and cutting position is based on the type of seabed and the decommissioning procedure used. The pile size, weight, and depth of penetration at the seabed are influencing the removal process. Apart from this, the total foundation removal for the monopiles involves a higher risk to personnel, increased costs, and adverse environmental effects due to the need for more complex excavation processes. Specialized equipment is needed for such an excavation as greater depths below the seabed need to be reached.

Tow cutting using diamond wire cutting or ultra-high-pressure water jetting can be used for the cutting process, depending on the method’s effectiveness in preventing unnecessary damage and its ability to remove debris from the site. The detached foundation is then loaded onto the chosen transportation vessel and shipped when the vessel has its full capacity [1], [10], [14]. Tow cutting may undertake external or internal cut strategies [3], [10], [14]. Seabed depth and the possibility of excavation surrounding the seabed are two main factors impacting the external pile cutting. However, internal cutting is preferable as it is not affected by water currents; it can be implemented from above the platform and through the pile top [18].

Selection of the cutting procedure should be aimed at enabling a single lift to save the costs of repeated vessel hiring for the transportation of decommissioned monopile and the transition piece; however, it is essential to consider the water depth limitation while selecting the appropriate strategy [19]. Each of the available methods has its own set of financial and environmental risks. Issues arising in either strategy have significant impacts on the project completion timelines due to the need for necessary repairs, remote operation of the system, and confined space [2], [20], [21]. Apart from these, the pile diameter and wall thickness also affect the cutting times. The part of the monopile that remains under the seabed after partial removal of the foundation limits any future operation with jack-up legs and presents a potential risk for the fisher nets. The cutting methods can be replaced by using new strategies and operations, such as vibration, internal dredging, jet grouting, buoyancy force, and air pressure [21] - [23]. These methods contribute to the full decommissioning of the foundation.

Vibratory pile driving is another common method of pile installation and removal. The process is based on reducing shear resistance and the resistance of the pile shaft by using a vibrio hammer (connected to the pile head) at 10 to 40 Hz to stimulate the soil to an acceptable liquefaction level. The crane then pulls out the pile and hammer [21] [22]. Internal dredging, airlifting, and excavation are used to remove the soil inside the monopile. A high-pressure jet from the jet nozzles of the dredging toll weakens the sand, clay, and debris, while the jet pressure is determined by the soil condition and density [22], [23]. External jet drilling or jet grouting uses a cutting fluid composed of water, soil, and binder suspension to cut and destroy the surrounding soil and granular structure when used at pressures of 30 to 60 MPa [22], [23]. Moreover, the problem of breakout resistance could be overcome using the buoyancy force or air pressure. The implementation of the buoyancy force allows the removal of the pile out of the seabed, while the in-built air pressure in a pile guides the pile to a crane by using a gripper [22], [23].

2.2.1.2.2 Jacket

Jacket foundations are valid options as we transition to deeper waters and before floating foundations become economically feasible [24], [25]. Jacket legs are normally smaller in size than monopiles. Hence the requirements for cutting are more limited. Initially, each leg is cut at the selected level below the seabed, followed by lifting. The legs include the pile under the seabed, the sub-pipe under the structure, and the grout among them to fill the space. Before cutting the legs, it is essential to install the rigging equipment on the jacket from the crane vessel. After excavating the seabed near the foundation, a diamond wire cutting tool is used with the help of ROVs. The process may proceed via one-cut, one-lift or two-cuts, or two lifts depending on the depth of the sea and the overall weight of the jacket; however, the former strategy is preferable due to less time and preparation required. The jacket can easily be lifted and transported by a vessel after the legs are cut [1], [19], [26].

2.2.1.2.3 Gravity-based

Gravity-based foundations have been successfully deployed, mainly in shallow water wind farms, due to their suitability to work in rocky or sandy soils, their high bearing capacity, where pile driving can be complicated, and their potential for reduced costs [27]. It is necessary to provide the base structure integrity as well as the lifting attachment. The ballast which belongs to the base should be removed and disposed of, and then the vessel capable of suction dredging needs to be mobilised. The process should be inspected by ROVs or divers for confirmation. The foundation can be lifted out from the seabed by disaggregating compacted sediments which are under the foundation. After lifting and vessel-loading of the foundation, the seabed is monitored for debris to remove [1], [19].

2.2.1.2.4 Bucket/suction

A suction bucket is open at the bottom and completely sealed at the top, like an upturned bucket. It is penetrated into the seabed to a certain depth under its own weight, with the outlet valves on the top open to allow water inside the caisson to escape [28]. The foundation can be separated from the seabed by pumping pressure into the bucket. The structure becomes buoyant by pumping the seawater or ballast inside the foundation, making it easier to transfer the structure on the vessel for transportation. This method has a low environmental impact as no excavation or cutting is required, and the foundation is fully removed from the root.

2.2.1.3 Transition piece

This structure is used to connect the lower part of the tower to the foundation by using a bolted flange or grouted connection. It includes elements such as J tube cable guides, access ladders and a platform weighing around 300 tonnes [1], [29]. The lifting operation will only be possible after disconnecting and cutting the cables connected to the tower and foundation. While cutting the J-tube, the cutting tool should be fitted with the airtight platform of transition pieces. The transition piece will be cut when the crane is in a position to support the load. The transition piece and foundation can be lifted together as well; however, this lift may become heavier than 1000 tonnes and thus require more safety measures and specialised cranes [2], [14].

2.2.1.4 Cables

There are two types of cables; inter-array cables and export cables buried more than a meter under the seabed. Buried cables do not pose a significant risk to marine life and hence have a less environmental impact [30]. Further, removing the buried cables is a cost-intensive process as constant monitoring with ROVs is required to ensure minimum damages to and from the cable. Flow execution and grapnels are used to take out the cable from the seabed at crossings of the buried cables, followed by cutting of the selected length. Afterwards, the cut cables are weighed while the rest are returned to the seabed or lifted onto the vessel.

Complete removal of the cables is challenging because of its negative environmental effects regarding seabed damages and disruption. Leaving the cables in situ and buried is an appropriate choice; however, it is possible to reuse or refurbish the cables made of copper, aluminium, and cross-linked polyethene, which can be used as electrical insulation [19]. It is important to note that more research is required to develop methods of pulling out the cables cost-effectively and with lower environmental risk.

2.2.1.5 Scour protection

Scour is the phenomenon caused by the movement of the seabed and jeopardizes the operating capacity of offshore structures since it compromises their stability [31]. Scour protection prevents the exposure of piles during this movement and as assets reach the end of their service life, scour protection may be left on the site or removed. Removing it will require dredging and shipping to potentially reuse it at another site. Removal of scour protection has similar environmental risks associated with its installation.

2.2.1.6 **Cutting methods**

Decommissioning the OW farms requires extensive cutting work. Various techniques are used for cutting, such as diamond wire cutting, water jetting, and explosives, while other techniques may also be feasible depending on the type of farm:

- Diamond wire: It uses friction between moving diamond wire and the structure. This method can be used for any type and shape, and it is recommended based on oil and gas decommissioning experience to cut the horizontal parts and cables [32]. Key advantages of this method include no vibrations and low pollution. However, proper access to the cutting location is an important consideration [5].

- Water jetting: It uses a high-pressure water jet to cut any material. It can be easily automated; however, the process becomes expensive and unsafe due to the components flying off. Therefore, this method is suitable for vertical piles [32].

- Explosives: It uses explosive products in the lined or unlined cavity. Less time is required for the process of structure demolition using explosives, and it is controllable too. The risks involved with this method are high due to exploration and the need for many accurate plans.

2.2.1.7 Vessel options

Using appropriate logistics arrangements for the decommissioning process is essential in the planning phase of an operation. The selection of vessel(s) should be based on the low risk, cost, and time of operation. Various types of vessels are available; however, it is challenging to select a suitable one. Important considerations for this include the farm's number of turbines, the foundation's weight and the method used for its removal, water depth and the seabed's type, and the vessel's availability in the market. The latter element is particularly relevant as it is expected that the same vessels will compete for installation and decommissioning operations in the next few years. Apart from selecting a suitable vessel, it is also important to select an appropriate transportation strategy, which is influenced by the distance to the port as well as the number of wind turbines on the farm.

The Jack-up vessel is a mobile platform with a buoyant hull, jib crane, and several movable legs. This type of vessel comes at a high cost and requires provisions for mobilisation and demobilisation. The barge vessel is a flat-bottomed boat which transports heavy components. The availability of lifting vessels and the weather conditions can negatively impact the decommissioning operation's time and cost.

2.2.2 Service life extension

Despite having more challenges to overcome regarding the safety, efficacy, costs, and social and environmental issues, extending the service life of the asset is an interesting option for the owners of the offshore industry, investors, developers, and operators, as it can maximise the value of their assets [33], [34], [36]. This is a common approach for offshore oil&gas assets where the nominal service life of 25 years has been extended to 40-45 years. The possible life extension strategies reviewed in the literature for OWTs include reusing, retrofitting, replacement, reconditioning, remanufacturing, and add-on safety/process control measures [34]–[37].

The offshore wind turbine might have residual life at the end of its nominal service life. Considering that many of the critical subsystems may be approaching or already passed to the wear-out failure rate region in a hypothetical bathtub curve, rigorous inspection and maintenance should take place, identifying the most critical internal parts, such as generator and blades, in an optimal technology qualification scheme [38], [39]. In some cases, the energy production of a wind turbine reduces to 75% at the end of its life [33]. However, with an established supply chain and detailed log of asset integrity KPIs (key performance indicators), the potential of extending the operation of the asset by five years or more is an economically plausible option. In some cases, this extension could be longer and more beneficial due to modern, low-cost wind turbine inspection and maintenance techniques [2]. The profitability of the OWF based on its current condition is an important aspect to consider while selecting extension strategies. The life extension involves the replacement/maintenance of minor components in the farm, such as rotors, blades, gearboxes, etc. [34].

Identifying the main life extension requirements of offshore wind turbines is very important. According to the UK Continental Shelf (UKCS), the offshore energy deviation within the health and safety executive (HSE) is applied for this identification. It has developed two HSE programmes, namely KP3: asset integrity [40] and KP4: ageing and life extension [41], regarding OWTs in the UK. Application of life extension strategy saves the investment costs; however, it is necessary to prepare an integrated plan to anticipate and manage the equipment condition as well as the rate of degradation during its extended life [36], [37], [42]. Better inspection and O&M activities of the OWTs increase the chances of having successful life extension plans [33]. Structural Health Monitoring and Condition Monitoring (SHM/CM) systems, as part of Condition Based Maintenance (CBM), are essential to have a successful life extension [33], [43]–[45]. The failure modes and risk identification and assessment of the factors influencing O&M costs can be implemented to determine the possibility of wind turbine life extension [33].

The Petroleum Safety Authority (PSA) of Norway has provided requirements, activities, and issues of ageing assessment and life extension in the OWTs in a comprehensive report [46]. The integrity of load-bearing structures in life extension is discussed in NORSOK N-006 (2009). Furthermore, two standards were also developed, namely NORSOK Y-002 (2010) and NORSOK U-009 (2011), for life extension management of transportation systems and subsea systems [34], [37], [47].

2.2.3 **Repowering**

Although designed for a period of 20-25 years, some critical components mainly related to the foundations and electrical infrastructure (also referred to as the BOP), are designed for longer lives. For instance, the foundation can have a life exceeding 50 years, while the transmission cables and internal arrays can remain in operable condition for nearly 40 years. Despite the reusability of some components, the site needs to be monitored for about two years after decommissioning to ensure its suitability for the installation of a new OW farm.

In the case of repowering, keeping the existing foundation and original electrical systems can save costs while installing more giant wind turbines with modifications to some components, such as drive trains and electronic devices, for efficiency improvements are vital features of repowering. These bigger OWTs can be direct drive, i.e. without a gearbox, and produce power exceeding 6 MW. A significant weight reduction is achieved by excluding the gearbox in the nacelle, while chances of technical failure related to the gearing mechanism are also minimized [9]. Repowering may be executed either partially or fully. The full repowering considers the replacement of the previous offshore wind turbine with the new one; nevertheless, service life extension has involved the installation of minor components in the OW farm, such as rotors, blades, and gearboxes. Repowering has developed into practice for onshore wind energy assets in Germany and Denmark due to sustainability concerns and the potential expense savings from recycling or reusing the disassembled spares. Relevant studies have shown a possible energy cost reduction of 12.93%[48]. In a separate consideration of partial repowering, a selected number of units can be repowered, constrained by the total capacity that the electricity infrastructure can accommodate.

The profitability of full and partial repowering has been shown by using the net present value (NPV) in [49]. An optimisation approach can be used to analyse the economic feasibility of either of the repowering approaches. LCoE can be used as the evaluation index for investment in repowering.

2.3 Factors influencing the selection of end-of-life scenarios

Evaluation of the end-of-life strategies must be based on appropriate criteria and influencing factors. These criteria allow decision-makers to aggregate the performance of decision alternatives towards well-informed decisions. It is imperative that the selection, assessment, and ranking of these criteria align with the stockholder's expectations, both internally and externally [50]. A wide range of criteria can be considered regarding the decommissioning of OWFs, such as potential environmental, financial and schedule impacts.

2.3.1 Environmental impact

The OWF is an artificial reef during its lifetime as marine biota colonises it. This can be observed in the biofouling of buoys [13], [51], functioning communities around shipwrecks [52], [53], oil rig bases [52]–[54], and growth of the epibiota, such as mussels and barnacles, on man-made structures as well as natural materials [13]. There is extensive research regarding the process of habitat colonisation in the marine environment. The installation of a wind turbine changes the environment and ecology, and it establishes a new equilibrium. Although the presence of wind turbine structures can benefit the marine ecosystem, decommissioning will certainly return the site to its original state, but at the cost of ecological disruption similar to the first one [9], [10].

Artificial reefs develop on the monopile foundations as well as the armouring. These reefs impact the marine environment in a three-dimensional manner; the micro-scale, which includes the material, texture and heterogeneity of the construction materials; the mesoscale, which includes the revetments and scour protection; and the macro scale, which covers the wind farm [55]. The foundations of an OW farm provide a potential net habitat gain during 25 years of a lifetime that would be disrupted by decommissioning the farm. A new ecological community will develop over time after decommissioning; however, it will be different from the pre-installation habitat [55], [56]. Therefore, as per the guidelines of the UK government for removing the foundations of OWTs, it is preferable to leave scour protection in place during decommissioning to prevent repeated disruptions to the marine ecology.

The sustainability and environmental impacts are important considerations in cost determination. Four disposal methods for the materials from decommissioning of wind turbines can be adopted; scrap, reuse, refurbish and landfill. Offshore wind turbines and their monopile foundations indicatively account for 3.4 Megatons of steel, 192.393 kilotons of cast iron, and nearly 12.710 kilotons of copper [9]. This shows how important it is to have a structured procedure for the recycling of OWTs.

Steel components of the wind turbine are suitable for scrapping and recycling, but the economic aspect needs to be considered first. The value of recycling can be determined by the component’s weight, dismantling/cutting and transportation costs, and the price of scrap metals. Dismantling/cutting and transportation of steel and metals are expensive activities. Therefore, it is recommended to compare the costs of resale with recycling. Moreover, cutting the monopiles adds to the cost of breaking the grout into pieces, making recycling the only economically feasible course of action [10], [57].

The marine environment introduces corrosion in the materials of wind turbines. A corroded component and its assembly and disassembly process make selecting a refurbishing strategy difficult [14]. Steel components are gathered in the shipyards in the oil and gas industry. Scrapping introduces possible profitability from steel. Landfilling the material can opt if there is no way of recycling, scrapping, or reusing it; the value stream of raw materials should be considered, though, ensuring that landfill becomes the ultimate solution. The blades, plastic parts from power cables, some parts of the nacelle, and the grout are candidates for landfilling due to the absence of cost-effective technological solutions [57]. Blade recycling is a recognised challenge, and it is a key topic of current interest research, also considers the cast amounts of composite materials that need to be decommissioned from onshore wind turbines. This process may use various methods, such as biotechnological, chemical, electro-chemical, fluidised bed, high voltage fragmentation, mechanical, microwave pyrolysis, and pyrolysis [58]. There are two main considerations for the recycling of wind turbine blades; the first is about the economic aspects of the methods used, and the second is related to the recycling location. An anticipated increase in decommissioning of OW farms, combined with landfilling restrictions in the European countries [1], [9], [59], calls for further research in the pertinent field to recommend feasible recycling techniques that also account for transportation costs of the decommissioned wind turbine blades.

About 80%-90% of the material of the total weight of a wind turbine can be recycled, but there is still no suitable method to recycle the rotor blades. Nearly 20% of the decommissioning cost can be paid by applying recycling strategies. The nacelle, hub, and ancillary materials such as handrails, boat landing, ladders, etc. can be disassembled and recycled as scrap materials, while the internal equipment of the monopiles and transition pieces can be cut into smaller pieces for sale [59]. The scrap metal price volatility significantly influences the decommissioning cost; therefore, considering the timing of scrapping is essential from an economic point of view [9].

2.3.2 **Financial impact**

Estimation of cost is the most important aspect of the selection of an end of life strategy. Accurate evaluation is a difficult task primarily because of the following factors:

- Limited experience in decommissioning of offshore wind farms
- Changing legislation and regulatory framework
- Supply chain bottlenecks
- Challenges in fair comparison of all three strategies due to lack of reliable data

Cost is the most influential factor when deciding between the end-of-life strategies; however, considerations for safety and potential risks should also be included. The process of calculating the decommissioning cost is similar to the installation cost; however, it is essential to add costs related to cleaning and monitoring the site [35]. This is so because, for a wind farm site distributed as 0.1 – 0.3 km^2 per MW, the debris accumulated over a time of 25 years would be significant [10]. The estimated cost of decommissioning a 240 MW OWF is £40,000 [13], which includes the total removal of OWTs and the foundations and cables 1 to 2 meters under the seabed. However, the cost of waste management and post-monitoring is not included in this estimate. For an OWF with 25 years of estimated life, the decommissioning costs can lie between 3% [7] or 2.5% [13] of the total cost of a wind farm. Decommissioning costs have been estimated to be between £34,000 and £38,000 per MW and £23M to £60M for a whole farm [1]; however, recent research by DNV GL has concluded that decommissioning costs could reach 200,000 to 600,0000 per MW, which is nearly 70% of the installation cost. Evidently, there is significant uncertainty regarding the estimated cost of decommissioning, and it is difficult to find original research that presents a detailed breakdown of the decommissioning cost. It is important to note that the foundation removal, even without the cable removal costs, accounts for 35% of the total decommissioning cost. Experience with decommissioning of OWT farms, implementation of newer technologies, and applying the experience from the oil and gas sector might reduce these costs to adequate limits.

As far as service life extension and repowering is concerned, costs can significantly vary depending on the asset's integrity status and the extent to which the full capacity of the OWF is considered. For this purpose, common CAPEX models can be used to assess costs and revenue [60], [61].

2.3.3 **Schedule Impact**

Estimating the time for various end-of-life-related activities is a challenging process. Major contributors to schedule impact include the following:

- Lack of site-specific information: Early experience in planning such processes has shown that the original decommissioning plans, which usually form part of the planning phase of a wind farm project, are not sufficient to capture the specificities of an asset after 20-25 years of operation, and hence delays may occur.

- Vessel selection and availability: As mentioned earlier, there is a high demand for vessels to deploy wind farms that meet the current targets for decarbonisation of the energy mix [62]. Considering that the same vessels are required for end-of-life operations, the lead time of such vessels can cause further delays.

- Weather conditions: Offshore operations are normally planned around the summer period as weather conditions may restrict the use of vessels and certain lifting operations when wind speed and wave height exceed operational limits. This impact on installations and O&M activities is shown in [63], while a similar approach can be followed for decommissioning.

- Type and number of turbines and foundations: End-of-life operations are at large repetitive, and the total duration is directly related to the number of stations that will be treated.

- Distance to the port: Receipt of large modules following a decommissioning process or storage of components for repowering poses certain handling and storage requirements that limit the number of ports that can be utilised. The distance from an appropriate port will denote the travel time and ultimately affect the total time of operations.

The project management team should consider all the important aspects while estimating the time required for each decommissioning activity. The decommissioning time should not exceed 60% of the installation time. Previous researchers have used an overly optimistic method for estimating the decommissioning time of OWTs, adversely affecting the total cost and schedule estimations of the ongoing and future decommissioning projects [3]. It should be noted that although decommissioning can presumably be done in a few months, the whole process would most likely be completed in up to three years [8], taking into account the influencing factors mentioned above.

2.4 Lessons from the oil and gas industry

The removal of a wind turbine is an expensive process. Therefore, finding cost-effective and time-efficient methods is imperative. The methods used by oil and gas sector for cutting the platform structure can also be applied to the decommissioning of OWTs. The first step involves the removal of fluids and hazardous materials in the nacelle (similar to the topside). Further, the turbine's tower is cut and fell into the sea, identical to the reefing-in-place method used for removing oil/gas platforms in the ocean. Significant challenges to using this method include the following:

- safety of personnel and marine life (i.e. ensure that no additional risks are introduced during the operation)
- integrity of the structure (i.e. avoid breaking the turbine components),
- flotation (i.e. avoid sinking of the components)
- weight (i.e. the need for heavy-lifting vessel)

Foundation removal of an OWT is similar to the oil/gas platform removal from the seabed. The jacket structure is pulled out from the seabed and barged onshore for recycling or reuse at another site. Subsea pipeline removal methods, such as using diamond cutting wire and high-pressure abrasive water jet used in the oil/gas industry can be applied to remove OWT cables from the seabed. Cable laying vessels, ROVs, or divers can be utilised for this purpose in shallow waters.

There are two methods used to serve the structure attached to the seabed: mechanical severance and explosive severance. Mechanical severance includes various cutting techniques, such as abrasive-water jets, sand cutters, diamond-wire saws, carbide-cutters, shears, and guillotine saws. It is time-consuming and requires personnel, i.e. divers, and additional equipment. The risk of injury to personnel and higher cost limit the use of mechanical severance to certain scenarios. The use of diamond-wire and sand cutters recently has helped to improve the underlying safety and cost issues [64].

Explosive severance is a reliable method to cut conductors, well casings, jackets, and piles. Usage of this method depends on the platform's configuration and location and the diameter and wall thickness of the pipe. Explosive severance must be more controllable, using a detonator or otherwise, per the health and safety requirements. Newer technologies, such as modern blasting caps, have made the process more controllable and less risky to the personnel. While the condition of less personnel, equipment, time, and cost are the main advantages of explosive severance, the adverse environmental impacts, such as fish-killing as a result of the explosion, make mechanical severance a method of choice [8], [64]. Moreover, when combined with heavy lifting equipment, this method can significantly reduce the time and cost of OWTs decommissioning.

With respect to reefing methods used for removing oil and gas platforms, either explosive or mechanical severance can be used for this purpose. The structure may be fully removed, using explosives to cut the conductors, pilings, and support legs 5 m under the seafloor and towing the facility to shore. The system may also be left in place horizontally after toppling it using the explosives or cutting it [8], [64]. The platform structure may also partially be removed by cutting it at 26 meters under the waterline and placing the cut part beside the existing one.

2.5 Conclusion

With many offshore wind turbines (OWTs) coming to the end of their estimated service life, there is an increasing need for developing and evaluating end-of-life strategies that can maximize these assets' value while simultaneously satisfying the stakeholders' requirements. This chapter aims to perform a detailed review and consider multiple criteria in the decision-making process, presenting and discussing available technologies and strategies and influencing factors such as schedule, cost and environmental impact. Service life extension, repowering and decommissioning are included in this review as the main end-of-life strategies.

Chapter 3

3 Decommissioning vs Repowering of offshore wind farms – a techno-economic assessment

3.1 Techno-economic assessment

3.1.1 Introduction

The offshore wind industry in Europe is a key driver toward achieving the EU set goals for sustainable power generation in the next few years, with more than 22GW installed from 5,047 grid-connected wind turbines across 12 countries by the end of 2019 [65]. The trend to move production into deeper waters and further offshore is based on the higher and steadier wind shear, increased availability of space and less social impact than onshore. Since the first offshore installation in 1991, the Vindeby Offshore Wind Farm (OWF), there has been a continuous trend to install more units of higher capacity within a wind farm; however, with many of the first generation installations approaching or having already exceeded their nominal service life, the discussion on the selection of the optimal end of life (EoL) scenario has become very relevant as such decisions can increase profitability, potentially reducing costs. Normally, decommissioning should be considered even at the planning stage of the wind farm; however, before this occurs, repowering or service life extension may be pursued, taking into account any residual capacity of key wind farm components, as suggested by Topham et al. [9].

The current academic literature about EoL scenarios is limited, forcing operators of wind farms to adopt their own practices when supporting relevant decisions. While in other industries, systematic approaches have been established to support EoL decisions, this is not currently the case for OWFs [66]–[69]. Luengo and Kolios [33] have reviewed in detail the risks involved in service life extension based on a detailed failure mode identification and with a view to qualifying which are the key components to drive such decisions. It is claimed that extending efficient operation and increasing the overall energy production may significantly increase the return on investment and reduce the LCoE.

Topham and MacMillan [1] investigated key stages of the decommissioning phase, such as the disassembling procedure for the wind turbine and lifting, and cutting methods for the removal process of foundations and cables, with a view to comparing various transportation strategies to reduce the decommissioning cost. Fowler et al. [70] studied the benefits of leaving offshore infrastructures in the ocean, mainly from an environmental point of view, while in a similar study Topham et al. evaluated the environmental impact of recycling wind turbines [9]. Judge et al. have developed a life cycle financial analysis model for OWFs, exclusively investigating decommissioning [71], while Myhr et al. [72], proposed a framework based on Multi-Criteria Decision Analysis (MCDA) techniques to select the most appropriate decommissioning methods for OWFs. In addition to this, Gjødvad and Ibsen have introduced a tool to assign the decommissioning process to stakeholders [73]. Sun et al. studied OWF layout optimization based on the decommissioning strategy [74]. Beauson et al. studied offshore wind decommissioning regulations for the USA. Beauson and Brøndsted have focused on the fate of offshore wind turbine (OWT) blades, based on the first wind farm in the world that will undergo decommissioning [75], and Lichtenegger et al. have focused on the blade waste that OWTs are expected to generate, pointing out the significance of the problem [76]. In a different study, Hou et al. [77] determined that repowering is considered a sustainable alternative solution to increase the OWT life. Cabboi et al. have analysed technical issues related to decommissioning, investigating novel methods for vibration-assisted decommissioning of a slip-joint [78]. Hinzmann et al. have summarised problems and solutions in typical issues associated with decommissioning offshore monopiles [23], while Topham et al. have summarised the challenges of decommissioning based on European best practices [79].

With respect to repowering, Hou et al. presented a method for optimization of OWF repowering through the selection of different ways of replacing wind turbines [2]. Himpler and Madlener, studied economics and optimal timing of repowering and presented a case study application in Denmark [80], while Sun et al. investigated OWF repowering in the context of Hong Kong [81]. Bezbradica et al. applied multi-criteria decision analysis for the ranking of a number of wind farm repowering scenarios for a case study in Gotland [82]. Finally, Safaei et al. presented a model for finding the best topology and optimal time for repowering systems based on cost and availability functions [83].

A number of studies have investigated the techno-economic feasibility of OWF with only a few considering in detail EoL scenarios [60], [72], [84]–[89]. Kaiser and Snyder proposed a model to calculate the cost of decommissioning and installation based on data from European OWFs [90], [91]. Common key performance indicators (KPIs) to systematically assess the cost of OWFs include Net Present Cost (NPC), Life Cycle Cost (LCC) and Levelized Cost of Energy (LCoE). The NPC concept is used to show the total present value of cash flow, including the initial cost of all the components, any replacement cost, maintenance cost, investment cost and discount cost during the lifetime of the system [92]. LCoE is a common economic metric for comparing different energy technologies [61]. The LCoE shows the cost of produced energy rather than determining the potential profit of an investment, which can be estimated through other economic metrics such as the return of investment and internal rate of return [93]. LCoE is calculated in £/kWh or £/MWh and is used to evaluate the feasibility of a power generation technology commercially and compare its implementation with other technologies considering LCCs and power production. Net Present Value (NPV) aims to account for the time value of money, which is a particularly important factor, considering the length of these investments. A detailed techno-economic model incorporating both concepts has been presented by Ioannou et al. [60] and will stand as a basis for subsequent work in this research.

It should be noted that a number of variables influence the LCC modelling of investment, and considering that the offshore wind energy market is still developing, considerable uncertainty can be introduced in the analysis [94], [95]. To this end, it is meaningful to transition from a deterministic to a stochastic assessment, expressing the calculated KPIs instead of single values in joint probability density functions, which accumulate the effects of the randomness of specific variables [96]–[98]. This approach would allow the assignment of certain confidence levels to the cost analysis results.

This chapter aims to develop a framework for a preliminary analysis and comparison of two key EoL scenarios: repowering and decommissioning, to present the impact of key influencing factors from a deterministic and stochastic approach, also adopting the economic model of risk aversion to calculate the certainty equivalent of LCoE based on each of the examined EoL scenarios. To achieve this, results from a detailed techno-economic assessment have been extended to calculate the LCoE based on the Capital expenditure (CAPEX), Operational and maintenance expenditure (OPEX), Decommissioning and disposal (D&D) or Cost of repowering (REPOW), to inform the decision of the optimal strategy. The novelty of this approach lies in the fact that a high-fidelity cost model is applied, and two of the EoL scenarios are compared directly based on their NPV and LCoE. With a few hundred wind turbines expected to reach the end of their nominal service life in the next five years, outcomes of this work can inform current best practices on supporting decisions related to EoL scenario selection and can stand as the basis for more advanced numerical studies which will account for higher fidelity calculations of the operations and maintenance (O&M) costs and also involve service life extension as an alternative EoL scenario. It should be noted here that service life extension has not been considered in this analysis, as the approach to quantification of the underlying costs would be different and would demand a fully integrated cost model with detailed modelling of the O&M phase requirements; further, this option highly depends on the current condition of the wind turbine units and representative component reliability data, which is beyond the scope of this research.

3.1.2 **End life scenarios**

Once the 20-25 years of nominal service life of a wind farm lapse, a decision is required from the operator as to what would be the optimal EoL scenario and how it should be selected considering associated costs and risks. Operators need to evaluate the current condition of their assets, and the state of the technology that was originally procured, and maximise the value of their initial investment. Similar decisions have been made over the past decades in the offshore oil & gas industry, with platforms originally designed for 20 years and eventually ceasing operations after 40+ years from commissioning [99]. **Error! Reference source not found.** 3 presents the most common EoL scenarios for OWFs, which will be further discussed in this section.

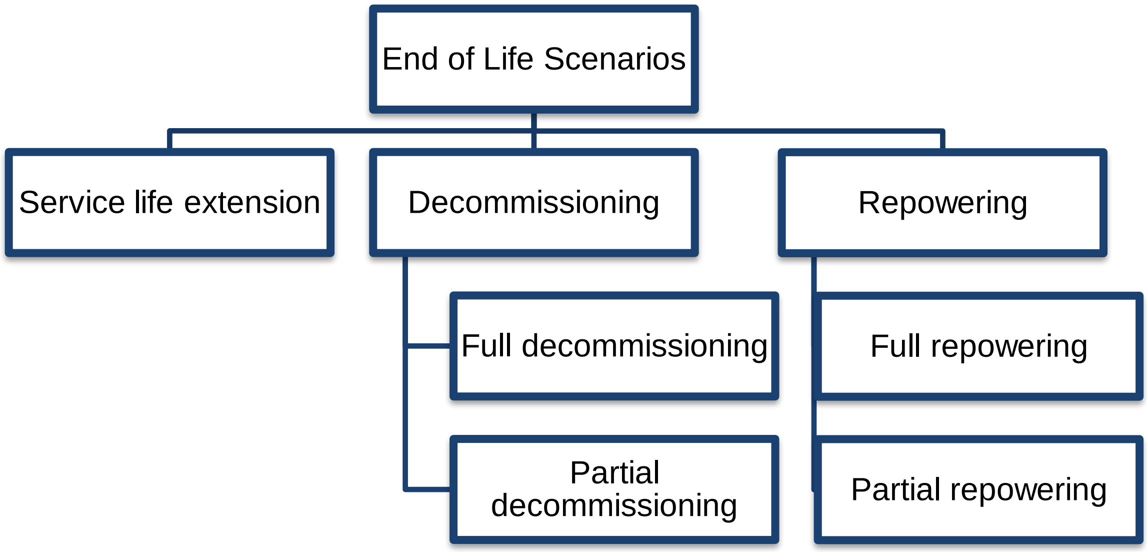


Figure 3. End of life scenarios of offshore wind farms.

3.1.2.1 **Decommissioning**

The decommissioning process is known as the final stage of an OWF project as even if operations are extended, eventually, the deployment area should return to its original, before-installation conditions [1], [2], [5]. Technically, the process is implemented reversely to the installation process, e.g. using vibrations to remove the piles from shallow water installations. Vindeby was the first wind farm to be decommissioned by Dong Energy, a process which was completed in September 2017 after 25 years of operation. The driver behind choosing this strategy was associated with the difficulty of finding spare parts as the technology was becoming obsolete and costs of repairs and upgrades were not sustainable [1], [2].

Planning of the decommissioning process is essential in order to reduce operational risks and reduction of costs. Weather and seabed conditions are crucial to this end. The type and number of foundations, the capacity of the wind turbines and distance to port are key factors influencing the process. Decommissioning starts with the turbine removal phase, which includes disconnecting and de-energizing the wind turbine from the grid, dismantling the blade, nacelle and tower [12] and transportation to shore for recycling or disposal where appropriate. With respect to the foundation, two strategies can be considered: partial or full removal. The partial removal of the foundation can be done with the external or internal cutting of the foundation, normally two metres below the mud line and is more relevant to heavy foundations deployed in deep waters. In this strategy, parts such as the cables and scour protection should be considered separately, taking into account the option that will cause the least disturbance to the environment [10], [100]. In full removal, the whole foundation is de-piled using vibrations and transferred to the port facilities on a barge.

3.1.2.2 Repowering

Current practice has shown that core components of an OWF, such as cables, foundations and offshore substations, do not have a similar service life to the turbines. This implies that after 20 years, there can still be some capacity in the OWF, and the cost of harvesting its value should be investigated before making EoL strategy selection decisions. It should be noted here that the high cost of the decommissioning process raises an additional argument in favour of delaying this process for as long as possible.

Repowering can be applied to the whole wind farm or part of it, potentially with more modern turbines of higher capacity [77]. New generation OWTs have direct drive technology without gearbox, producing more energy with an average capacity of 6MW [101]. Reducing the weight of the nacelle and component failures reduces loads and operational costs and hence increases the profitability of the initial investment. Repowering allows the OWF operator to use the existing foundation and the original electrical system, commonly known as the balance of plant (BOP). Installing higher capacity WTs, as well as modifying some key components, such as drive trains or electronic equipment to improve their efficiency, will extend the operational life of the OWF with a limited additional cost of installation [5], [19], [30]. It should be noted that the extent to which repowering can occur can often be restricted by the capacity of the offshore substation and cable infrastructure.

3.1.2.3 **Service life extension**

Extending the life of assets is always an interesting option for OWF owners as they can continue to operate as usual, provided they have sufficient information on their integrity status. Available data from monitoring schemes and inspection reports are a key requirement as the 20 years of operation often stipulates the design service life of major components, such as the drive train, and such repair or replacement activities bear high costs to the operators; therefore, identifying the most critical parts such as the generator and blades could help reduce inspection and maintenance costs [45], [48]. Although operational data are not excessively available from operational wind turbines, it is expected that the failure rates and associated costs will increase during the second half of their service life, and it is also anticipated that the costs for inspections, monitoring and maintenance will also increase during this latter part of their operation, and certainly within the extended period, especially related to the modification and replacement of critical components [102]. A failure mode-based, risk identification and evaluation exercise of the factors influencing operation and maintenance (O&M) costs are pertinent to optimizing service life extension strategies [33], [38], [103].

Service life extension can potentially add five or more years of additional operation before deciding on repowering or decommissioning at the end of this period [77]. The rapid technological evolution of wind turbines' inspection and maintenance programmes and relevant certification schemes can enable service life extension, increasing the profits from existing OWFs with less investment [34], [36].

3.1.3 Boundaries of this study

This research focuses on the techno-economic comparison of decommissioning and repowering with the latter option depending on a higher level assessment of the technology rather than a detailed integrity assessment, even at a unit level, which is required for the service life extension option. Consideration of service life extension requires evaluation of failure rates of maintenance-significant components, e.g. drive train components, along with their variance throughout the asset's service life, which are difficult to retrieve considering the lack of data from operational wind farms. This information is not generally required to the same extent for a repowering strategy, and also, considering that technology has significantly advanced since the first generation of wind farms, this research focuses on repowering as a competitive EoL scenario.

3.2 Methodology

3.2.1.1 Techno-economic analysis framework

This section documents the framework for the techno-economic evaluation of the two EoL scenarios: the foundation of the specific features that are included in the analysis and the KPIs that will be investigated. As mentioned earlier, the results of this analysis are based on an existing techno-economic model presented by Ioannou et al. [60], which also included a sensitivity analysis illustrating key influencing factors to standard KPIs, as presented in **Error! Reference source not found.**, while **Error! Reference source not found.**, presents in a flow chart the key concepts of the methodology developed in this research and how these will interact during the analysis.

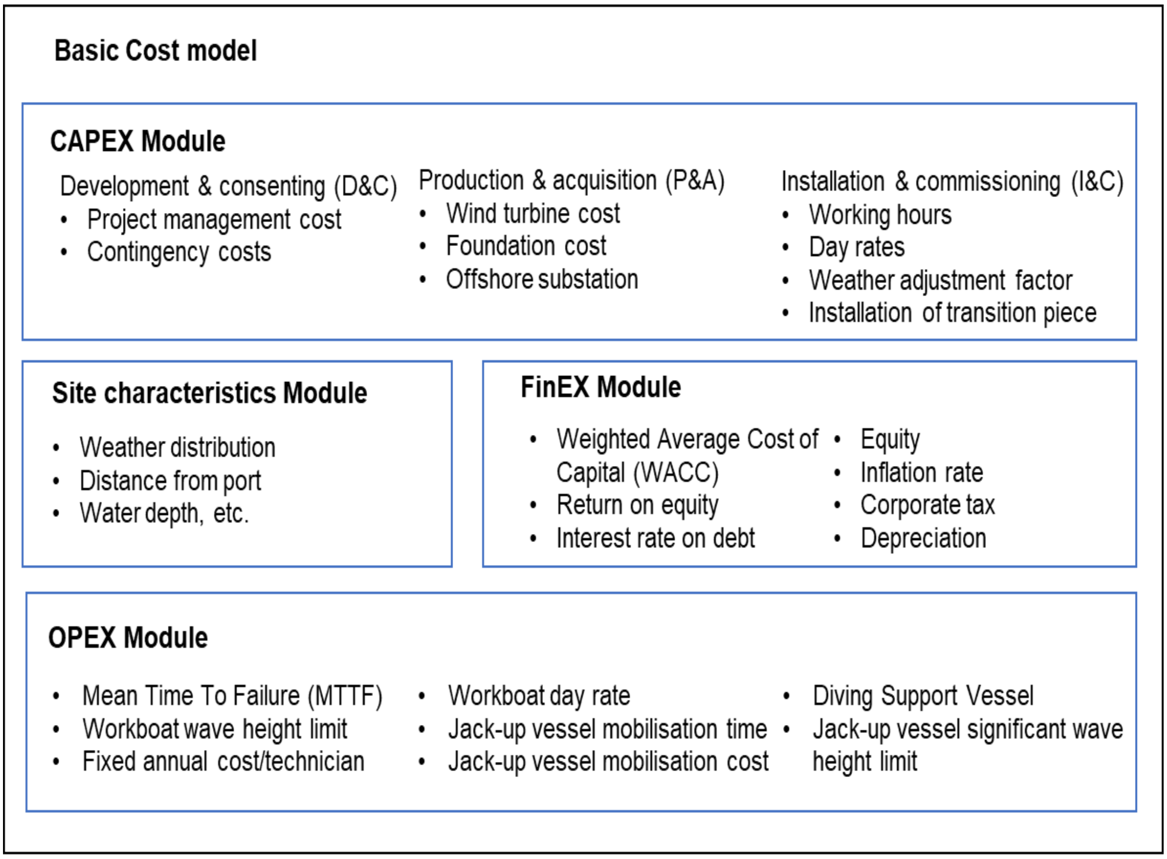


Figure 4.Structure of basic model and key influencing parameters.

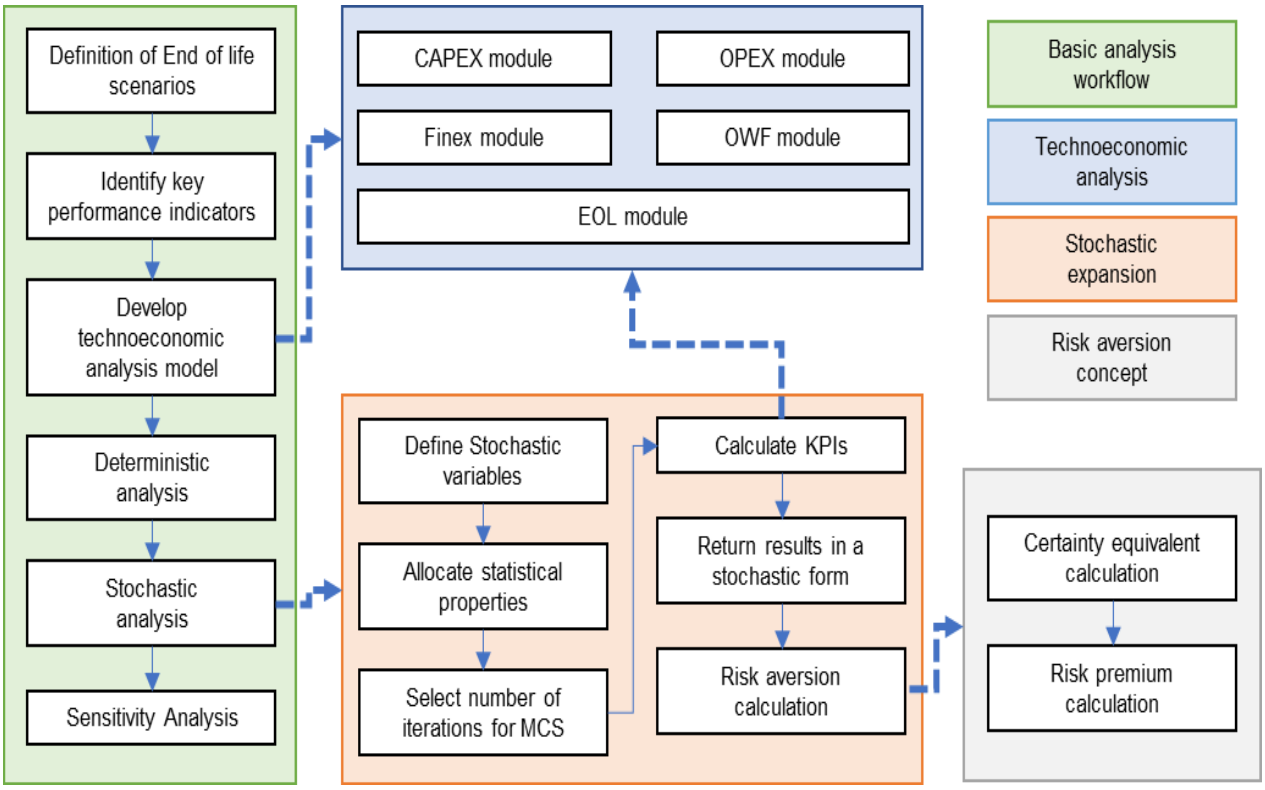


Figure 5.Overview of analysis framework.

The analysis starts with the definition of the EoL scenarios, which for this case, are the concepts of repowering and decommissioning. Next, the KPIs will be selected, as presented in the following subsection. The core techno-economic analysis framework, which was presented in Figure 5, is then extended, with the inclusion of the EoL module, which will calculate the additional costs of each alternative, in addition to the initial CAPEX (capital expenditure), OPEX (operational expenditure), FinEx (financing expenditure) and OWF (offshore wind farm) modules. The developed EoL module based on the KPIs, as well as the role of energy production based on the asset's whole life, provides the deterministic result of LCoE, and it will stand as a basis for the stochastic expansion of the initial model. For this, once the stochastic variables have been determined, appropriate statistical properties are assigned, together with the number of simulations that will run for the Monte Carlo Simulations (MCSs). Then, following an iterative algorithm, the KPIs are calculated, and the results are expressed in histograms, allowing the risk aversion parameters to be calculated. Once this has been completed, a sensitivity analysis will take place to determine the impact of key variables on the selected KPIs.

3.2.2 Key performance indicators

3.2.2.1 Levelized Cost of Energy

The levelized cost of electricity considers the costs and power output throughout the whole life of an energy asset. The global weighted average LCoE for offshore wind in 2018 has been estimated at \$0.127/kWh, according to IRENA [104]. For the accurate estimation of the cost of energy in this study, a high-fidelity LCC analysis was performed, considering the different phases of the asset's development and operation: Development and Consenting (D&C), Production and Acquisition (P&A), Installation and Commissioning (I&C), Operation and Maintenance (O&M) and Decommissioning (DECOM).

The total levelized cost of electricity of the OWF can be calculated by levelling and discounting the investment as well as the O&M cost during its lifetime and then dividing it by the annual electricity production technology [105]. Eq. (1) presents the fundamental definition of LCoE [106].

$$\mathrm{LCoE}\ (\$/\mathrm{Wh}) = \frac{\sum_{t=1}^{T} \frac{C_{tot,t}}{(1+r)^{t}}}{\sum_{t=1}^{T} \frac{AEP_{t}}{(1+i)^{t}}} \quad 1$$

where, $C_{tot,t}$ is the total cost during year t ($), AEP_t is the electricity production during year t (Wh), i denotes the discount rate, and T represents the design life of the asset. The discount rate is identified based on the market value of both equity and debt, the so-called Weighted Average Cost of Capital. It is necessary to consider the project risk as well as the return yield. The discount rate has been identified as a key parameter affecting the LCoE value in various studies [60], [94], [95]. The equation of LCoE can be modified based on the type of analysis. The deprecation tax shield and salvage value at the end of the asset life should be considered in the total life cost of an asset.

To accurately predict the LCoE, a life cycle cost model of an OWF has been developed, and the sensitivity of important parameters such as availability, distance to the shore and load factor was considered in [72]. For this research, the initial model is expanded considering the EoL costs for each option, and additional stochastic functionality is added through MCSs to allow for the stochastic calculation of the KPIs. Similar applications of the integration of MCS to compare the LCoE has been presented for coal-fired power plants as well as the generation of natural gas [107]–[109]. Further, the LCoE of various sources of energy has been stochastically calculated based on MCS in [110]. Even though there are studies associated with the cost estimation of partial and full decommissioning, the literature review has indicated that no research is associated with the detailed economic consideration of the EoL scenarios based on the whole life of the OWF [106].

Based on various methods to calculate the LCoE, this chapter also considers the concept of net present value (NPV) based on summing the discounted capital, operational expenditure in each year of the OWF's life and the associated expenditure, which depends on the examined EoL scenarios, taking into account the actual value of money which considers the timing of the transactions, as shown in Eq.(2).

$$\boldsymbol{NPV_{Total\ Cost} = \sum_{n=0}^{T} \frac{CAPEX_n + OPEX_n + DECOM}{(1+i)^n}} \qquad 2$$

As mentioned above, to calculate LCoE, the discounted electricity output has to be estimated based on Eq. (3). As such, by dividing the NPV of the OWF lifetime cost shown in Eq. (1), into the NPV of produced energy in the OWT farm, the LCoE is calculated as:

$$NPV_{Yield} = \sum_{n=1}^{T} \frac{AEP_n}{(1+i)^n} \qquad 3$$

$$\mathrm{LCoE} = \frac{NPV_{Total\ Cost}}{NPV_{Yield}} \qquad 4$$

LCoE is calculated in this study parametrically based on the different EoL scenarios for fixed-bottom OWTs. The LCoE can be estimated separately for each case, considering respectively OPEX, CAPEX, decommissioning or repowering cost and expected yield of the OWF.

3.2.2.2 Capital expenditure (CAPEX)

Capital expenditure covers the costs associated with the building and commissioning of the OWF. It is divided into three main categories: Development and consenting (D&C), Production and acquisition (P&A), and Installation and commissioning (I&C). This is translated into the following equation:

$$\mathrm{CAPEX} = \mathrm{C}_{\mathrm{P\&A}} + \mathrm{C}_{\mathrm{D\&C}} + \mathrm{C}_{\mathrm{I\&C}} \tag{5}$$

It should be noted that in order to improve the accuracy of the cost consideration, several critical factors, such as geographical location and meteorological conditions, capacity factor, reliability, availability and accessibility of transportation, should be taken into consideration [35].

3.2.2.3 Operational expenditure and maintenance (OPEX)

The costs during the O&M phase are associated with planned and unplanned maintenance and account for interventions that aim to ensure safety and reliability and the continuous operation of the OWF. Operational costs further involve rental payments, insurance costs, and project management.

$$OPEX = C_{repair} + C_{rent} + C_{insurance} + C_{Project\ management} \tag{6}$$

A detailed description of the key characteristics of O&M models and calculation tools can be found in [111], while multiple groups to date have proposed different approaches and have engaged in various comparative analyses [112]–[114].

3.2.3 Decommissioning and disposal cost

Decommissioning and disposal is the final stage of the wind turbine life cycle and is assumed to be the reverse of commissioning and installation processes. It covers the costs associated with the removal of the wind turbine (nacelle, tower, and transition piece) as well as the balance of the plant (foundations, scour protection, cables, and substations) ($C_{Removal}$), site clearance $C_{Site\ Clearance}$, transportation to the disposal sites $C_{Transportation}$, port preparation ($C_{Port\ preparation}$), disposal process $C_{Disposal}$, and finally hiring vessels costs $C_{Hiring\ vessels\ and\ personnel}$ [35]. The disposal process of an OWT depends on the waste management strategies, and the main available disposal options include reuse, recycling, incineration with energy recovery and disposal in a landfill site [101].

$$\begin{aligned} \mathrm{DECOM} = \ & \mathrm{C_{Removal}} + \mathrm{C_{Transportation}} + \mathrm{C_{Disposal}} + \mathrm{C_{Site\ Clearance}} \\ & + \mathrm{C_{Hiring\ vessels\ and\ personnel}} + \mathrm{C_{Port\ preparation}} \end{aligned} \tag{7}$$

For the purpose of this work, costs of full and partial decommissioning are calculated based on assumptions from [3]. More specifically, full decommissioning is assumed to be 30% more expensive than partial decommissioning, and the ratio between partial decommissioning through the internal and external cutting of the foundation is assumed to be 1.052. The difference between partial decommissioning through internal and external cutting is negligible, therefore, the internal cutting of the foundation has been investigated in the subsequent parts of this work. In the case of decommissioning as the qualifying EoL strategy, the maximum value of T in $NPV_{Total\ Cost}$ and NPV_{Yield} would be based on the nominal life of the asset, i.e. 20 years. The total duration of the decommissioning process itself is assumed to be one year at the end of the 20 years.

3.2.3.1 **Repowering Cost**

When assuming repowering as the EoL strategy, the Repowering Cost (REPOW) is estimated instead of DECOM. The assumed initial service life of 20 years is considered, after which the OWF will be repowered, in this case, with a turbine of the same capacity. **Error! Reference source not found.** illustrates this strategy and the calculation of LCoE for each part of the asset life in the repowering case. The maximum value of time T_1 in $NPV_{Total\ Cost}$ and NPV_{Yield}, which are the main parameters of $LCOE_1$, would be based on the nominal life of the asset, which in this case is assumed to be 20 years. The total duration of the repowering process is assumed to be one year added at the end of the nominal service life of the asset. In the case of asset life extension for a further 20 years, the LCoE would be assumed for the next 20 years (T_2), which is denoted as $LCOE_2$.

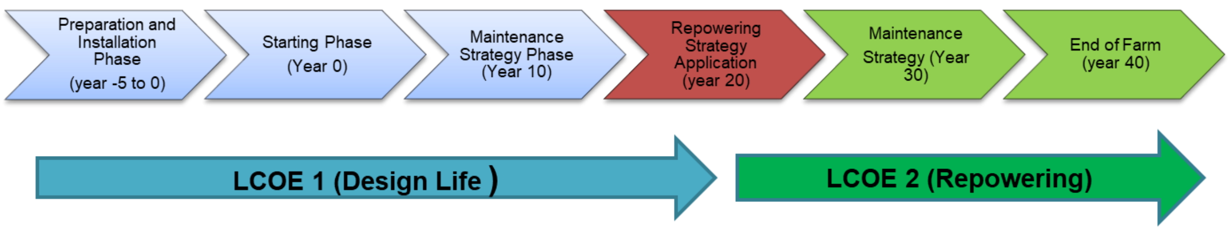


Figure 6.Repowering Strategy for an OWF.

The costs of the repowering process of OWFs with same capacity turbines include the cost of removing the current wind turbine ($C_{Removal}$), transportation ($C_{Transportation}$), disposal ($C_{Disposal}$), new wind turbine acquisition ($C_{New\ WT}$), hiring vessels and personnel ($C_{Hiring\ vessels\ and\ personnel}$), operation ($C_{Operation}$) and maintenance ($C_{Maintenance}$), as shown below:

$$\mathrm{REPOW} = \mathrm{C}_{\mathrm{Removal}} + \mathrm{C}_{\mathrm{Installation\ new\ WT}} + \mathrm{C}_{\mathrm{New\ WT}} + \mathrm{C}_{\mathrm{Operation}} + \mathrm{C}_{\mathrm{Maintenance}} \quad 8$$

3.2.3.2 **Energy production**

The amount of energy produced depends on the technology type, capacity factor and the system scale. Energy performance is key in computing the LCoE during the wind farm's life. The capacity factor (CF) plays a crucial role in the energy performance estimation and is defined as the ratio of the real energy production to the maximum potential energy outcome. OWF reliability would influence the capacity factor indirectly, implying that a higher power plant capacity would reduce the LCoE; however, it is essential to consider the demand for energy from the power plant. To calculate the annual energy production (AEP) of the OWF, different power curve modelling techniques can be implemented [115]:

$$\mathbf{P_S(v) = \frac{1}{2}\rho\pi R^2 C_{p,max} v^3} \qquad 2$$

Where, ρ is the density of air (1.225kg/m^3), R is the radius of the rotor, $C_{p,max}$ is the coefficient of the maximum effectiveness of power, and v is the instantaneous wind speed. The simulated power curve, $P_{sim}(v_a)$, is based on the mean wind speed as shown in Eq. (10). The $P(v, v_a)$ shows the probability distribution of wind speed based on the turbulence intensity factor and v_a [116], [117].

$$\mathrm{P_{sim}(v_a)} = \int_0^\infty \mathrm{P_S(\,v)P(v, v_a)dv} \qquad 3$$

The AEP of the wind farm can then be calculated as:

$$AEP = Z\ \ (1 - \eta_w)h\eta_A \int_0^\infty P_W(\,v_a)P_{sim}(v_a)d_{v_a} \qquad 11$$

where, Z is the number of turbines, h is the number of hours in a year, η_w represents the factor accounting for wake losses, η_A is the availability of the wind farm and $P_w(v_a)$ signifies the Weibull distribution as a function of v_a. The AEP is assumed to be constant in this study. The net AEP, which is computed based on these inputs, is 1,734,792 MWh/year.

3.2.4 **Stochastic expansion of the techno-economic model**

As mentioned earlier, the input variables of the LCoE are often characterised by considerable uncertainties, which deterministic models are not able to handle systematically. Even adopting a scenario analysis including the assumption of upper and lower inputs for each variable, distinguishing conservative/unconservative scenarios for LCoE, this approach would not be able to support decisions under uncertainty. Therefore, to achieve a meaningful assessment, a systematic approach should be considered in order to quantify the cumulative impact of these uncertainties. Based on reviewing KPIs, the uncertain variables with a significant impact on the LCoE can be modelled stochastically and then MCS can be employed to compute the LCoE through a joint probability distribution histogram. The MCS approach generates sets of inputs of the stochastic values, which feed an iterative calculation loop of calculating output KPIs through the deterministic model. This approach can efficiently consider multiple stochastic variables; however, it becomes inefficient when calculating low probabilities of failure. Estimating LCoE through a stochastic analysis has proved to be more insightful than a deterministic approach since, instead of returning a deterministic value with limited context, it can provide an LCoE value with an associated confidence interval (CI).

The result as a stochastic distribution provides an opportunity for quantitative analysis of the risk or uncertainty in comparison to average LCoE. The constant in relation to the risk aversion utility function is implemented in this research based on [118] and [110] to calculate the certainty equivalent of LCoE for each

EoL scenario. The certainty equivalent indicates a fixed value of LCoE which the decision maker should be indifferent towards, relative to the uncertain LCoE that they face. Moreover, the uncertainty or risk premium (RP) indicates the amount of money that should be paid to reduce the uncertainty and is used as a method to monetize the risk of investment in terms of an uncertain outcome. To calculate a certainty equivalent LCoE for each EoL scenario, it is necessary to find the uncertainty or RP. Eq. (12) shows RP as function of risk aversion of LCoE, r as the number of iterations and the gamma valueγ. The LCoE value is obtained based on each iteration within the MCS.

It is assumed that a gamma γ coefficient of relative risk aversion, equal to 2, is used in the analysis. The case of a more risk averse decision maker may be modelled through increasing the value of gamma [110]. After computing the RP for each EoL scenario, Eq. (13) is implemented to calculate the certainty equivalent C_{eq}.

$$\mathrm{RP} = \frac{\sum_1^r \mathrm{LCOE}}{r} - \left((\frac{\sum_1^r \frac{(\mathrm{LCOE})^{1-\gamma}}{1-\gamma}}{r} \times (1-\gamma) \right)^{(1-\gamma)} \quad 12$$

$$\mathrm{C_{eq}} = \frac{\sum_1^r \mathrm{LCOE}}{r} + \mathrm{RP} \quad 13$$

The relative risk aversion is assumed to be constant due to being positive as well as decreasing the utility function of the LCoE. The higher certainty equivalent would be based on the higher risk aversion and the RP.

3.3 Results

3.3.1 Case Study

This section presents the assumptions and characteristics used in this paper, aiming to refer to a realistic but hypothetical OWF deployed in UK waters. The cost of labour and vessels, environmental conditions, wind turbine, monopile foundation and the capacity of the wind turbine are assumed to be the same as in [60], which is the basis of this study, and account for a 504 MW wind farm capacity, with a nominal service life of 20 years, five years of construction time, availability between 92.2-92.5% and an interest rate of 8%. The distance to the port is assumed to be 36 km, water depth 26 m, and the turbine characteristics are as follows: Rotor diameter 107 m, Hub height 77.5 m, Pile diameter 6 m, Rated power 3.60 MW, Cut-in speed 4 m/s and Cut-out speed 25 m/s. The key assumptions with respect to CAPEX (k£) and OPEX (k£/y) are presented in Tables 1 and 2. The reader is referred to [60] for the detailed methods and data that are utilised for estimating each field of the table; this information is not presented here to avoid repetition.

Table 1.CAPEX (k£) and OPEX (k£/y) estimation in OWF

Total D&C costs	205,750	**Total I&C costs**	305,742
Project management cost	42,327	Installation of wind turbines (tower, hub, nacelle and blades)	62,619
Legal cost	16,698	Installation cost of foundations	102,224
Environmental surveys cost	19,162	Installation cost of cables	115,070
Engineering cost	1,144	Installation cost of substation	3,991
Contingency cost	126,419	Installation cost of scour protection	873
Total P&A costs	1,040,230	Insurance cost during installation	20,966
Wind turbine cost	546,056	**Total O&M costs**	56,597
Foundation cost	212,699	Repair cost	28,403
Cables cost	120,525	Rent cost	5,040
Offshore substation (x2)	121,337	Insurance cost	7,338
Onshore substation	30,334	Project management cost	15,816
SCADA cost	9,278		

Table 2.Repowering Cost (k£)

The total cost of Repowering process	707,035
Turbine cost	546,056
Removal cost	41,763
Installation cost	62,619
Operation and maintenance	56,597

3.3.2 **Deterministic analysis result**

LCoE is calculated parametrically in order to allow multiple iterations to run in an efficient way. Results for the three scenarios that have been studied in this work are presented in a stack bar chart in **Error! Reference source not found.**. It is indicated that the repowering option has the lowest LCoE compared to the other scenarios. The output reduction of energy of the OWF after the installation is 1.6 ± 0.2% for each year [119]. The repowering strategy provides the opportunity to the owner of the wind farm to improve the efficiency of energy production by avoiding further energy losses with less investment cost (reduction of the maintenance cost, installation cost, as well as existing current structure). More specifically, for the case where the same capacity of a wind turbine is selected, the recalculated LCoE, which accounts for after the end of the nominal service period, becomes 65.8 £/MWh. The repowering strategy would reduce the LCoE of the OWF by nearly 35% compared to partial decommissioning and 36.5% compared to full decommissioning. The estimated expenditure of partial and complete decommissioning is close, as shown in Figure 7.. However, this relies on those dependent variables in deterministic cost modelling, such as cutting technique, number of OWT or even duration of involved activities. Improvement or any innovative approach can directly impact this consequence.

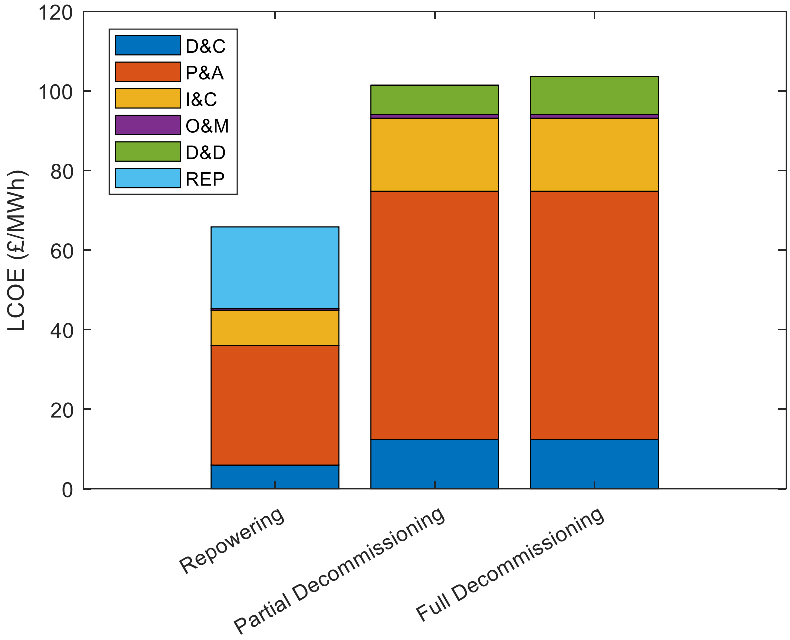


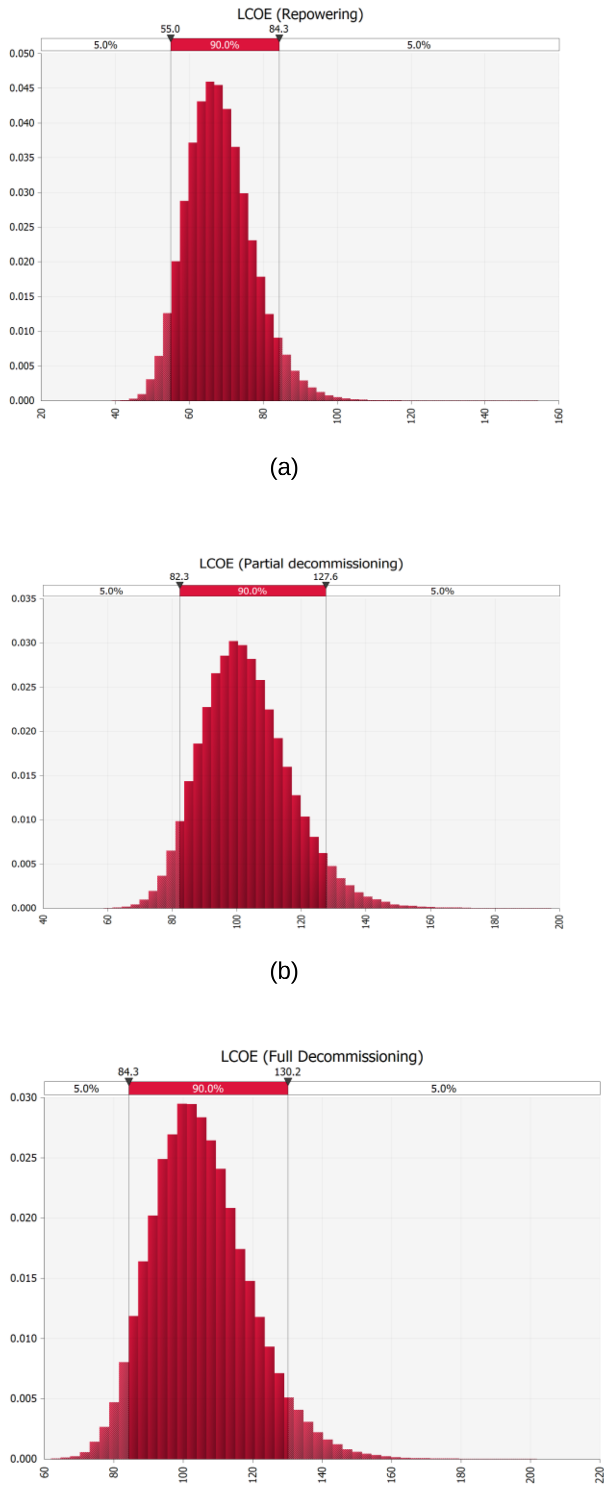
Figure 7.Estimated LCoE for EoL scenarios investigated.

3.3.3 Stochastic analysis result

Following the expansion of the deterministic model to account for uncertain inputs, a total of 100,000 iterations was executed, considering the statistical properties listed in **Error! Reference source not found.**. In the absence of real data, normally distributed variables were chosen; it should be noted, however, that the developed algorithm could equally easily treat statistical distributions of any type. A fixed CoV of 0.1 was chosen for this analysis. **Error! Reference source not found.** presents the normalized probability histograms of LCoE based on the different EoL scenarios which were investigated in this exercise.

Table 3.Mean values (μ) and standard deviations of variables ($\boldsymbol{\sigma}$)

Variable	Distribution	Characteristic values
P&C costs (£000s/MW)	Normal	$\mu = 205{,}750$, $\sigma = 20{,}575$
P&A costs (£000s/MW)	Normal	$\mu = 1{,}040{,}229$, $\sigma = 104{,}022$
Total I&C costs (£000s/MW)	Normal	$\mu = 305{,}742$, $\sigma = 30{,}574$
O&M costs (£000s/MW/yr)	Normal	$\mu = 56{,}597$, $\sigma = 5{,}659$
Repowering process Cost (£)	Normal	$\mu = 707{,}035$, $\sigma = 70{,}703$
Full Decommissioning Cost (£)	Normal	$\mu = 159{,}718$, $\sigma = 15{,}971$
Partial Decommissioning Cost (£)	Normal	$\mu = 122{,}860$, $\sigma = 12{,}286$



(a)

(b)

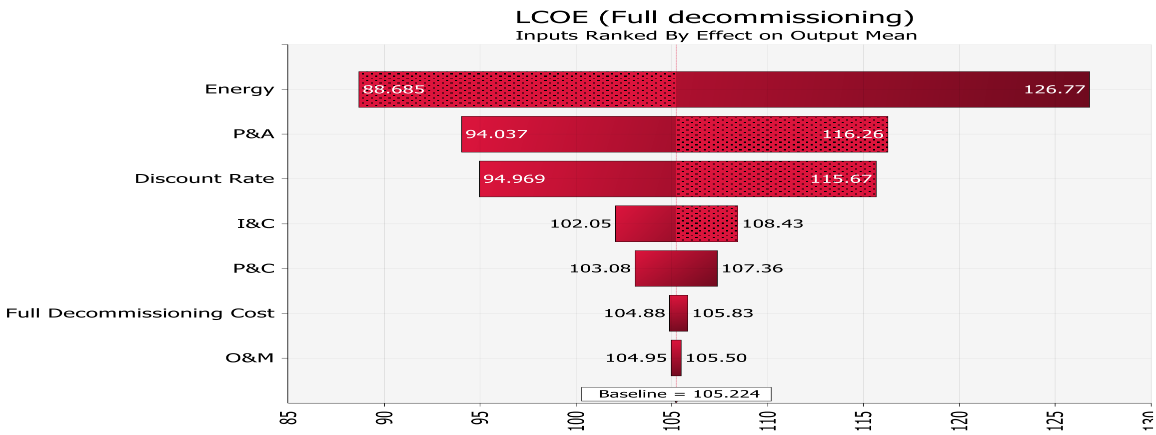
(c)

Figure 8. Stochastic assessment of LCOE, (a)Repowering, (b) Partial decommissioning, (c) Full decommissioning.

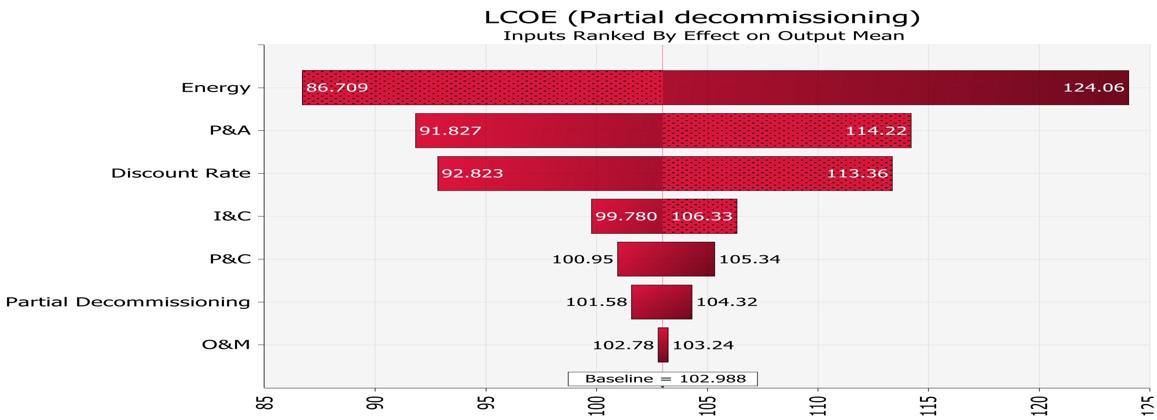
For the case of repowering, the mean value for LCoE is £68.4/MWh and is bound within a 90% CI from values £55-£84.3/MWh based on 20 years' additional service life. Similarly, for partial decommissioning, the mean value is £102/MWh and in the 90% CI within values of £82.3-127.6/MWh. Finally, the mean value for the case of full decommissioning is £105.2/MWh, and in the 90% CI within values £84.3-130.2/MWh. The variance of repowering ($\sigma = 8.99$) is more minor compared to the others ($\sigma = 13.94$ and $\sigma = 14.12$, respectively), showing that the LCoE values are grouped closely around the mean (expected value). It can be observed that the results between partial and full decommissioning are very close to each other.

3.3.4 Sensitivity analysis

Due to the parametric nature of the model, a sensitivity analysis is performed in order to qualify the highest contributors to the stochastic calculation of LCoE. Results are presented in a series of tornado plots in **Error! Reference source not found.**, where inputs (influencing factors) are ranked accordingly. More specifically, for the repowering option, energy yield is found to have the highest impact, followed by the discount rate and P&A costs. For partial decommissioning, energy yield is again the prevailing option, followed by P&A and discount rate, and finally, for full decommissioning, energy yield is again the prevailing factor, followed by P&A and discount rate values. This indicates the function of energy yield in the drop of LCoE. Investigating the increasing level of energy production based on the repowering strategy is necessary. It assists the investors in justifying financing and dealing with challenges such as losing energy due to unavailable turbines.



(a)



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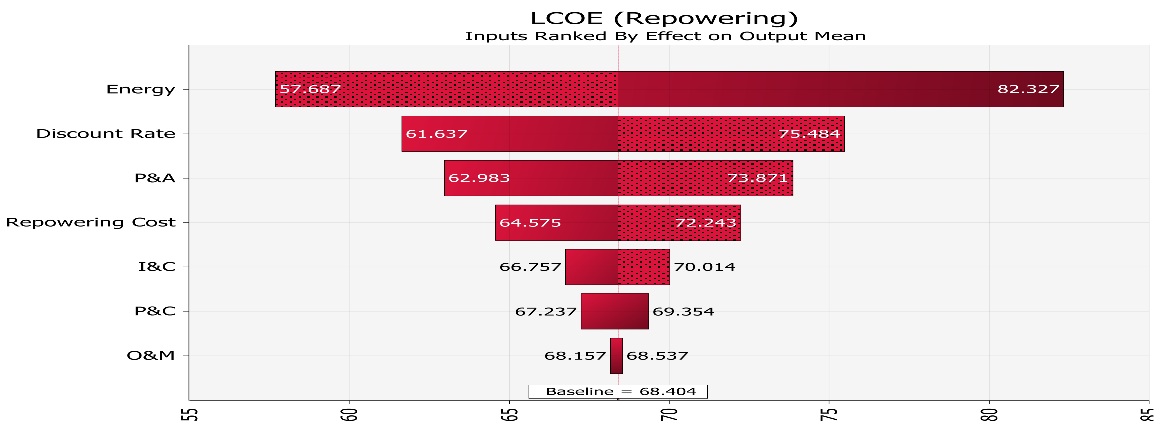

(c)

Figure 9.Sensitivity analysis LCOE, (a) Repowering, (b) Partial decommissioning, (c) Full decommissioning.

3.3.5 Risk aversion concept

Error! Reference source not found. presents the impact of LCoE variability on the risk averse decision maker. The uncertainty premium shows the amount of money the decision-maker must pay to reduce the uncertainty and shows the risk monetization of investment in the case of uncertain results. The distribution of LCoE based on various EoL scenarios was determined in the previous step. The wider distribution shows the higher uncertainty premiums and is calculated throughC_{eq}. The certainty equivalent measures the price which the decision maker must pay due to being indifferent towards the related uncertainty. Repowering has the lowest RP and C_{eq} compared to the other options, with the amounts of 1.136 £/MWh and 69.821 £/MWh, respectively.

Table 4.The RP and $\boldsymbol{C_{eq}}$ for EoL scenarios in OW farm

End Life Scenarios	RP (£/MWh)	$\frac{\sum_1^r LCOE}{r}$ (£/MWh)	C_{eq} (£/MWh)
Partial Decommissioning	1.815	103.017	104.832
Repowering	1.136	68.685	69.821
Full Decommissioning	1.823	105.254	107.077

3.4 Conclusions

Offshore wind turbines are normally designed for a nominal service life of 20 to 25 years; however, with a significant number of units approaching the second half of their service life, the discussion on selecting the most appropriate end of life scenario becomes ever more relevant. Scenarios to be investigated mainly include decommissioning, repowering or service life extension, while such decisions depend on a number of criteria which should be taken into account and should ultimately inform a techno-economic and risk assessment. This paper performs an initial comparative evaluation between two of these scenarios, repowering and decommissioning, through a purpose-developed techno-economic analysis model which calculates relevant key performance indicators. The economic model of risk aversion is further adopted to calculate the certainty equivalent of LCoE (Levelized Cost of Energy) based on each of the examined end-of-life scenarios and a stochastic expansion of the deterministic model. An application to a typical, hypothetical offshore wind farm qualifies the full repowering scenario as the prevailing option, under the assumptions considered, with a lower amount of risk premium (1.136 £/MWh) and certainty equivalent (69.821 £/MWh) in comparison to other scenarios, reducing LCoE by nearly 35% compared to partial decommissioning and 36.5% compared to full decommissioning.

Chapter 4

4 Selecting appropriate End-of-life scenarios for offshore wind farms based on multi-criteria decision-making method

4.1 Introduction

The offshore wind farm is a moderately new technology, and its development was inspired mainly by the increasing markets for more promising energy-production efficiency[2]. The offshore wind industry is expected to rise considerably to meet the decarbonisation purpose in 2050. the critical role of end-of-life (EoL) strategies in offshore wind industries are often ignored, even though their evaluated lifetime stands about 20-25 years[1], [2]. In Europe, about 30% of OWT were over 15 years in 2020. The number of OW farms reaching their planned service life will increase between 2021 and 2030. Thus, it is vital to evaluate the position of these EoL strategies, including service lifetime extension, repowering, decommissioning, or the combination of them for offshore farms. Three main stages, planning, permitting, and implementation, are defined to deliver each EoL process. Effective EoL methods planning relies on considering those main influencing elements such as schedule and planning, risk and safety, cost, and environment to maximize assets' value.

Regarding the economic consideration of EoL strategies, Jadali [120] delivers the first detailed farmwork, which computes relevant key performance indicators to investigate an initial comparative review between two scenarios, repowering and decommissioning, via a purpose-developed techno-economic analysis. Planning and estimating the duration of activities involved in any EoL scenario is challenging due to a lack of experience. The planning procedure of EoL scenarios depends on contributors such as previous project experience, number and types of wind turbines, foundation types, vessel selection, availability of trained crew and experts, assessment of weather and wave conditions, and distance to the port [1], [3]. This presents complexity with developing a generic procedure for OW farms' decommissioning. To solve this issue, Jadali [121] suggested a multi-attribute framework for supporting optimum decision regarding main conditions, such as the possibility of EoL strategies based on the individual characteristics and influencing factors. The research provided the framework to maximize the profitability of asset farms while decreasing those risks involved in the safety, technology, environment, and facilitating planning.

There is an issue with the high uncertainty-related decision-making of EoL strategies in OW farm due to insufficiency of experience and data. For instance, The Lely and Vindeby offshore wind farms reached their initially designed service life [1], [71], [79]. The asset's lifetime in the Vindeby farm operated based on a service life extension strategy until 26 years. However, it was challenging to implement the service life extension scenarios for another farm.

The preferable selection of EoL scenarios has become very appropriate as such a decision can reduce costs and enhance profitability. Typically, the decommissioning should be assumed even at the planning step of the offshore wind farm [9]; however, before decommissioning happens, repowering or service life extension may be sought, considering any residual capacity of essential wind farm elements. The owner found it difficult to decide whether the repowering or decommissioning strategy for the end of the farm or beneficial to have a specified period as service life extension before any decision. The process was found to be complex due to several uncertainties involved in the decision-making. To solve this issue, this paper introduces a methodological framework to guide decision-makers based on a comparative study of widely-applied Multi-Criteria Decision Making (MCDM) techniques. In the first step, a comprehensive literature review identifies the main EoL strategies in the offshore wind farm to achieve this aim and objectives. After this stage, the TOPSIS analysis as the MCDM method applies to select the EoL strategy. The TOPSIS method has been selected for this research; considering its verified applicability, it provides a simple and effective tool for dealing with multiple criteria and is computationally efficient. These observations encouraged using the TOPSIS technique for the EoL strategies. Attempts to find the most influential criteria should be defined for TOPSIS analysis by a literature review and brainstorming with experts. This provides an integrated evaluation of several economic, social, environmental, and technical criteria. The data would be collected based on the designed questionnaire. The data obtained through experts' opinions are presented together with results from the implementation of each method deterministically. A review of the results is carried out to emphasise the differences and discrepancies to draw practical conclusions.

4.1.1 End of life scenarios

Before the nominal service life of OW farm lapses, a classification is required from the possible EoL strategies. The current condition of assets, the updated state of the procured technology initially, and maximizing their initial investment would help the operator make optimal decisions. Figure 10 presents the essential EoL strategies which are considered in this research as alternatives.

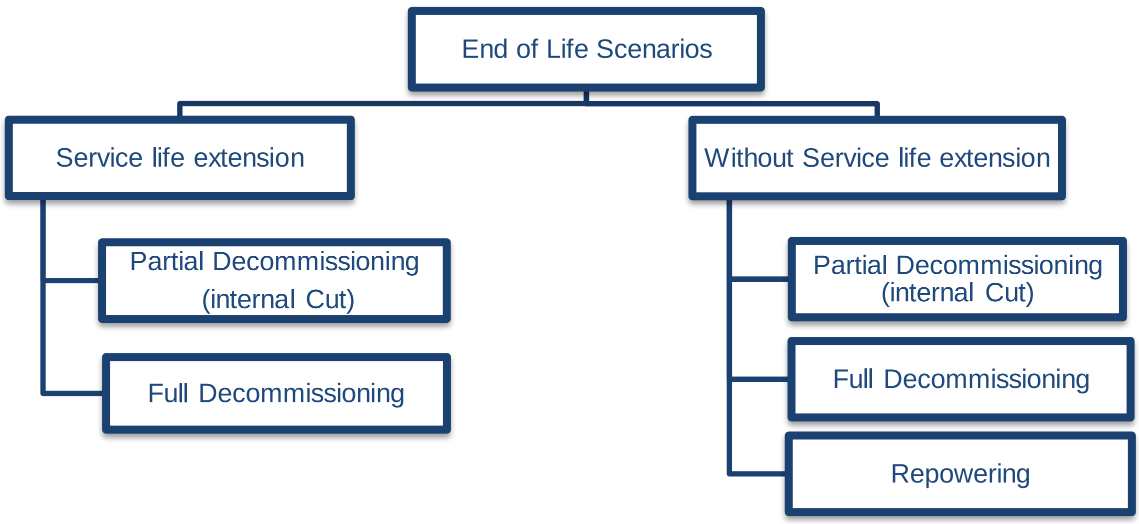

Figure 10.End of life scenarios of offshore wind farms.

4.1.2 Multi-criteria decision making in offshore wind turbine

Multi-criteria decision-making (MCDM) is the operational research technique to optimise the quantifiable or non-quantifiable/qualitative multiple criteria. Different MCDM such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Decision Making Trial and Evaluation Laboratory (DEMATEL), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), ELimination Et Choix Traduisant la REalitéwas (ELECTRE) and VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje), is used to solve the various ranges of decision-making matters in the offshore wind energy.

MCDM methods have evolved increasingly comment in the decision-making of renewable energy power plants regarding site selection, support structures and risk assessment. It provides consideration of various multiple conflicting aims and decision-maker preferences [122], [123], [131]–[136], [124]–[131]. The research review has been provided in [137] regarding the MCDM issues associated with power generation optimization, technology, policy, and site selection in marine and offshore applications. The TOPSIS method presents a systematic assessment for benchmarking offshore wind turbine support structures by considering several criteria to select the preferable support structures[131], [131]–[134], [138].

A fuzzy-based MCDM methodology is implemented to select the site for offshore wind farms. Those main parameters, including depth, height, environmental issues, proximity to facilities, and economic aspects, are identified and selected as the decision-making criteria. The accuracy of the analysis was increased in this research by integrating interdependent relationships among the criteria[139].

Multi-criteria site selections based on the geographical information system and bespoke site-selection support tools for offshore renewable energy platforms concentrating on the availability of energy resources have been studied in[140]. The results show the leading prospect for offshore renewable energy platforms focused to the north and west due to acceptable depth conditions and substantial resources; however, there are still problems concerning the constructability and accessibility of the location. An interval type-2 fuzzy set has been developed based on MCDM to evaluate Ireland's most promising offshore wind sites regarding technical, economic, environmental, and social criteria [141]. A fuzzy-MADM method is based on a three-layer decision-making framework of the Analytic Hierarchy Process implemented in [127] to comprehensively assess the feasibility of installation and maritime safety feasibility for offshore wind farm site selection.

4.2 Criteria Selection

Defining the optimization parameters to evaluate the EoL strategies as alternatives in decision-making is necessary. It helps to consider those varieties of technical and non-technical criteria to select the optimum solution. This part of the research identifies quantitative attributes associated with the reviewing literature and qualitative features based on the expert's opinion due to limited data availability. [3], [50]. Figure 11 presents the main criteria of this research.

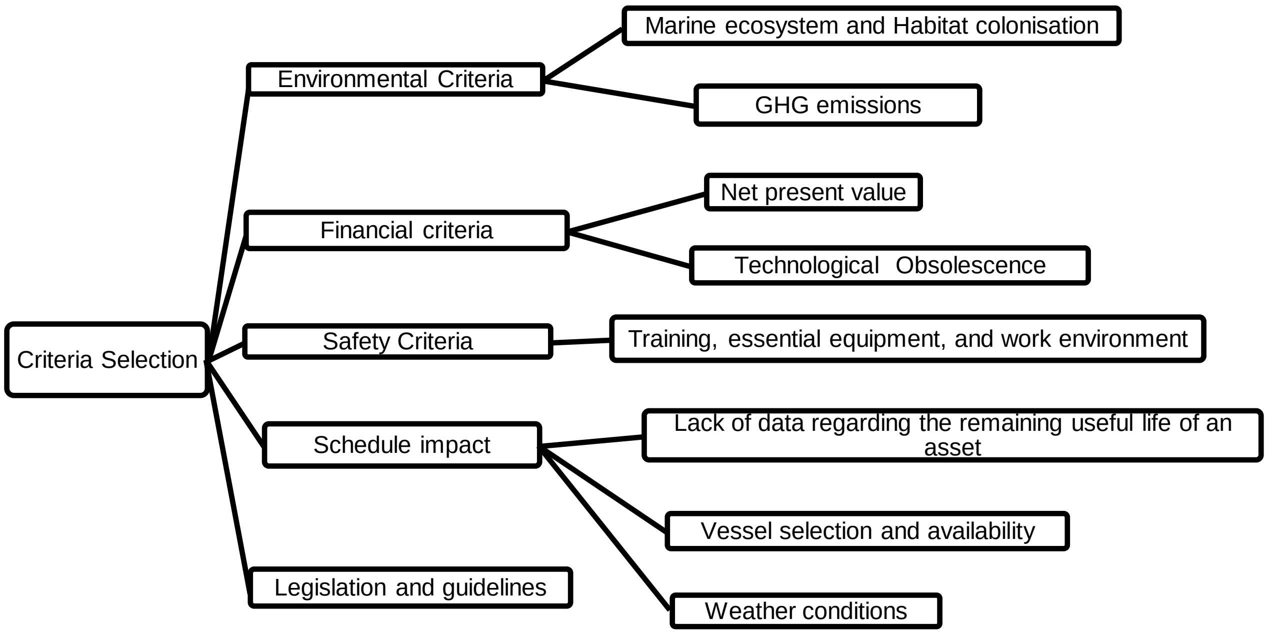

Figure 11.Criteria selection.

4.2.1 Environmental Impact

4.2.1.1 Marine ecosystem and Habitat colonisation

The wind farm can be known as an artificial reef during its lifetime. Much research was done regarding habitat colonisation in the marine environment[13], [51]–[54], [100]. These reefs impact the marine environment on three scales, the micro-scale, involving material, texture, and heterogeneity of the construction materials; the mesoscale, including the revetments and scour protection; and the macro scale, covering the wind farm [55]. OWT installation and decommissioning have harmful and beneficial environmental consequences and create a new equilibrium. Complete decommissioning would help return to the previous situation [9], [10]; however, this will negatively impact the development of net habitat gain around 25 years lifetime of an asset. After decommissioning, there will be a new community; however, it will be different from the previous habitat and challenging to come back to the situation before installation [55], [56]. Excluding shipping of fisheries for safety reasons around OW farm increases local rates of fish during 20 years of asset life.

4.2.1.2 Life-cycle greenhouse gas (GHG) emissions

In this research, life-cycle greenhouse gas (GHG) emissions are associated with four stages: manufacturing, transportation and erection, operation, dismantling, and disposal. Each step contained several processes.

4.2.2 Financial criteria

4.2.2.1 Net present value (NPV)

Net present value (NPV) is evaluated based on the cash flow of composing expected revenue and expenditure items. The value of cash is modified due to inflation. NPV provides an opportunity to have the final value of an asset over plant life at present. It can be used to measure the feasibility of a business. A positive NPV means that revenue is more significant than expenditure as well as the profitability of the investment [142].

4.2.2.2 Technological Obsolescence

The availability of spare parts will be essential during operation. The Yttre offshore wind farm was decommissioned due to a lack of spare parts. This made the continuance of OWT operation too expensive.

4.2.3 **Safety Criteria**

4.2.3.1 **Training, essential equipment, and work environment**

The probability of an accident is the fundamental parameter used in the risk assessment method. It is challenging to propose the probability calculation method based on the accident rate in project or workplace exposure limits to assess the safety of EoL strategies in offshore wind turbines. Training skilled technicians should deliver activities related to repowering and decommissioning in the OWT. The OSHA standard mentions the importance of training in reducing risk 850 times, especially in fatalities and failure equipment in Lifting, working at heights, falling objects, nacelle electrical and mechanical, and contact with a substance. Improving and modifying the courses associated with technical training in OWT could significantly influence risk reduction. Most training courses are not designed based on the specific safety criteria in OWT; they are based on broad industrial experience and construction topics. The experimental part of training would be valued after any theoretical course[143]. The collision among the vessels could be a known risk of failure of the decommissioning process. This could happen as a result of human error or harsh environmental conditions.

4.2.4 Schedule Impact

Time estimating for various end-of-life-related activities is challenging due to a lack of experience and data. Significant contributors to schedule impact include the following:

4.2.4.1 Lack of data regarding the remaining useful life of an asset

The availability of reliable data is essential for assessing the structural integrity of wind farms. It provides an accurate estimation of the residual life of the assets and more clarification regarding the options of end-of-life strategies.

4.2.4.2 Vessel selection and availability

Planning is essential to access the appropriate logistics for the decommissioning process. The Vessel selection should be based on the operation's type of process, cost, and duration. The high demand for vessels to deploy wind farms to meet the current targets for decarbonizing energy mix [62] limits the availability of vessels. In addition, the forecasting duration of activities involved in EoL strategies can be challenging in construction projects due to the harsh environment.

4.2.5 Weather conditions

When wind speed and wave height exceed operational limits, harsh environmental conditions restrict vessels and certain lifting operations.

4.2.6 Legislation and guidelines

Variability of the removal legislation and guidelines in different countries significantly influences the planning for EoL strategies, and it is harmful to the environment. The increasing demand for decommissioning OWFs in the coming years calls for bridging the research gap in this field and highlights the vital role of legislation planning.

4.3 Methodology

This section introduces the framework for investigating the EoL strategies in OWT farm and applying the TOPSIS as a multi-criteria decision method under deterministic inputs to rank the appropriate process. **Error! Reference source not found.**. A flow chart presents the critical concepts of the methodology and interaction during the analysis.

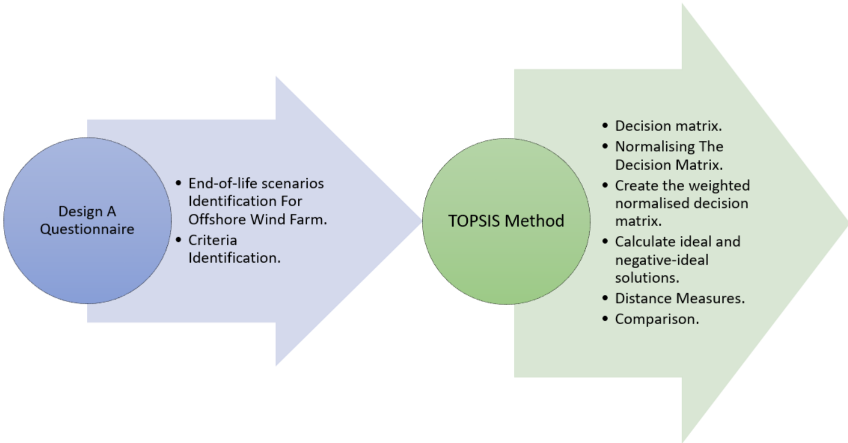

Figure 12.Critical concepts of the methodology.

4.3.1 **TOPSIS Method**

The TOPSIS method is known as a standard method to optimise the problems. The method selected for this study is due to the suitability of its basic concept for this analysis. TOPSIS method is able to rank those EoL strategies against individual criteria automatically. The method takes into account both quantitative and qualitative criteria to provide the realisation of objective benchmarking among EoL strategies. TOPSIS is based on the idea that the preferred choice should have the shortest geometric distance from the positive ideal solution (PIS) and the most extended geometric distance from the perfect negative solution (NIS). [144]. Hwang and Yoon[145] developed the TOPSIS method, and the short distance assumed between the positive ideal solutions and optimised result and the longest distance between the perfect negative solutions and optimized result. The decision-making can be optimised on the condition of being close to the ideal solution area. It aims to translate qualitative and quantitative data into a geometrical problem and optimize criteria according to weighting[146] .

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The process of the TOPSIS method to rank a set of options includes:

Step 1 – decision matrix.

Concocting an evaluation matrix consisting of m alternatives and n criteria, with the intersection of each option and criteria given $\boldsymbol{f_{ij}}$, we therefore have a matrix $(\boldsymbol{f_{ij}})_{m\times n}$

Step 2 – Normalising the decision matrix.

Normalising the decision matrix by applying the formula below:

$$r_{ij} = \frac{\boldsymbol{f_{ij}}}{\sqrt{\sum_{j=1}^{m} \boldsymbol{f_{ij}}^{2}}} \qquad 15$$

$R = (\boldsymbol{r_{ij}})_{m\times n}$ Using the normalisation method

Step 3 – Create the weighted normalised decision matrix V_{ij}.

The relative weighting factor should be applied to a normalised matrix characterising the variables as positive or negative.

$$V_{ij} = W_i * r_{ij} \qquad 16$$

W_i is the i th weight of alternative and $\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} W_i$=1

Step 4 - Calculate ideal and negative-ideal solutions.

The positive ideal solutions (PIS) and negative ideal solutions (NIS) are the best and worst results.

$$x_{ij}^{+}=\max_{0\le j\le 1}(\boldsymbol{x_{ij}}) \quad \text{and} \quad x_{ij}^{-}=\min_{0\le j\le 1}(\boldsymbol{x_{ij}}) \qquad 17$$

Step 5 – Distance Measures.

The n-dimensional equivalent of Pythagoras' theorem would be used to calculate the relative distance of each result from the NIS and PIS.

$$\boldsymbol{D_i}^{+} = \sqrt{\sum_{i=0}^{m}(\boldsymbol{a_{ij}}^{+} - \boldsymbol{a_{ij}})^2} \quad \text{and} \quad \boldsymbol{D_i}^{-} = \sqrt{\sum_{i=0}^{m}(\boldsymbol{a_{ij}}^{-} - \boldsymbol{a_{ij}})^2} \qquad 18$$

Step 5– Comparison.

The final scores are implemented to rank interaction methods according to their performance, distinguishing the most suitable concept.

$$P_i = \frac{Di^{-}}{Di^{-}+Di^{+}} \qquad 19$$

4.4 Result and discussion

4.4.1 Case study

In this case study, we collected data to consider monopile foundation from a panel of senior academicians and industrial practitioners involved in the wind energy field. The study investigated OW farm deployed in UK waters. The study investigated OW farm deployed in UK waters. The selected wind farm has a 504 MW capacity, assuming 20 years of nominal service life, five years of construction time, and availability between 92.2-92.5%. The expenditure of labour and vessels and environmental conditions are assumed to be the same as in [147] .The distance to the port is supposed to be 36 km, water depth 26 m, and the turbine elements are as follows: Rotor diameter 107 m, Hub height 77.5 m, Pile diameter 6 m, Rated power 3.60 MW, Cut-in speed four m/s and Cut-out speed 25 m/s [147].

4.4.2 Discussion

As shown in Figure 10, five possible alternatives are identified based on the literature review. The attributes of each option are then exported in excel spreadsheet format, providing the decision matrix to evaluate such opportunities. Tables 6 shows those allocated weights by the group of experts involved in this decision process and the TOPSIS matrix.

NPV is recognized with the highest weight, and it follows with the availability of data for residual life estimation of subsystems. The type and number of turbines and foundations is the lowest among those criteria. This result indicates that experts pay close attention to technical performance and cost in selecting EoL strategies in offshore wind turbines. TOPSIS implies that the best alternative is most comparable to the ideal scheme but is far from the worst scenario in the scheme sorting stage. Even though the combination of service life extension and full decommissioning has nearly the same average score as full decommissioning, the combination of service life extension and partial decommissioning are selected as the best alternatives, as it is shown in table 5. While both repowering and partial decommissioning are not far from each other, they are the lowest options compared to the rest. To further illustrate the effectiveness of our research, we compare it with the result of this research [3]. The partial removal with the external cut method was selected as the most suitable method, as it confirms our result. However, Jadali [147] constructed an initial comparative assessment between two of these methods, repowering and decommissioning, using a techno-economic analysis model that computes essential performance indicators. The full repowering method was a suitable option compared to other strategies, reducing LCoE by nearly 35% compared to partial decommissioning and 36.5% to full decommissioning. The result confirms the need for research to investigate the type of repowering strategies for the farm. Apart from this, the baseline decision matrix and weight are based on expert opinion. Currently, there is a lack of experience regarding EoL strategies in OW farms, which negatively influences the reliability of human judgment. The level of energy production based on the repowering strategy should be considered an essential factor. This confirms the benefits of quantitative criteria in MCDM to achieve more reliable results.

Table 5.Shows the result of the TOPSIS method.

Alternatives	$\boldsymbol{P_i}$
Partial Decommissioning (internal Cut)	0.464
Full Decommissioning	0.551
Repowering	0.480
Service life extension +Full Decommissioning	0.550
Service life extension +Partial Decommissioning	0.588

4.4.3 **Sensitivity analysis**

This section observes those weight's impacts on the result by increasing 20% of each weight and maintaining the rest the same. As it is shown in figure 13, in most cases, the primary choice would be Service life extension +Partial Decommissioning; however, the selection is changed to Full Decommissioning by a 20 % increase of NPV. This confirms the vital role of the economic aspect in End-of-life decisions in OW farm.

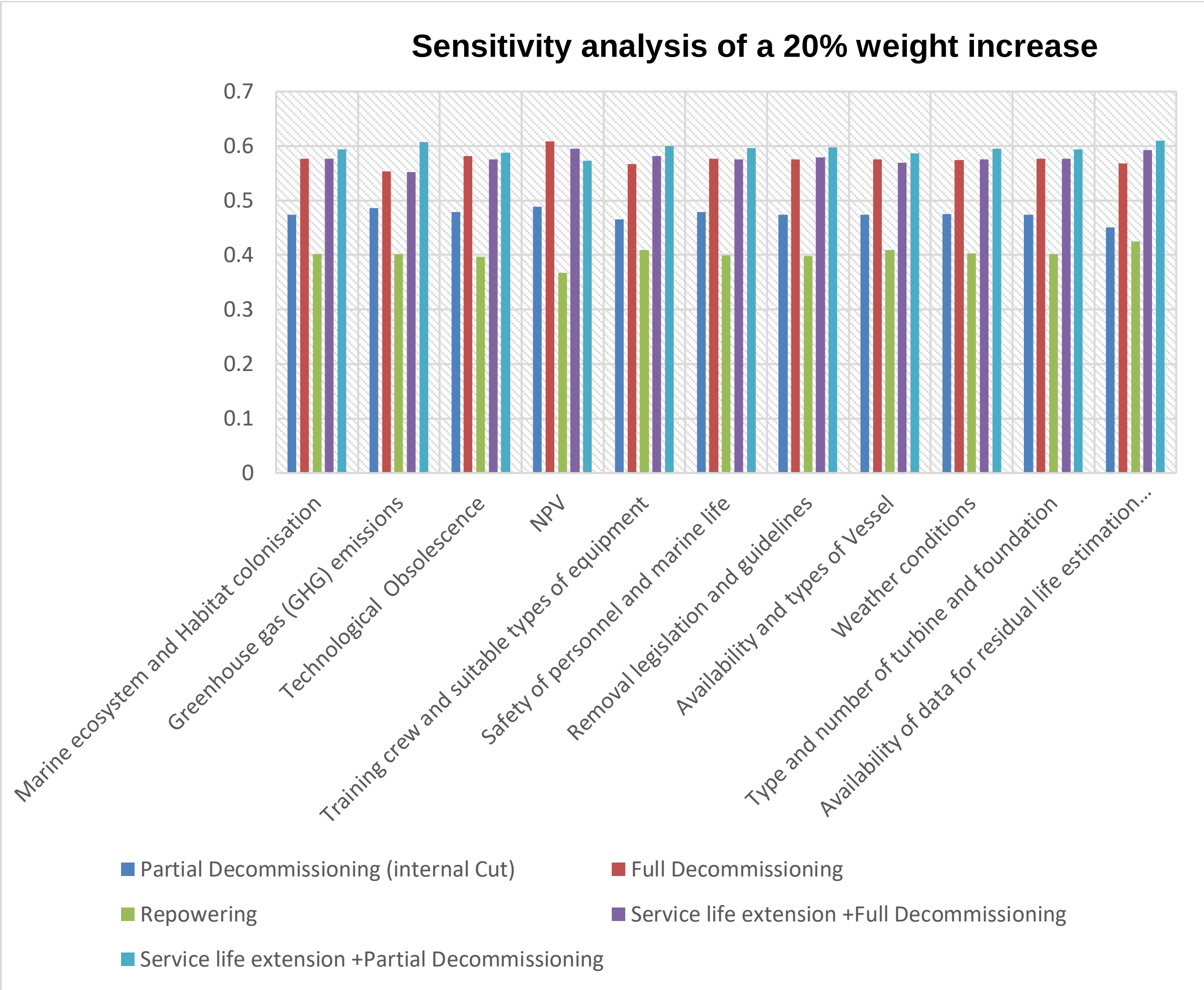


Figure 13.Sensitivity analysis of a 20% weight increase.

Table 6.Shows TOPSIS matrix

	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Type and number of turbine and foundation	Weather conditions	Availability of data for residual life estimation of subsystems
Partial Decommissioning (internal Cut)	5	5	6	5	3	8	7	6	7	5	3
Full Decommissioning	8	4	9	3	3	7	7	6	5	6	5
Repowering	3	8	8	8	6	6	5	7	7	6	7
Service life extension +Full Decommissioning	8	6	5	4	7	7	9	5	6	6	8
Service life extension +Partial Decommissioning	4	7	6	6	7	8	9	5	8	5	8
Weightage	8	5	7	10	5	9	5	8	4	3	8
Negative or Positive	N	N	P	N	P	P	P	P	P	P	P

4.5 Conclusion

Many Offshore wind turbines are approaching the second half of their service life, and the discussion on selecting the most appropriate end-of-life scenario in the next few years has become one of the major concerns for all the stakeholders. This study has reviewed the different end-of-life strategies for offshore wind farms and the influencing criteria for optimised decisions.

Different alternatives have been assessed through a TOPSIS method as a multi-criteria decision-making procedure to select an appropriate way according to environmental, financial, safety Criteria, Schedule impact, and Legislation and guidelines. Setting the right end-of-life scenario helps internal and external stakeholders maximize asset farms' profitability. This comprehensive study shows that the combination of service life extension and partial decommissioning are chosen as the best alternatives. While both repowering and partial Decommissioning are not far from each other, they are the lowest options compared to the rest. NPV is recognized as the most substantial influence, and the type and the number of turbines and foundations are the weakest among those criteria. Due to the limited experience in wind farms that have already reached the end of their nominal service life, further research is needed to consider the role of various classifications of repowering strategies on end-life strategy selection.

Chapter 5

5 Multivariate and univariate time series forecasting of ML models

5.1 Introduction

The first-generation installations of offshore wind turbines (OWT) are approaching their nominal service life. Any discussion on effective planning of end-of-life (EoL) strategies for OW farms to maximize assets' value should take into account those main influencing factors such as schedule and planning, risk and safety, cost, and environmental impact. Regarding the economic consideration of EoL strategies, Jadali [120] provides the first detailed model, which calculates relevant key performance indicators to investigate an initial comparative assessment between two of these scenarios, repowering and decommissioning, through a purpose-developed techno-economic analysis. Planning and time estimation of activities involved in any EoL scenario is challenging due to a lack of experience. The planning process of EoL scenarios depends on contributors such as previous project experience, vessel selection, availability of trained crew and experts, assessment of weather and wave conditions, and distance to the port [1], [3]. The mitigation of operational risks and costs is known as the main achievement of this stage. Weather and seabed conditions' harsh environment can limit the accessibility of offshore farms and the vessel's stability during marine construction work, such as installation, maintenance, life extension, decommissioning, or repowering. Local wave climate and sea-state forecasting are considered critical in deciding whether access can be achieved safely[148], [149]. The lack of sufficient wave condition data due to the limited length of its records at nearshore regions is another challenge for designing, planning, and constructing ocean structures.

Accurate forecasting of significant wave height prediction is essential for the planning and operation maritime activities regarding hazard warnings and safety [150]. Having reliable estimation of wave height as a vital parameter in wind farms provides this opportunity to have safer with less cost regarding the marine transportation, crew transfer, and decommissioning or repowering process. Characterizing waves helps to have reliable forecasting; however, it is difficult due to its stochastic nature. The uncertain, nonlinear, and non-stationary physical process of wave generation estimates wave height prediction challenging.

Time-series models were implemented for probabilistic forecasting of wave height based on recent observations[151], and a cost-loss model was provided to show these forecasts' values. Wave height limits were investigated for various vehicle forms, including helicopters and various sea vessels [152]. The role of wave height limits was studied to find the service vessel's duration in the offshore farm's maintenance. A novel method has been discussed to generate density forecasts of significant wave height and peak wave period for producing probabilistic forecasts of safety-critical access conditions during crew transfers. It is found that probabilistic access forecasts of vessel motion during crew transfer up to 5 days ahead[153].

An economic impact metric for evaluating wave height forecasters' utility for offshore access has been introduced [154]. The metric presents the financial cost of two types of forecast error, including using the vessel to transfer the crew if it is impossible to access the farm and losing output due to failure to complete turbine repair.

The current academic literature is limited to detailed planning EoL scenarios for OW farms by considering the role of significate wave height forecasting even over a short duration. In general, ocean wave forecasting research is divided into two main categories. The first category is physics-based models based on the physics-based equations[155]–[158]. The majority of research regarding developing several forecasting approaches to ocean wave prediction is related to physics-based models. The physical concepts, such as environmental interactions and climatic pressure, would be exerted to forecast waves' behaviour. The frequency spectra of ocean waves are reproduced in [159]to predict the wave energy.

The three wave generation numerical models were implemented to parameterise wave interactions. The linear wave interactions are implemented to construct the first-generation model's spectral wave structure. The coupled discrete spectral structures are in such a way that the wave nonlinearities can parameterize. The discrete spectral structures related in Second-generation models like JONSWAP parameterize the wave nonlinearities. The third generation is known as mature wave models such as WAM, simulating waves nearshore(SWAN), and WAVEWATCH-III[160]–[162]. The disadvantage of numerical models for predicting waves could be expensive and time-consuming and low generalization ability or overestimation. Implementing numerical models to measure several parameters that can affect wave height for different points is not easy. The modelling procedure should be defined based on the impact of those complex parameters and high computational complexity in various local conditions to reduce numerical forecasting errors.

The second category includes the time series and statistical models[163]–[167]. The model-based data drive methods have been more interesting recently due to the advent of ML techniques. Artificial intelligence (AI) and machine learning (ML) methods are closer to the classical time series approach. ML techniques such as Support Vector Machines and Deep Neural Networks are based on the data structure [168], [169]. This makes uncertain forecast circumstances easier due to their ability to investigate any nonlinear and complex functions.

The ability of nonlinear modelling is known as an advantage of implementing ML-based approaches. This provides the model for forecasting wave height by considering the relationships between wave height and other meteorological and oceanographic variables [170]. Short-term and fast wave height prediction with better results can achieve by implementing the ML model compared to the numerical model; however, it is crucial to consider the role of appropriate feature selection for accurate forecasting. Recurrent Neural Networks (RNNs) are among the most potent tools for estimating any nonlinear and complex functional relation between wave height and other meteorological and oceanographic variables. RNNs show the temporal dynamic behaviour of data based on their internal memories; therefore, RNNs are a suitable framework for forecasting complex systems.

There are massive studies regarding ML algorithms; however, there is limited research to our knowledge; previous studies focused on feature selection's role in increasing wave high forecasting accuracy. In the above literature, no research has considered wave height's role in scheduling and planning EoL strategies for OW farms. This chapter investigates ML algorithms' role in wave height forecasting methods to predict future wave heights accurately enough to assist with EoL scenario planning in OW farms. The numerical models of predicting waves are used as input variables in those models, without consideration of effects from other relevant variables such as wind, pressure, and temperature, which conflicts with the physical process of waves. Apart from this, it has been argued that a forecasting model's cost and running time could be impacted negatively concerning irrelevant features. In this research, to solve these issues as well as improve the accuracy of forecasting, multivariate time series forecasting is proposed based on various models, including Long short-term memory (LSTM), Bidirectional long short-term memory (BiLSTM), and Gated recurrent unit (GRU) to consider those main features and their role in the accuracy of forecasting. Even though the comparative performance study of deep learning (DL) models is usually problem-dependent, this chapter gives more insight into time series forecasting methods and supplements the other comparative studies with a relatively novel application of the variety of DL architectures. The results are compared with univariate time series forecasting to understand the critical role of various predictors in having an optimum impact. Apart from this, Pearson correlation analysis has been used to have a feature selection for those suggested methods to understand better the input's role affects the output.

5.2 Methodology

A diagram shows the details of this research's proposed multi-step wave height prediction methodology. LSTM, BiLSTM, and GRU models can be implemented to forecast a time series according to historical data.

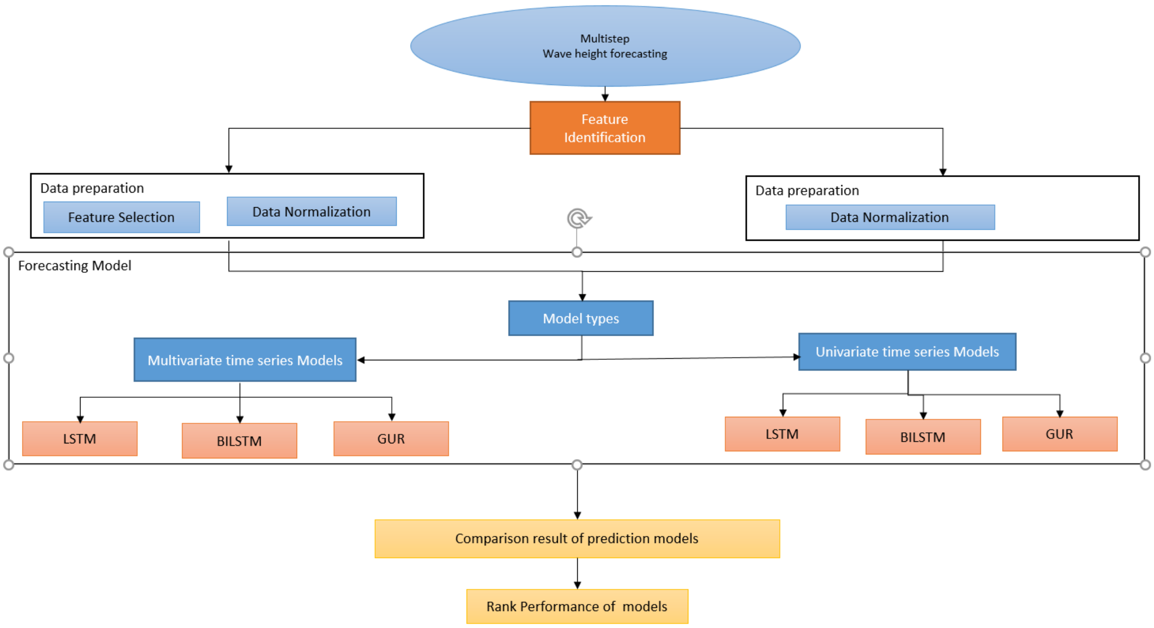


Figure 14.Methodology accurate forecasting of significant wave height.

5.2.1 **Data preparation**

The actual values used to train and test the ML algorithms refer to those essential predictors in forecasting wave height. Before applying ML techniques, the input data must be cleaned and normalized. Different peaks and non-stationary components due to uncertainty and fluctuating weather conditions are central issues in historical data, known as the main reason for high forecast error due to inadequate model training [171]. Feature extraction and identification is one of the most critical steps in wave height forecasting. It is necessary to identify which selected parameters from the user data and the associated meteorological variables include the most relevant information helping to provide an accurate forecast.

This research, after data visualization, takes action regarding concerns such as missing data and intervention to improve the quality of data and data consistency. Two separate parts are proposed based on feature selections, as shown in figure 14. The correlations between wave height and the other parameters are analyzed before normalizing and running the predictive models in one of the stages. For this purpose, Pearson correlations were used to determine which parameters impact each other most. This research tries to show the importance of feature selection in proposed multivariate or univariate time series wave height forecasting and argues that a strong correlation does not necessarily have a strong causality of results accuracy.

5.2.2 Univariate and Multivariate Input features

The time series prediction aims to use the existing target variable values to predict future values. Time series analysis can be further classified into univariate and multivariate according to the number of observed variables.

A single feature would be used in the univariate models to predict the future value. The advantage of implementing the univariate model is known as a small and lighter model that does not need extra data and future engineering; however, the model is limited to the use of a single variable. They exhibit more sensitivity to noise and reduced stability for recursive models. The multivariable type of modes is implemented multiple variables simultaneously and describes the features' interrelationships. The multivariate time series analysis design modifies from system to system, making the process more complex and challenging than univariate time series analysis. The correlation analysis and factor analysis helps reduce the attribute space from large numbers to smaller numbers of factors [172].

5.2.3 **Normalization of data**

It is essential to use a method to convert the datasets to normalized and smoothed data before training them. Normalization of data helps to adjust the negative impact of the data noise and improve the neural network's performance in efficiency and speed. This research applied min-max normalisation to normalise the features in the range [0,1] of the following equation 20 [173].

$$X_{in}(\mathrm{t})=\frac{X_i(\mathrm{t})-MinX_i(\mathrm{t})}{MaxX_i(\mathrm{t})-MinX_i(\mathrm{t})} \tag{20}$$

where $X_i(\mathrm{t})$ is ith training data and $X_{in}(\mathrm{t})$ denotes its normalized data.

5.2.4 **Recurrent neural networks models**

An accurate prediction result can be achieved based on the previous data; however, there is a possibility that recent data is not following the general trends recognized based on the earlier data. This issue is called long-term dependencies. A multilayer perceptron (MLP), as well as RNN, is not able to solve this problem. MLP is not able to consider the data as the time series. They have a network delay recursion as the main attribute of RNN, a description of systems' dynamic performance. However, RNN would not be able to learn the recent trend of data with distant past data[174]. It introduced the LSTM as one of the developed variations of the RNN model to solve this problem of RNN. This research's network models include LSTM, BiLSTM, and GRU.

5.2.4.1 Long short-term memory (LSTM) neural networks

The LSTM shows the ability to solve the long-term dependency problem by efficiently decreasing gradient issues' vanish. In case there is sequential data, the future result should be based on the current and previous values of the input.

The main advantage of LSTM is the use of gates to manage its memory by choosing to update or not the information that goes through the cell. The LSTM network can learn long-term dependencies from an input sequence due to the advantage of its internal memory cells. An example of an LSTM cell is described in Figure 15. The information will be added or removed according to the cell state defined by three gates: forgot gate, input gate, and output gate.

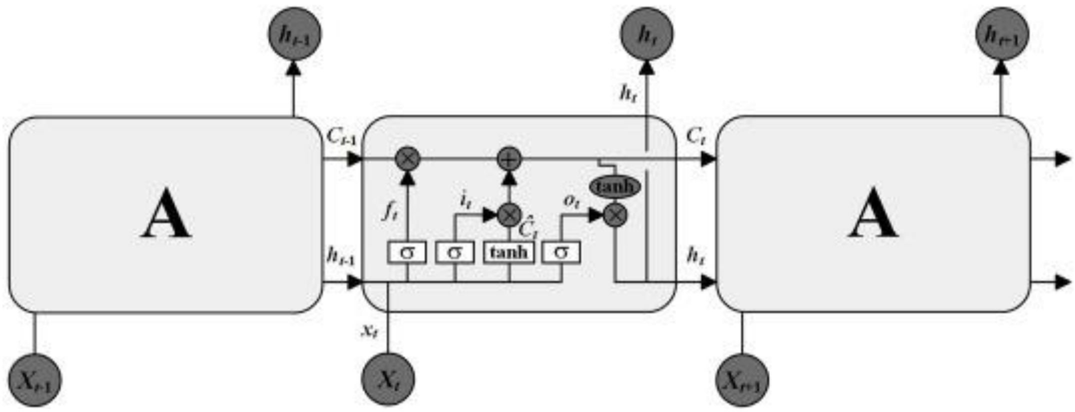


Figure 15.Long short-term memory (LSTM) neural networks.

Forget Gate(f_t): the decision regarding that information should be discarded from the cell state would be made in Forget Gate(f_t). The process is done with the sigmoidal layer combining previous output at t-1 with period $h_{\mathrm{t}-1}$ and inputx_t. The output of this forgets Gate is either 0 or 1, which is then multiplied by its internal state.

$$f_t=\sigma_1\ (w_f\ .[\ h_{t-1},x_t]+\ b_f\ ) \quad 21$$

Input gate (I_t): the decision would be made in this gate regarding the type of information that should be stored in the cell state. In the first part, the information of previous output and present input is passed to the sigmoidal layer σ2, and decisions would be made regarding the updating. The value of this input gate is assumed to be either 0 or 1, and it multiplies with the output of the candidate layer.

$$I_t=\sigma_2\ (w_i\ .[\ h_{t-1},x_t]+\ b_i\ ) \quad 22$$

The second part is the candidate layer. Tanh activation function implemented to its last output and current input and returns a candidate vector and then the new cell state (C_t) would be achieved based on the previous internal statement.

$$c_t'=\tanh(w_c\ .[\ h_{t-1},x_t]+\ b_c\ ) \quad 23$$

$$C_t=f_t *\ C_{t-1},+i_t*C_t' \quad 24$$

Output gate (O_t): The output gate selects the part of cell states as the output[175]. In the final part, the cell state $h_t$would be achieved by tanh multiplies with O_t .

$$O_t=\sigma_3\ (w_0\ .[\ h_{t-1}, x_t]+\ b_0\ ) \qquad 25$$

$$h_t=O_t * \tanh C_t \qquad 26$$

5.2.4.2 **Gated recurrent unit (GRU)**

The gated recurrent unit (GRU) was known as another model implemented to solve the vanishing/exploding gradient issue in the standard recurrent neural network (RNN). Learning long-term and short-term dependencies from the input is known as the advantage of this model in dealing with time series problems.

It is assumed three types of layers for the GRU network, including an input layer, a hidden layer, and an output layer. An update gate and a reset gate are located in the hidden layer. The GRU network structure is shown in Figure 16.

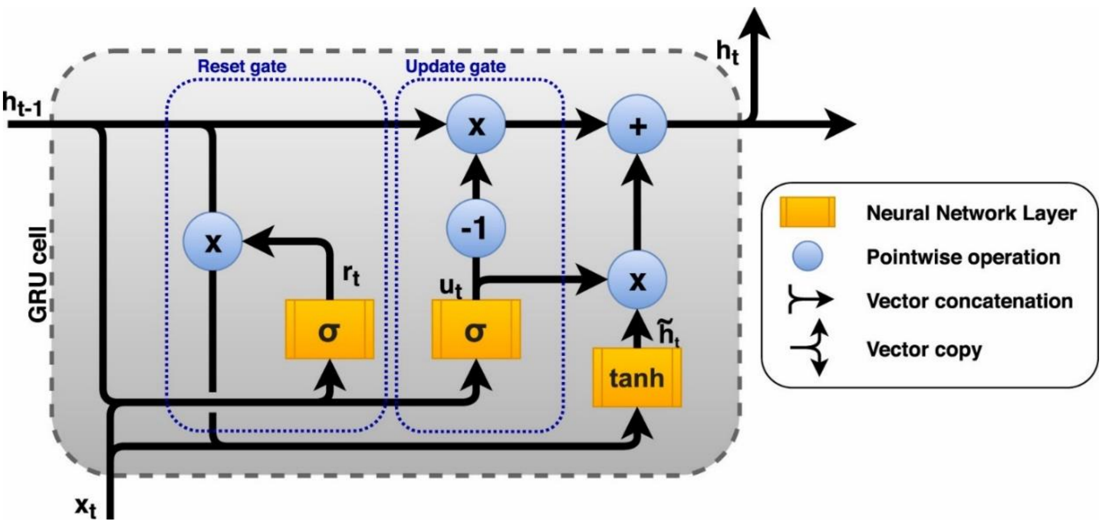


Figure 16.Representation of a GRU cell.

$$U_t = \sigma(w_z .[h_{t-1}, x_t]) \qquad 27$$

As it is shown in the formula, U_t is known as the update gate, output σ(·) is the sigmoid activation function, w_z are the weights of the update gate, h_{t-1} is the output of the last hidden layer, x_t is the input of this hidden layer. The update gate of GRU has the duty to specify the amount of information that should pass from the previous time steps to the future.

$$r_t = \sigma(w_r .[h_{t-1}, x_t]) \qquad 4$$

The reset gate output r_t is computed as shown in equation (8) where σ(·) is the sigmoid activation function, w_t are the weights of the reset gate, h_{t-1}, is the output of the last hidden layer, x_t is the input of this hidden layer. The GRU reset gate helps determine what should be removed from the previous time steps.

$$\tilde{h}_t = \tanh(w. [r_r \,.\, h_{t-1}, x_t]) \qquad 29$$

The current memory content $\tilde{h}_t$ is calculated by Where tanh(·) is the tanh activation function, w are the weights, r_r is the output of the reset gate, h_{t-1}, is the output of the last hidden layer, x_t is the input of this hidden layer.

The final memory at the current time step h_t, is calculated by

$$h_t = (1 - z_t)h_{t-1} + z_t\tilde{h}_t \quad 5$$

where z_r is the output of the update gate, h_{t-1} is the output of the last hidden layer, h_{t-1}, is the current memory content[176].

5.2.4.3 **Bi-directional long short-term memory (BiLSTM)**

The structure of LSTM would be deformed, and this includes forward and backward LSTM layers. The past and future information of data can be considered at the same time[176]. Figure 17 shows the structure of the BiLSTM neural network. It is assumed memory block contains two LSTM layers in BiLSTM.

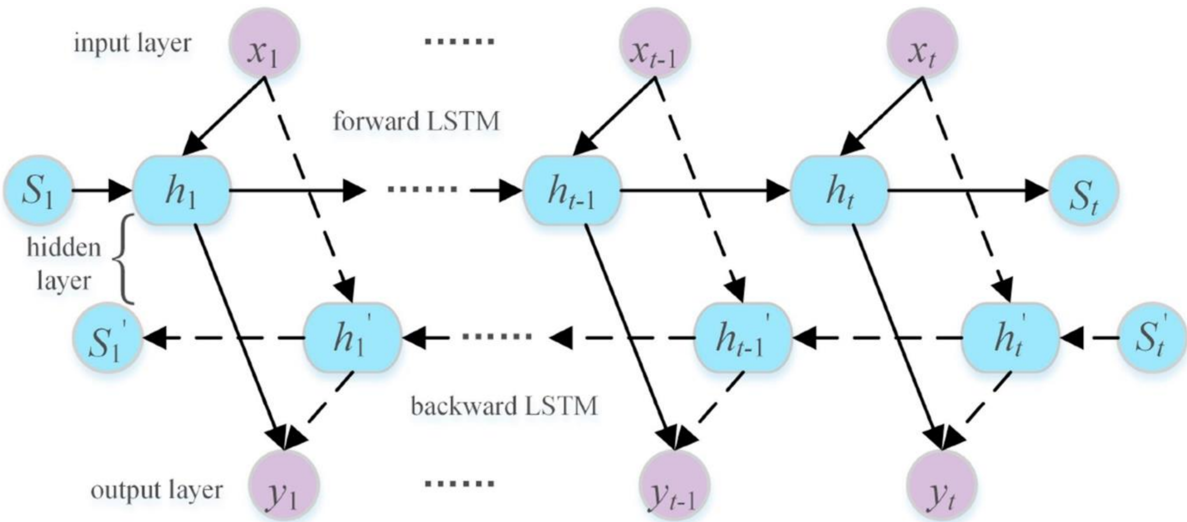


Figure 17.Structure of the BiLSTM network.

As can be seen in Figure 17 each memory block contains two LSTM layers, including forwarding and backward LSTM layers with opposite time sequences. The one output would be achieved as a result of connecting these two hidden layer states. Forward and backward LSTM layers receive the past and future information of the input sequence [176]. The current time step h_{t-1}, is calculated by

$$\overrightarrow{h_t} = \overrightarrow{LSTM}\,(h_{t-1}, x_t, c_{t-1}\,),\quad t \in [1,T] \tag{31}$$

$$\overrightarrow{h_t} = \overrightarrow{LSTM}\,(h_{t-1}, x_t, c_{t-1}\,),\quad t \in [1,T] \tag{32}$$

$$h_t = [\overrightarrow{h_t}\,, \overleftarrow{h_t}] \tag{33}$$

5.2.5 **Performance metrics**

It is essential to evaluate the accuracy of forecasting those proposed models. The root means square error (RMSE), and the mean absolute error (MAE) are selected as the model performance metrics to evaluate accuracy. The RMSE and MAE can be described as :

$$\mathrm{RMSE}(Y_i, \widehat{Y_\iota}) = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(Y_i - \widehat{Y_\iota})^2} \tag{34}$$

$$\mathrm{MAE}(Y_i, \widehat{Y_\iota}) = \sum_{i=1}^{N}(Y_i - \widehat{Y_\iota})^2 \tag{35}$$

where n is the number of test samples, Y_i is the actual data and $\widehat{Y_\iota}$ is the predicted data[176].

5.3 Model configuration and validation

Greater Gabbard is a 504 MW wind farm located on sandbanks 23 kilometres (14 mi) off the coast of Suffolk in England, selected to forecast significant wave height. The table shows those import measurements of significant wave height (Hs). The data recorded by the buoys and is from 1979 to 2020.

Table 7.Selected features of wave

Selected features of wave	
U10	Wind speed hourly at 10m
Hs	significant wave height (Hm0)
U10d	wind direction at 10m
Hsd	mean wave direction
Pd	peak wave direction
Tz	zero crossing wave period (Tm0,2)
Tm	mean wave period (Tm-1,0)
Tp	peak period

Before applying suggested forecasting models, the input data must be cleaned to avoid noise, inadequate model training, and high forecast error. In the first step, all data is loaded as appropriate data types. The dataset includes columns of date with a time step of 3 hours.

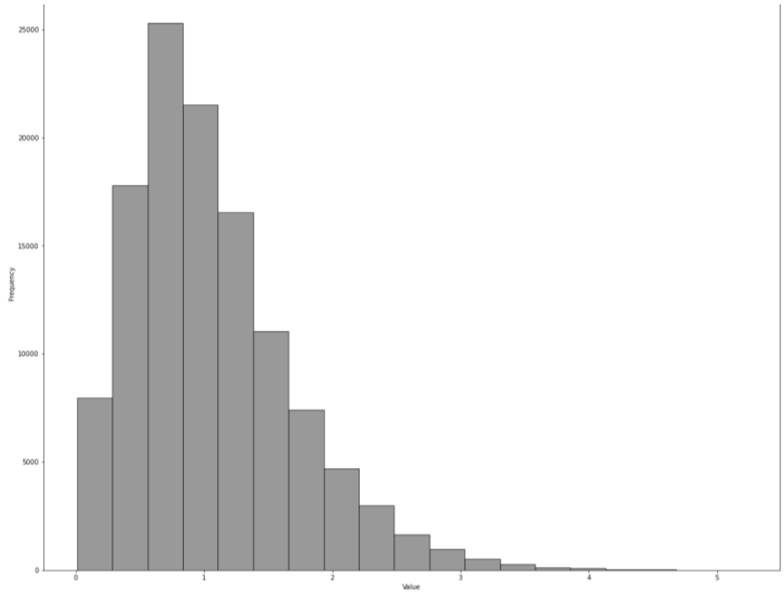


Figure 18.Histogram of the wave height.

Figure 18 shows the histograms of Hs; the unbalanced nature of the data can be clearly seen. Wind, swell seas, and possibly other sources like currents would impact wave characteristics such as height.

In the first step, we run the model without feature selection in the part of data preparation. The result of the prediction was analyzed for three hourly load predictions. Table 8 represents those important cases for consideration in the first part.

Table 8.Main data scenarios based on predictor

	Input assumption	Output assumption	Abbreviation
Multivariable case 1	Removal of (Hs)	Hs	MVR
Multivariable case 2	All features	Hs	MV
Univariable	Hs	Hs	UV

Univariate and multivariate time series forecasting techniques were employed to ensure a fair assessment procedure based on deterministic forecast assessment and walk-forward cross-validation (WFCV). The internal architectures for these models are discussed in the methodology part. In this study, these high parameters represent the number of layers, the units of layers, the activation functions, and the dropout values. The dropout is a sort of neural network optimizer used to avoid overfitting problems. The training and validation plots are illustrated for those cases in the first part in figures 19, 20, and 21, respectively.

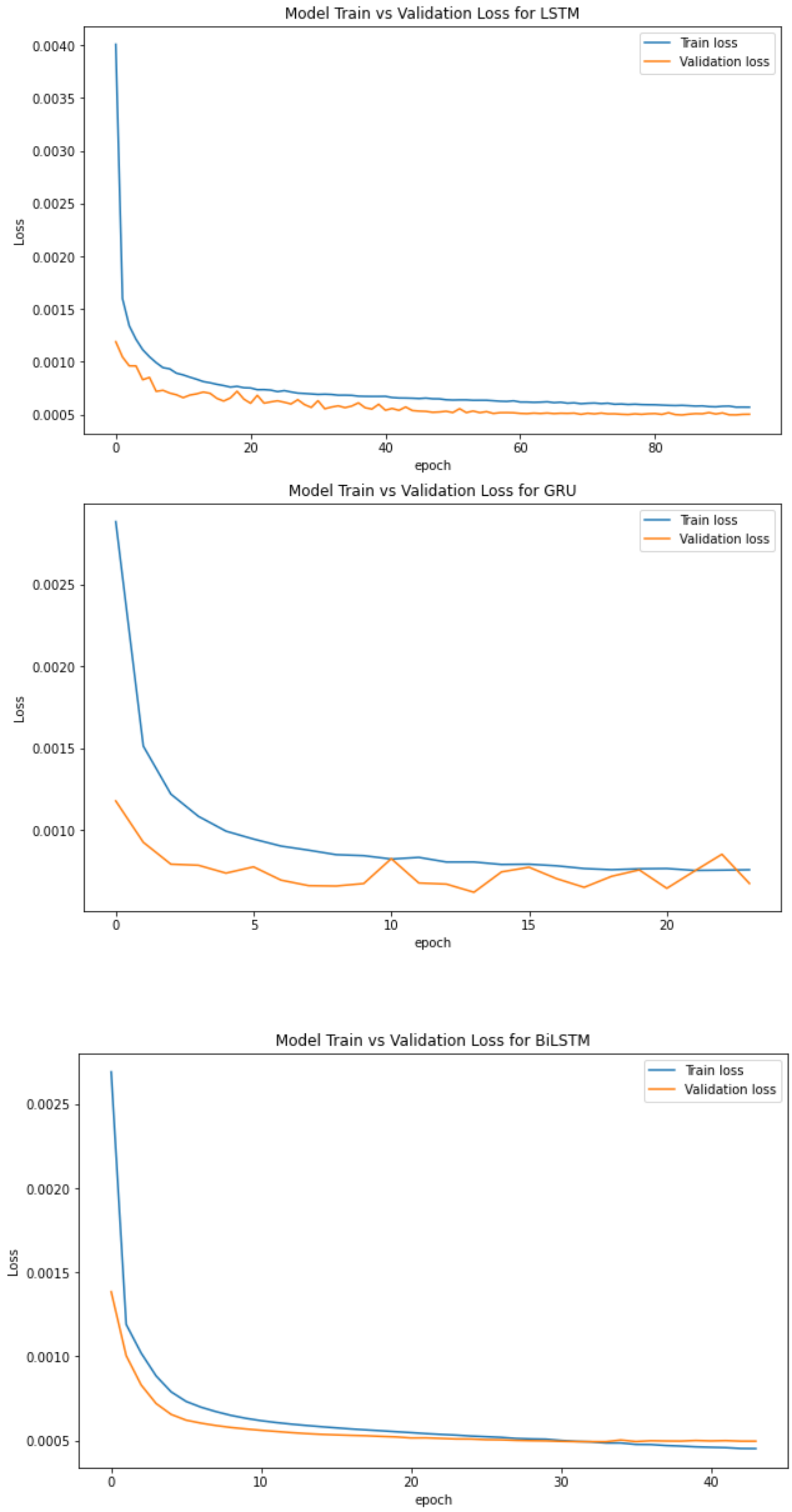


Figure 19. Training and validation loss plots for Multivariable case1.

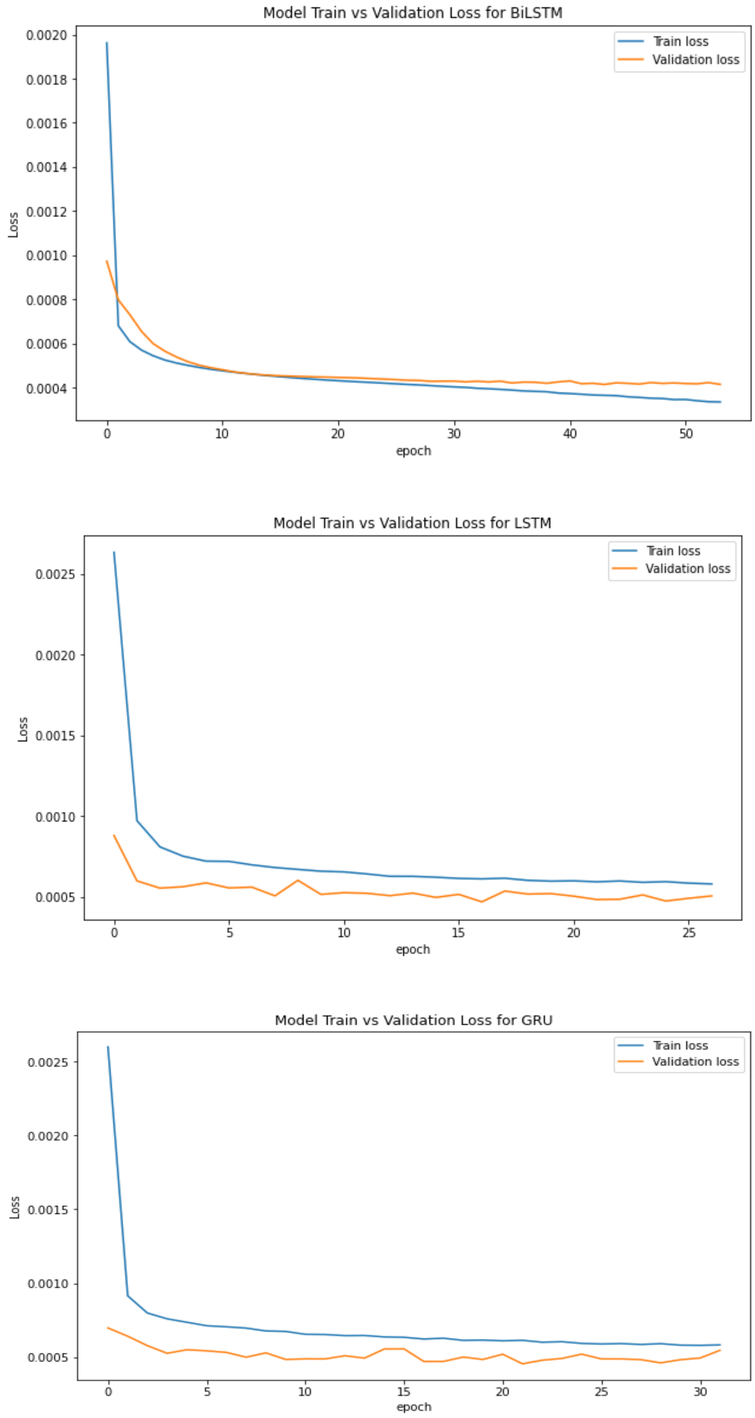


Figure 20.Training and validation loss plots for Multivariable case2.

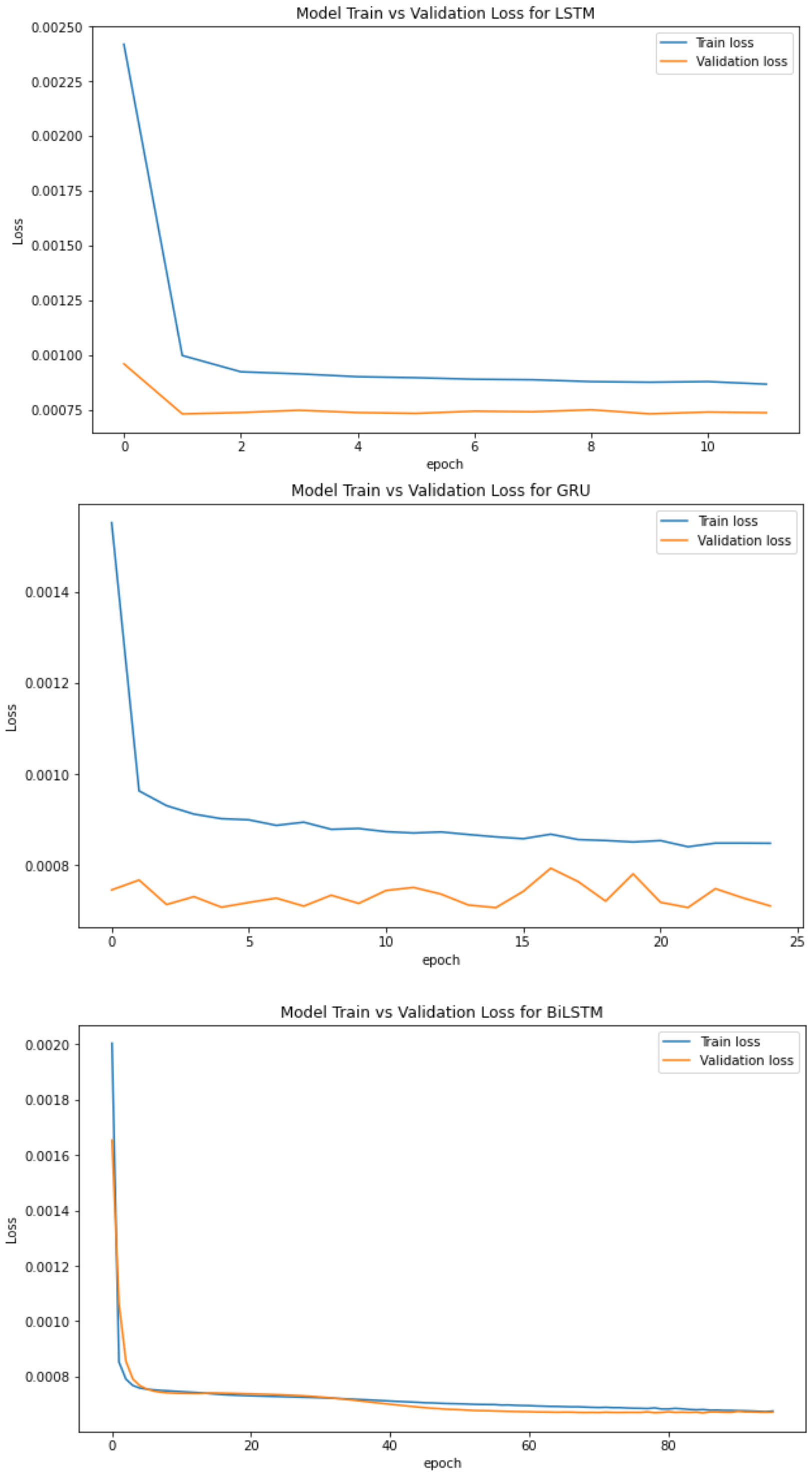


Figure 21.Training and validation loss plots for univariable.

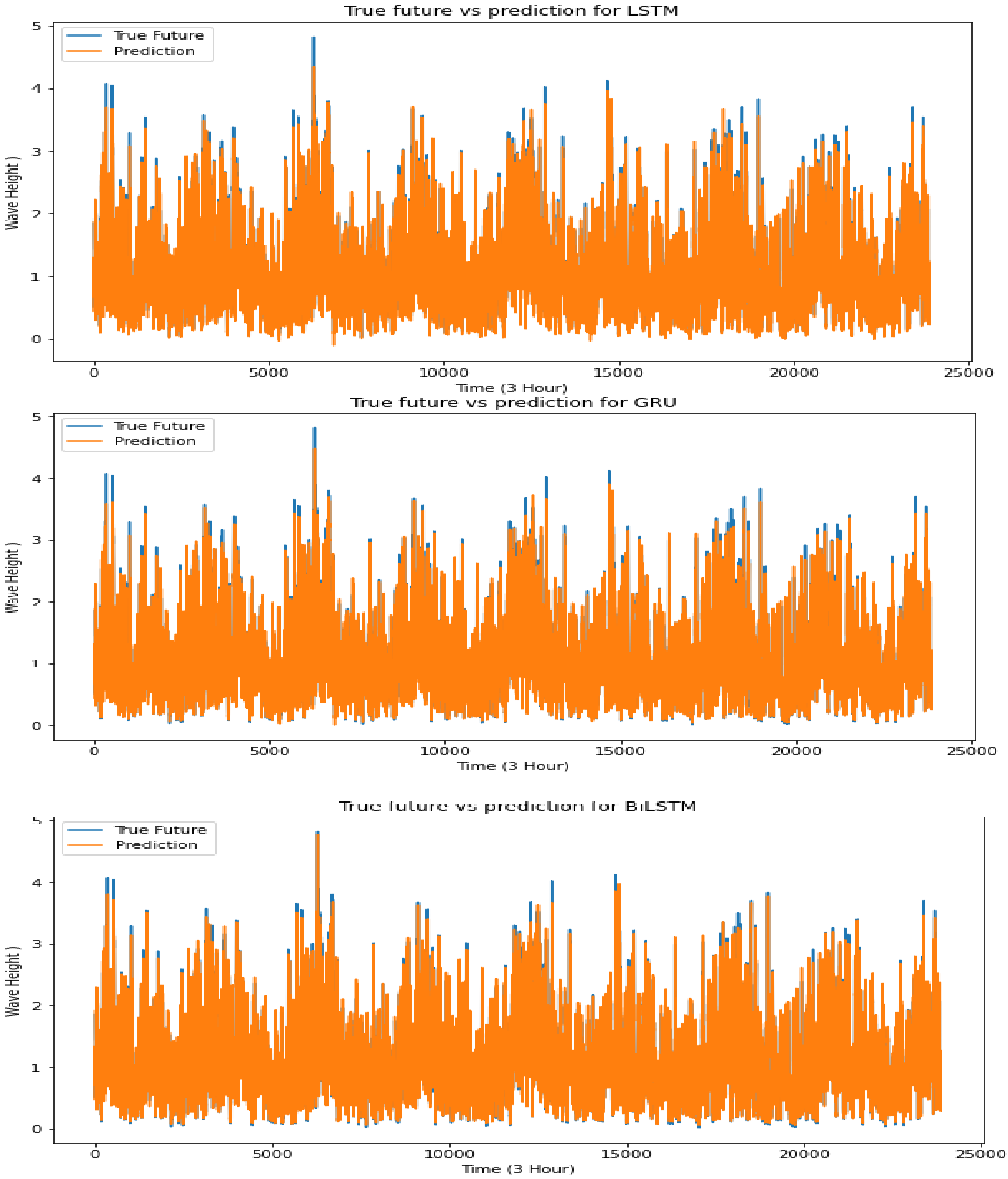


Figure 22.Comparison of the various modes of predictions result in univariable case 3.

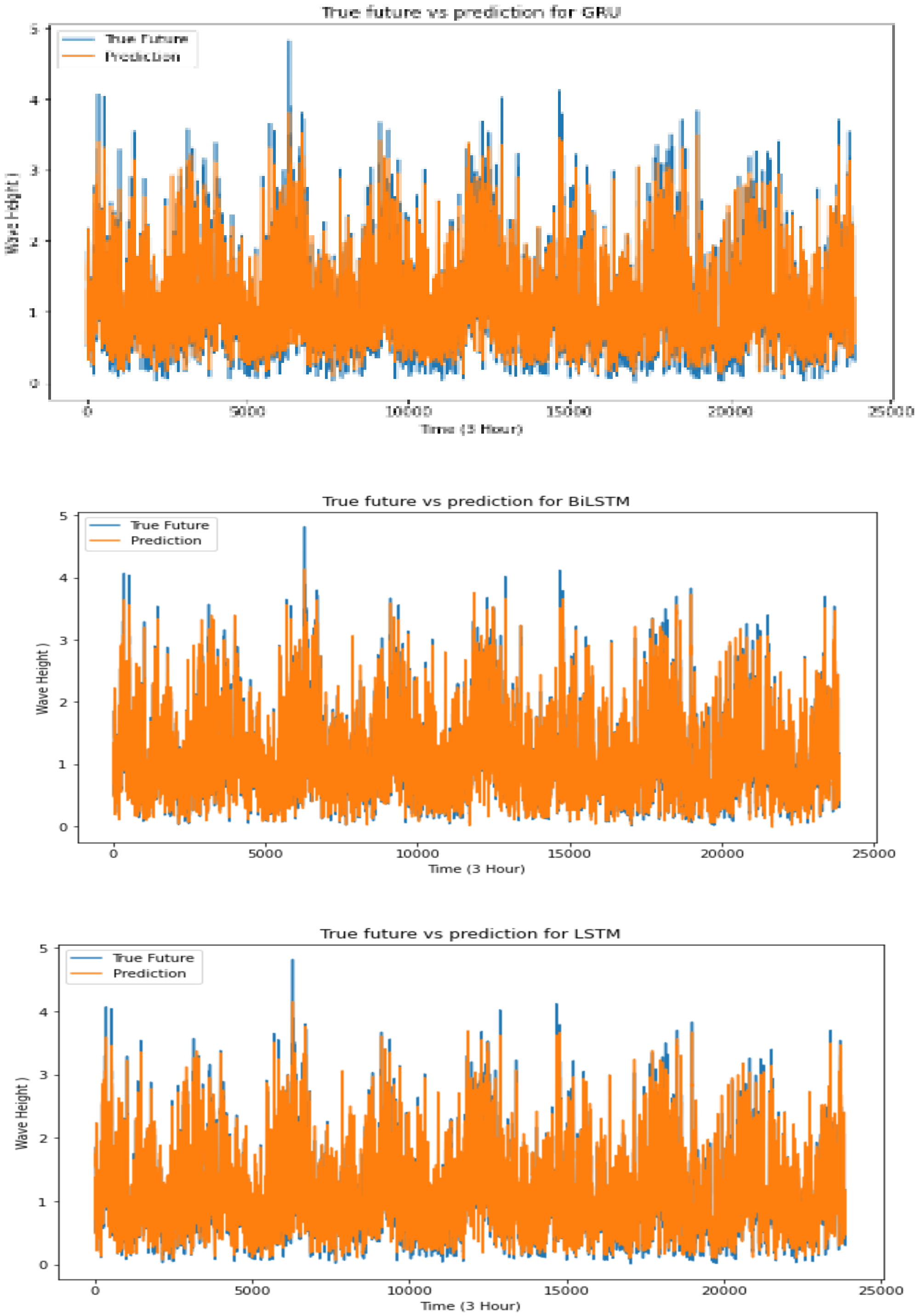


Figure 23.Comparison of the various modes of pre-dictions result in Multivariable case 1.

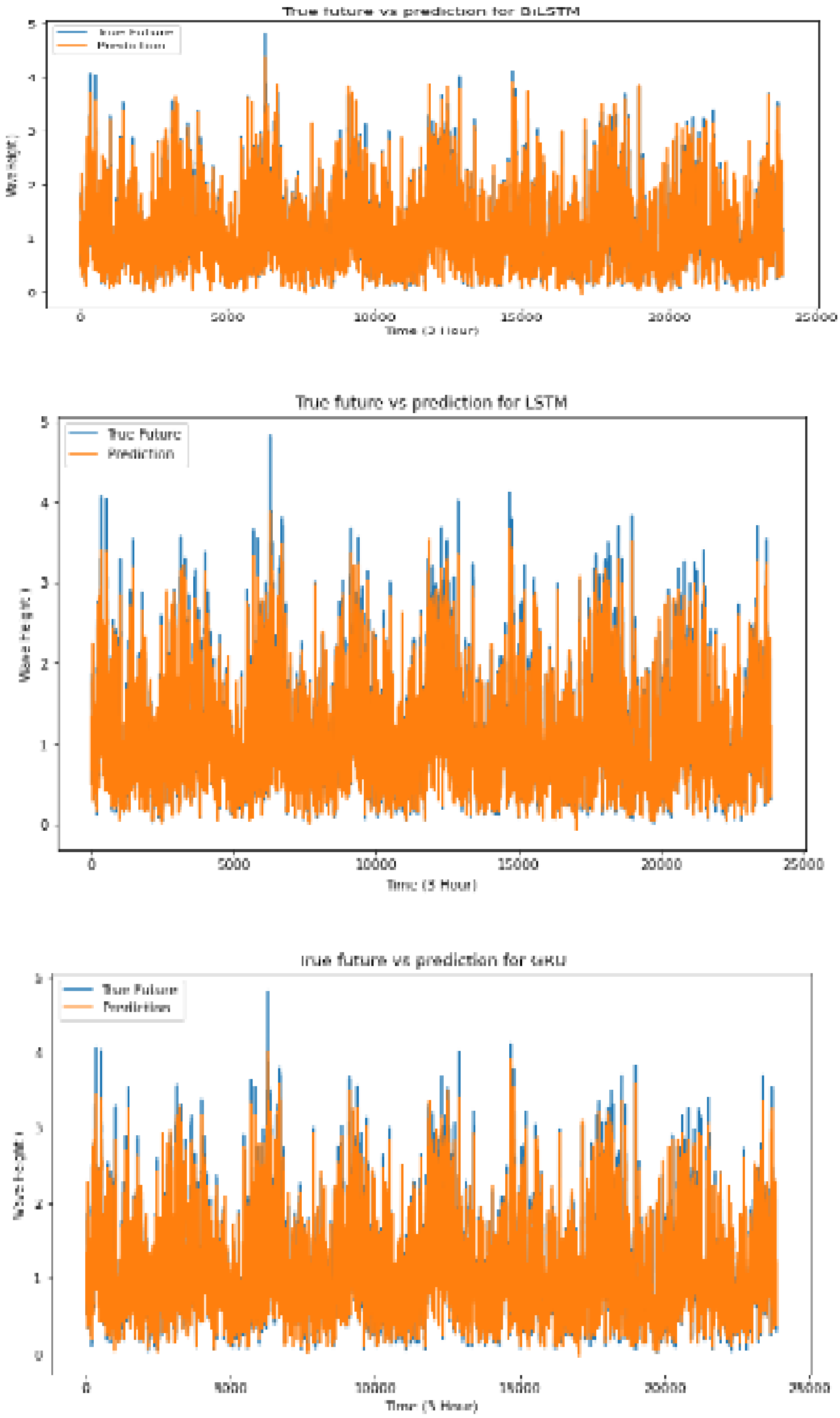


Figure 24. Comparison of the various modes of pre-dictions result in Multivariable case 2.

The training loss of the MV model reduces with the increase of the iteration number until it stabilizes. The reduction rate's stability depends on those futures involved in the models, which is changed from 0.0005 to below 0.00065 for all three models. The BiLSTM model found a high rate of train loss reduction compared to the others in the various scenarios. Also, as the validation loss presented in figures 19, 20, and 21, respectively, the BiLSTM has the lowest loss value and the highest convergence speed among all the models. We found a significant value in the training conversion and loss reduction for the BiLSTM.

Figure 22 to figure 24 present the plot of the different discussed hourly prediction DL models with WFCV. As shown, the predicted values follow the actual output in the BiLSTM. The BiLSTM outperforms the other models in terms of various assumptions. However, The simulation graph cannot represent an accurate, reliable evaluation of those forecasting models based on different scenarios; therefore, the score measures are implanted to quantify the resulting forecasting model.

Univariate model, multivariate model without wave height, and multivariate with all the features have been used to forecast wave height in this research. Table 10 shows the results for three hour-ahead predictions of our experiments for the recurrent neural networks:

Table 9.Accuracy of forecasting those main data scenarios based on various ML models

	MVW			MV			U		
	GRU	LSTM	BiLSTM	GRU	LSTM	BiLSTM	GRU	LSTM	BiLSTM
Mean Absolute Error (MAE)	0.1051	0.0915	0.0895	0.0857	0.0882	0.0794	0.0972	0.0978	0.0971
Root Mean Square Error (RMSE)	0.1480	0.1313	0.1302	0.1323	0.1358	0.1219	0.1542	0.1573	0.1508

It has been calculated the MAE and RMSE to consider the accuracy of performance of those models in multivariate and univariable data assumptions. According to most error measures, The BiLSTM was found with a high level of accuracy in time series forecasting compared to GRU and LSTM. The BiLSTM model achieves the lowest RMSE(0.1219) and MAE (0.0794) to implement all variables as inputs. At the same, MAE and RMSE of the GRU model would decrease 2.9172% and 2.6455%, respectively, compared with the LSTM model. We can see the same trend regarding the performance of the two mentioned models in univariable conditions; however, the univariate model's result confirms that ignoring the impact of other variables such as wind speed would lead to less optimal forecasts with higher errors in forecasted weight height.

In the model without assuming weight height as input, BiLSTM still provides a better result; however, among GRU and LSTM, the LSTM model found better forecasting results regarding reducing MAE and RMSE with 14.8634% and 12.719%, respectively.

In the second phase, we run the model based on feature selection. To achieve the result, based on training data, the correlation coefficient (CC) was calculated among various variables, as shown in Figure 33; correlation analysis illustrated the degree of relevance features and wave height. It can be summarized that the correlations between features and wave height are not varied highly. The correlations between different features should be considered as well. The Tm(s) found with highly correlated with Tp(s) and Tz(s). It is also considered with the Hsd(deg), and the Pd(deg) as these parameters influence the weight height.

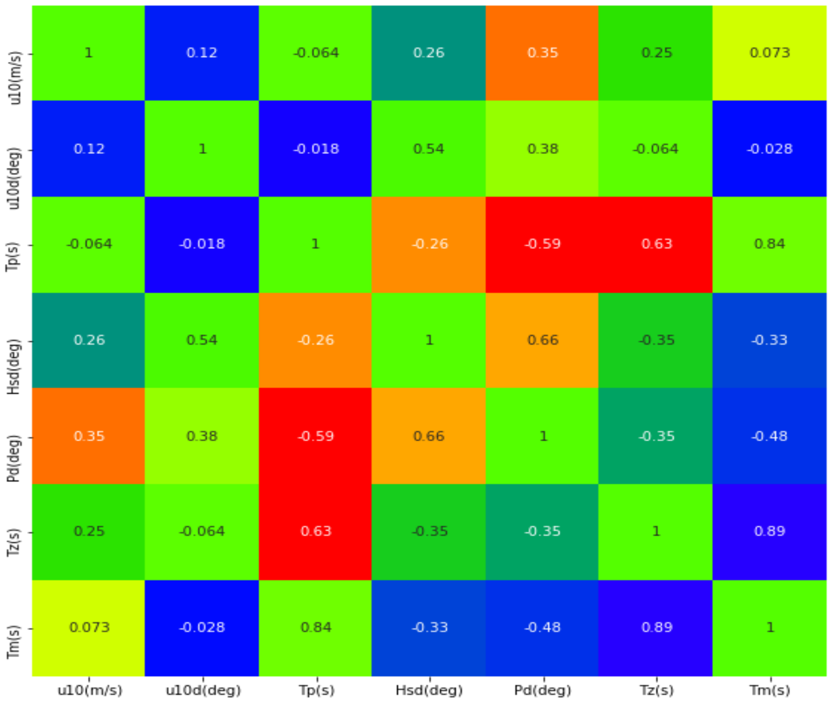


Figure 25.Correlation analysis.

Table 10.Accuracy of forecasting those main data scenarios based on correlation analysis

	MV without [Tm(s), HS]			MV without [Tm(s)]		
	GRU	LSTM	BiLSTM	GRU	LSTM	BiLSTM
Mean Absolute Error (MAE)	0.1083	0.0962	0.0903	0.0890	0.0864	0.0795
Root Mean Square Error (RMSE)	0.1538	0.1406	0.1313	0.1368	0.1329	0.1226

After identification and removal of the highly correlated feature, Tm(s), the multivariable model would run based on two different assumptions, including the removal of Tm(s) and removal of Tm(s) and H(s) as input. As shown in Table 11, BiLSTM can result in more petite MAE (0.0795) and RMSE (0.1226). The result confirms that the new condition (removal of Tm(s)) would increase MAE and RMSE results by 0.125% and 0.574 %, respectively. The result confirms the benefit of feature selection in result achievement in less time and cost consumption.

5.4 Conclusion

With a substantial number of OW farms approaching the end of service life, the discussion on planning the most appropriate end-of-life (EoL) scenario has become popular. The need for planning and scheduling those main activities of EoL scenarios depends on forecasting leading environmental indicators such as significant wave height. This paper proposed a novel probabilistic methodology based on multivariate and univariate time series forecasting of machine learning (ML) models, including LSTM, BiLSTM, and GRU. The accuracy of this forecasting provides the chance to mitigate those uncertainties and risks involved in planning the EoL scenarios regarding offshore wind accessibility. The research investigated the interaction of those quantitatively main features in forecasting the hourly wave height. For better understanding, feature selection in various scenarios based on correlation coefficient was implemented to improve the result accuracy with less time and cost consumption. The BiLSTM model achieves the lowest RMSE and MAE in inputting various variables.

Chapter 6

6 Discussion

6.1 Literature

Having reviewed potential end-of-life strategies and associated influencing factors through relevant literature, it becomes evident that decision support frameworks should balance costs and associated risks to maximise profitability while simultaneously fulfilling stakeholders' requirements. In this section, initial findings are discussed, strategies are compared and then synthesised herein into a generic decision support framework. Finally, associated uncertainties to the decision process is discussed.

6.1.1 SWOT analysis

Following the presentation of strategies and methods, Figure 34 categorises the various possibilities of end-life strategies into four main groups: repowering, leaving in place, partial removal and full removal.

Following this categorisation, a SWOT analysis has been conducted on the various possibilities of end-life strategies to evaluate their strengths, weaknesses, opportunities, and threats (Table 12). Thus, the advantages and disadvantages of the suggested cases can be assessed, informed by current literature and experts' opinions.

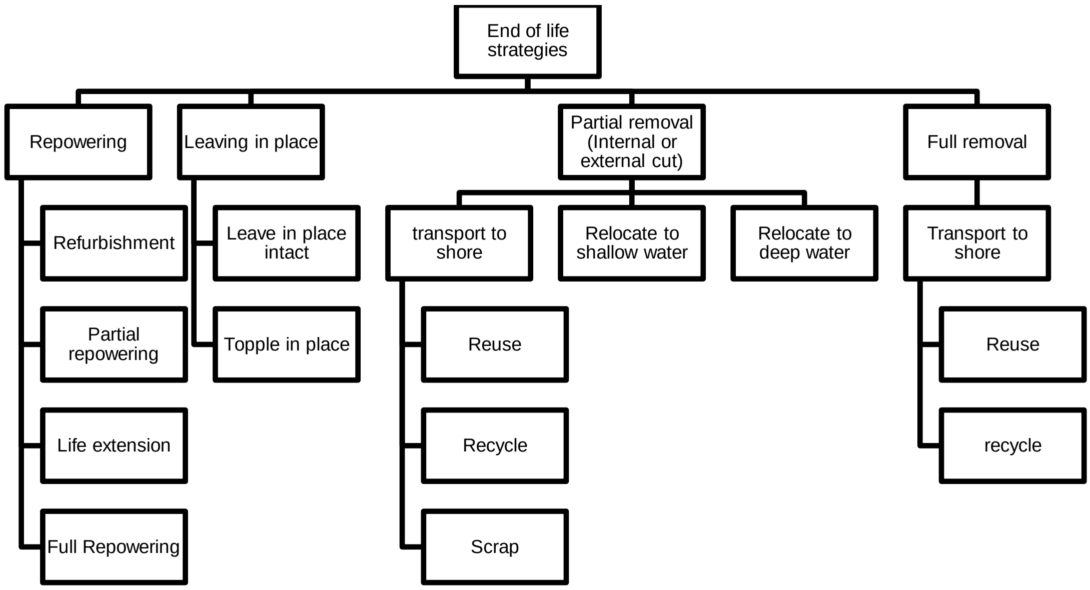


Figure 26.Categorisation of end of life scenarios.

As outlined in Table 12, repowering, limited by the type of wind turbine, improves energy production efficiency by reducing the maintenance cost, installation cost, and reuse of the existing structure. Wind farms estimate the annual output loss at 1.6 ± 0.2% [119]. Moreover, the current wind turbine foundation may not be suitable for a bigger wind turbine with higher energy output. To counter this issue, the turbine may be retrofitted using pins and drilling holes on the monopile, grout, and the transition piece [177]. Although renewable energy is an infinite source, energy harvesting is limited by the end-life estimation for the equipment and, in the case of OW farms, finding the most suitable location for optimum wind energy extraction. The sites selected previously for the OWTs have a better chance of being the optimum location for wind extraction; therefore, it is always reasonable to seek ways of utilising the exact location. Before reusing the site, several essential aspects must be considered, such as cost-benefit analysis and other pertinent issues that require further research.

Total removal is expensive compared to other end-life options, but it helps restore marine traffic and fishing activity. Partial removal can be considered after repowering options are exhausted. It concentrates more on ecological benefits, such as habitat life, and presents several advantages over the repowering option. Further research must be conducted to develop appropriate selection criteria between partial removal and repowering. Moreover, consideration of the economic aspect only for decision-making is only part of the decision-making process; however, it is essential to consider other factors involved in the project, such as risks related to operating time, environmental impact, number of heavy lifts, specialised equipment (logistics), health and safety, and insurance. To the best of the author's knowledge, currently, there is no research comparing these factors with each other or assessing their impacts on the project.

Leaving in place is a controversial end-life scenario due to its legal implications and actual environmental impact. It may not be considered an independent strategy, but it can be viewed in conjunction with the structure's condition, possible modification to the system, removal options, etc.

An OWT may be removed as a single structure, enabled by a heavy-lifting vessel, such as the Pioneering Spirit, which can deal with most offshore turbines. This vessel can accurately cut the selected location of the wind turbine and effectively lift heavy parts. It is flexible and can be modified based on the requirements [178]. After lifting the top side of a wind turbine, the decommissioning process is followed by lifting the transition piece and foundation together with the rest of the wind turbine. Minimum disassembling is required for this method; therefore, it can be finished without delays that may occur due to unfavourable environmental conditions. The implementation of this process is expensive due to the higher cost of vessels and high risks involved; however, the risks are limited due to the absence of hazardous liquid, unlike the scenario in oil/gas structure removals.

The use of flotation is recommended by applying buoyancy techniques (flotation chambers or bags) on the foundation piece to reduce the need for heavy-lift cranes during the foundation removal and towing to the shore [32].

Vessel availability is another challenge in this industry. Using the same vessels for installation and decommissioning incurs lower costs; however, the increasing demand for vessels in the OWT and the oil and gas industry for building or decommissioning activities makes the availability of vessels a challenge. This is further worsened by the limited time of the year that the vessels can operate due to extreme weather conditions. Effective management of these resources is key to executing the installation/ decommissioning activities of OWTs successfully. One of the ways this can be done is to plan the decommissioning activities based on the capability of available vessels and ship-building capacity.

Variability of the removal legislation and guidelines in different countries significantly influences the planning for decommissioning. Lack of this guidance might be harmful to the environment as well. The increasing demand for decommissioning OWTs in the coming years calls for bridging the research gap in this field and highlights legislation's important role in planning.

Table 11.SWOT analysis of end-of-life strategies

SWOT	Leaving in place	Repowering	Total removal	Partial removal
Strengths	Less cost and time	Improving the technology	Restoration of previous habitat, all fishing and shipping activities	Less environmental impacts at scour protection and foundation
	Less environment damages	Increasing power output capacity and productive	Recycling or reusing the equipment	Less time and cost operation
	Less complex removal methods	Free and inexhaustible energy	Minimize the impacts on the marine ecosystem by removing the foundation and cables	Less complexity, and noise
	Less vessels	Less cost, shorter installation time, more environmental friendliness comparing with new wind farms		Recycling or reusing the dismantled spares.
		Less vessels and planning		Less complex technology
		Avoid maintenance cost		Less risk of personnel comparing with full removal
		Information availability from existing wind farm		
		Install bigger WTs or change some components		
		Optimize the use of available land to increase the power		
Weaknesses	Programme of ongoing monitoring negative impacts on shipping, fishing	Lack of experience	Negative impacts on current habitats	Cost of sit monitoring
	Lack of experience	Need the optimized plan	Complexity of process heavy lifting	Lack of experience and knowledge
	Shadow water issues based on toppling		Expensive method	Vessel availability issues
	It depends on the regulation of countries		Complex technology for removal	Limitation of future development site

	No option for recycling or reusing the equipment		Cable removal	Spread of non-indigenous and/or invasive species by leaving components in place
			Lack of vessel	Cable and
			Inspection needs before and after the removing the foundation	Inspection needs before and after the cutting the foundation
			Lack of experience	
			Two-year period of monitoring and remediation	
			Site clearance	
			High risk to personnel	
Opportunities		Adopting farm with new technology	New opportunities such as the aggregate dredging	Commercial activities such as crustacean ranching
		Increasing the life of wind turbine between 5 to 25 years	Possibility to have an Aquaculture	
Threats	Negative environment effects	The modification of energy at the market price	The liabilities of financial	Collision risk of fishing gears
	Environment emissions		Alienation of certain user groups	Spread of non-indigenous
	Shipping interruption			Species
	Cable issues			Alienation of certain user groups

6.1.2 Development of a decision support framework for the selection of end-of-life strategies

Having reviewed state of the art in end-of-life strategies and their associated influencing factors, a generic decision support framework shown in Figure 35 is proposed here to ensure a systematic approach that will consider all key aspects and influencing factors.

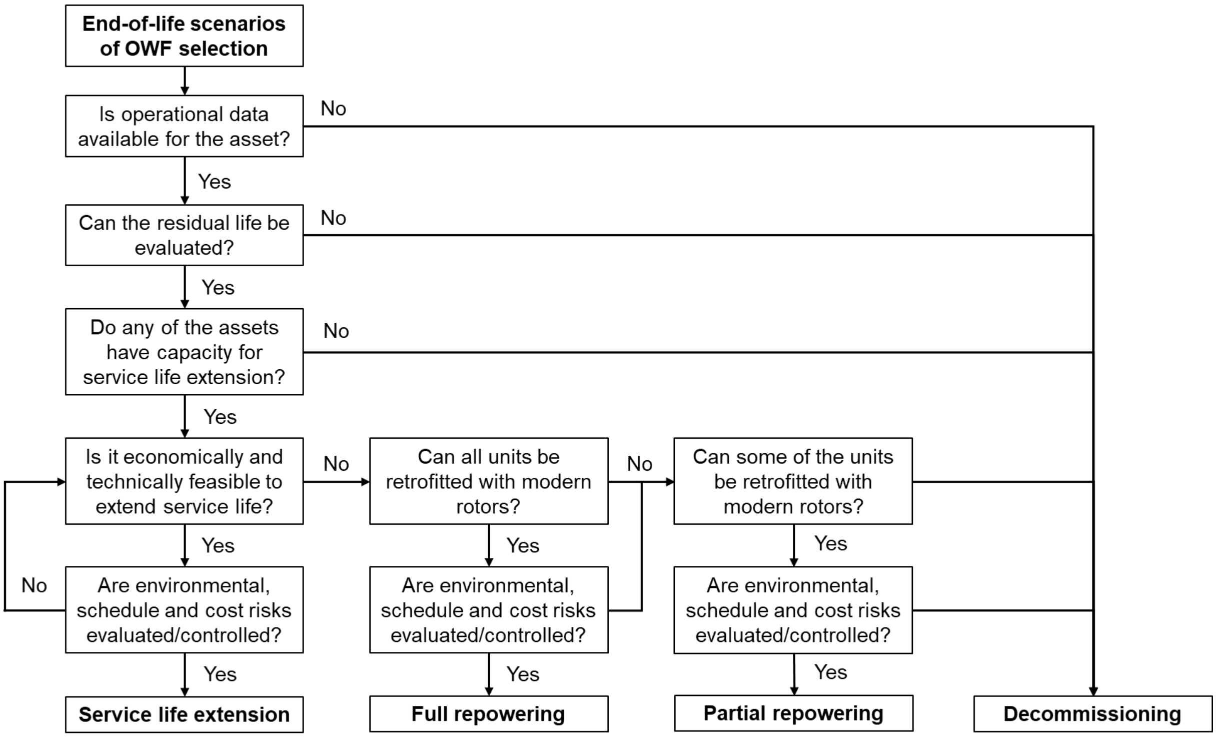


Figure 27.Decision support framework.

The process starts with identifying available data for assessing the integrity of the wind farm as an asset. The absence of such data or inability to estimate the residual life of the assets limits the options of end-of-life strategies for decommissioning as no quantitative analysis can take place to quantify the risks and benefits of alternative methods. The same stands for the case where the evaluation of the service life extension potential returns as an outcome in a brief period, which cannot justify the extension. If it is economically and technically feasible to extend service life, continuing to use the assets through their standard operational management process, and after evaluation of environmental, schedule and cost risks, service life extension should be chosen as the most appropriate option. If these risks cannot be evaluated and/or controlled, this should inform the techno-economic assessment and explore the strategies further. If this option is not economically or technically feasible, the option of repowering some or all of the units should be explored. If related risks can be evaluated and controlled, these options qualify; if not, decommissioning should be selected as the preferred option.

The framework presented above aims to structure the decisions of stakeholders, linking the top question with the primary option that are listed on the bottom. It is deliberately intended to stand as a generic framework that should balance costs and risks through appropriate quantitative assessments. It should be noted that it is essential to involve internal and external stakeholders, organisational strategies, and the applicable regulatory frameworks that could enable or make specific strategies less favourable.

6.1.3 Uncertainties on influencing factors

Providing accurate estimations for environmental impact, schedule and cost impacts plays a vital role in selecting end-of-life strategies. Lack of data and experience, specifically from offshore wind energy assets, are the main limitations for an accurate estimation at the moment. Cost estimations published so far seem to be very often and sometimes cannot be generalised to conclude applicable to assets deployed in different conditions. Assumptions around factors such as the cost of cable removals, seabed monitoring, and increased maintenance requirements during the extended period can introduce significant uncertainty in calculating the updated life cycle costs. Availability of vessels imposes a further delay on schedule and cost due to the limited fleet that can handle heavy lifting operations. Operational limits of vessels will also introduce schedule uncertainty. Finally, restoring the natural environment to its pre-deployment condition presents requirements such as site monitoring and remedial actions that can impact costs and schedules.

This study developed a framework that will consider multiple criteria in the decision-making process, presenting and discussing available technologies and strategies, as well as influencing factors such as schedule, cost and environmental impact. Service life extension, repowering and decommissioning are included in this study as the leading end-of-life strategies considered by asset owners.

6.2 Decommissioning vs Repowering of offshore wind farms – a techno-economic assessment

With many OWT approaching the second half of their service life, determining the most applicable end-of-life scenario becomes crucial. This chapter proposes a techno-economic framework for the study and comparison of two critical end-of-life scenarios: repowering and decommissioning. Service life extension has not been evaluated in this study as the approach of quantifying the underlying costs would be different and demand a fully integrated cost model with detailed modelling of the O&M phase. In the case of accepting the repowering strategy as EoL scenarios, the initial service life of 20 years is assumed for the farm, and then OWF will be repowered with a turbine of the same capacity. There might be other repowering strategies; however, the current one is identified as more practical for the study regarding technical assumption, the determined cost of components and the installation process.
Results from a detailed economic assessment have been developed to calculate the LCOE based on the Capital expenditure (CAPEX), Operational and maintenance expenditure (OPEX), Decommissioning and disposal (D&D) or Repowering cost to achieve an optimal strategy. Several variables influence the techno-economic framework for comparison of two critical end-of-life scenarios in terms of investment planning, such as an unstable energy market. To this end, it is meaningful to transition from a deterministic to a stochastic assessment. The uncertainty in the analysis is considered systematically as results are presented and discussed deterministically and stochastically.

Results from the deterministic analysis clearly show that the option of repowering is the prevailing one as, although it involves the cost of acquisition of the new turbine and critical components, it has a reduced P&A cost compared to the decommissioning option. The results of the stochastic analysis reveal that the AEP and the energy yield parameter play a significant role in calculating LCoE across the different scenarios. This implies that these parameters should be evaluated as accurately as possible, and at the same time, underlying uncertainties should be reduced, narrowing the scatter around the expected values. The certainty equivalent indicates a fixed value of LCoE, which the decision maker should be indifferent towards, relative to the uncertain LCoE they face. At the same time, the RP suggests the amount of money that should be paid to decrease the uncertainty. Among the different options, repowering again performs better with a lower value of RP and certainty equivalent. A full repowering scenario is found as an overall chance under the assumptions viewed, with a lower risk premium and certainty equivalent to other methods.The decision of the most appropriate EoL scenario should be based on risk, and techno-economic assessment and the proposed approach considers both factors. There are, however, practical issues that the decision maker should consider. For repowering, the capacity of the critical infrastructure should denote the extent to which repowering can be realised, both in aspects of the number of positions considered and the maximum capacity that the offshore substation can accommodate. Decommissioning should ensure that partial or full removal should be based on sound reasoning, and the process should be optimized to reduce operations and associated costs. Although the decommissioning process is considered part of the D&D stage, the specificities of investment and related assets, which account for the deployment location and integrity of the structures, should inform the final decommissioning plan.

6.3 Selecting appropriate End-of-life scenarios for offshore wind farms based on multi-criteria decision-making method

The selection of preferable EoL strategies has become very applicable as such a decision can increase profitability and reduce costs. Typically, the decommissioning should be considered even at the planning stage of the wind farm; however, before decommissioning occurs, repowering or service life extension may be pursued, taking into account any residual capacity of key wind farm components. This chapter identifies and determines the optimum EoL strategy regarding the condition of the farm. The decision regarding selecting the appropriate end-life scenario for the OW farm is involved various uncertainties, such as environmental factors. It is challenging for the owners to determine whether the repowering or decommissioning strategy for the end of the farm or beneficial to have a specified period as service life extension before any decision. The decision process is complex due to several uncertainties involved in the decision-making. To solve this issue, we introduce a methodological framework to guide decision-makers based on a comparative study of Multi-Criteria Decision Making (MCDM) techniques. In the first step, a comprehensive literature review identifies the main EoL strategies in the OW farm to achieve this aim and objectives. After this stage, the TOPSIS analysis as the MCDM method applies to select the EoL strategy.

Attempts to find the most influential criteria should be defined for TOPSIS analysis by a literature review and brainstorming with experts. The data would be collected based on the designed questionnaire. For the TOPSIS method, which is deterministic, the criteria would be assumed to the fixed value. It would be tough to consider whole aspects of it to real model cases because modelling would be based on the expert's idea, and his judgment might be unclear; in addition, it would be challenging to match human judgment with an exact numeric value.

NPV is recognized with the highest weight and follows with data availability for residual life estimation of subsystems. The type and number of turbines and foundations are the lowest among those criteria. This result indicates that experts pay close attention to technical performance and cost in selecting EoL strategies in offshore wind turbines. TOPSIS implies that the best alternative is comparable to the ideal scheme but is far from the worst scenario in the scheme sorting stage. Even though the combination of Service life extension and full decommissioning has nearly the same average score as full decommissioning, the combination of service life extension and partial decommissioning are selected as the best alternatives. While both repowering and partial Decommissioning are not far from each other, they are the lowest options compared to the rest. To further illustrate the effectiveness of our research, we compare it with the result of this research [4]. The result confirms the need for research to investigate the type of repowering strategies for the farm. Apart from this, the baseline decision matrix and weight are based on expert opinion. Currently, there is a lack of experience regarding EoL strategies in OW farms, which negatively influences the reliability of human judgment. The level of energy production based on the repowering strategy should be considered an essential factor. This confirms the benefits of quantitative criteria in MCDM to achieve more reliable result.

6.4 Multivariate and univariate time series forecasting of ML models

The planning procedure of EoL scenarios depends on contributors such as previous project experience, type of vessel selection, availability of trained crew and experts, weather and wave conditions, and distance to the port.The harsh environment can limit the operability of vessels during marine construction work. Storm waves can destroy infrastructure in offshore farm zones, cause economic damage, and threaten human life. The massive increase in the cost of any decision-related EOL operation might result from an inaccurate forecast of significant wave height. The approximate forecast of the wave height negatively influences the cost by limiting accessibility to the turbines, increasing the transfer time related to labour and vessels. Significant wave heights can be categorized into three main stages: mild level when considerable wave heights are less than 1 m, moderate when multiple wave heights are between 1 and 2.5 m, and extreme when significant wave heights are more than 2.5 m. In general, the feasibility of construction, especially the lifting process by a floating crane, depends on the condition of the wave height. A higher quality of wave forecast will undoubtedly contribute to finding the suitable time for the construction activities regarding the EOL strategy and optimum lifting power. The result of accurate significant wave height forecasts helps decide whether to launch service vessels for offshore wind turbines farm.

This work benefits from a novel probabilistic methodology based on multivariate and univariate time series forecasting of ML models, including LSTM, BiLSTM, and GRU, to assess significant wave height accuracy. These ML models are suitable frameworks to forecast complex systems due to using a dynamic behaviour of data based on their internal memories. The research presents a comparative performance of several ML methods regarding the accuracy-based multivariate and univariate time series forecasting in terms of the interaction of those quantitatively main features. This makes uncertain forecast circumstances easier due to their ability to investigate any nonlinear and complex function between significant wave height as output and other meteorological and oceanographic predictors as inputs. Apart from this, it considered the role of appropriate predictive variables selection for accurate forecasting.

In the first step, the model runs without feature selection in the part of data preparation. The MAE and RMSE were implemented to consider the accuracy of execution of those models in multivariate and univariable data assumptions. According to most error measures, The BiLSTM has a high level of accuracy in time series forecasting compared to GRU and LSTM. The BiLSTM model has the lowest RMSE(0.1219) and MAE (0.0794) to implement all variables as inputs. At the same, MAE and RMSE of the GRU model would drop by 2.91715% and 2.6455%, respectively, compared with the LSTM model. Univariable conditions have the same trend regarding the performance of the two mentioned models. However, the univariate model's result proves that neglecting the influence of other variables such as wind speed would lead to smaller optimal forecasts with higher errors.In the second phase, the model is run based on feature selection. The correlation coefficient (CC) was implemented among different variables. The correlations between features and wave height are not varied highly.

After identification and removal of the highly correlated feature, Tm(s), the multivariable model would run based on two different assumptions, including the removal of Tm(s) and removal of Tm(s) and H(s) as input. BiLSTM can result in more petite MAE (0.0795) and RMSE (0.1226). The result demonstrates the benefit of feature selection in result achievement in less time and cost consumption.

Chapter 7

7 Conclusion

7.1 A multi-attribute review toward effective planning of end-of-life strategies for offshore wind farms

With many offshore wind turbines approaching the end of their estimated operational life soon, there is an increasing demand for developing and evaluating end of life strategies that can maximise assets’ value while simultaneously satisfying stakeholders' requirements. This study aims to develop a framework that will take into account multiple criteria in the decision-making process, presenting and discussing available technologies and strategies, as well as influencing factors such as schedule, cost and environmental impact. Service life extension, repowering and decommissioning are included in this study as the main end of life strategies considered from asset owners. These are translated into four procedures applicable to offshore wind farms; repowering, abandonment, partial removal, and complete removal. A SWOT analysis is finally conducted to compare the different characteristics of the proposed procedures. The constraints contributing to the uncertainty of the processes as well as lessons learnt from the oil& gas industry are also discussed.

7.2 Decommissioning vs Repowering of offshore wind farms – a techno-economic assessment

Offshore wind turbines are normally designed for a nominal service life of 20 to 25 years; however, with a significant number of units approaching the second half of their service life, the discussion of selecting the most appropriate end-of-life scenario becomes ever more relevant. Scenarios to be investigated mainly include decommissioning, repowering or service life extension, while such decisions depend on a number of criteria which should be taken into account and should ultimately inform a techno-economic assessment. This paper performs an initial comparative evaluation between two of these scenarios, repowering and decommissioning, through a purpose-developed techno-economic analysis model which calculates relevant key performance indicators. This is presented with a view to evaluating the impact of key influencing factors from a deterministic and stochastic approach while further adopting the economic model of risk aversion to calculate the certainty equivalent of LCOE based on each of the examined end-of-life scenarios. Applying to a typical, hypothetical offshore wind farm qualifies the full repowering scenario as the prevailing option under the assumptions considered, with a lower amount of risk premium and certainty equivalent to other scenarios.

7.3 Selecting appropriate End-of-life scenarios for offshore wind farms based on multi-criteria decision-making method

Many Offshore wind turbines are approaching the second half of their service life, and the discussion on selecting the most appropriate end-of-life scenario in the next few years has become one of the major concerns for all the stakeholders. This study has reviewed the different end-of-life strategies for offshore wind farms and the influencing criteria for optimised decisions.

Different alternatives have been assessed through a TOPSIS method as a multi-criteria decision-making procedure to select an appropriate way according to environmental, financial, safety Criteria, Schedule impact, and Legislation and guidelines. Setting the right end-of-life scenario helps internal and external stakeholders maximize asset farms' profitability. This comprehensive study shows that the combination of service life extension and partial decommissioning are chosen as the best alternatives. While both repowering and partial Decommissioning are not far from each other, they are the lowest options compared to the rest. NPV is recognized as the most substantial influence, and the type and the number of turbines and foundations are the weakest among those criteria.

7.4 Comparative performance of Multivariate time series forecasting based on various DL models to consider effective planning of end-of-life strategies for offshore wind farms

Accuracy forecasting significant wave height is one of the primary needs for planning and scheduling those main activities of EoL scenarios. This short or long-term forecasting accuracy provides the chance to mitigate uncertainties in planning the EoL scenarios regarding offshore wind accessibility and operation. This work benefits from a novel probabilistic methodology based on multivariate and univariate time series forecasting of ML models, including LSTM, BiLSTM, and GRU, to assess significant wave height accuracy. These ML models are suitable frameworks to forecast complex systems due to using a dynamic behaviour of data based on their internal memories. Paper presents a comparative performance of several ML methods regarding the accuracy-based multivariate and univariate time series forecasting in terms of the interaction of those quantitatively main features. This makes uncertain forecast circumstances easier due to their ability to investigate any nonlinear and complex function between significant wave height as output and other meteorological and oceanographic predictors as inputs. Apart from this, it considered the role of appropriate predictive variables selection for accurate forecasting. The BiLSTM model achieves the lowest RMSE and MAE in terms of implementation of various variables.

7.5 Contribution to knowledge

This research contributes to understanding in a novel, scientifically sound form and provides value to stakeholders. Three scientific journals and four peer-reviewed scientific conference papers have been successfully published.

Section: A multi-attribute review toward effective planning of end-of-life strategies for offshore wind farms.		
Novelty	Value	Scientific soundness
This study performs a detailed review and develops a framework that will evaluate multiple criteria in the decision-making process regarding selecting end-of-life strategies. The research discussed available technologies, methods and factors such as schedule, cost and environmental impact in the methodology of end-of-life strategies selection. Service life extension, repowering and decommissioning are included in this review as the main end-of-life strategies.	A detailed study of the literature has shown an insufficiency of suitable frameworks which can oversee decisions on available strategies based on the particular characteristics and influencing factors. The study assessed the different end-of-life strategies for offshore wind farms, known technical possibilities and the influencing factors that declare such findings to deal with this issue. In addition, Different options have been qualitatively evaluated via a SWOT analysis. In the second part, This research indicated a multi-attribute framework for allowing optimum decisions regarding significant conditions, such as the possibility of end-of-life strategies based on certain features and influencing factors. This systematic literature review concentrates on the most relevant subjects published in high-quality science journals regarding end-life scenarios of OWF since 2010.	The study is not just of interest to researchers and academics but also provides the opportunity to internal and external stakeholders to maximis the profitability of offshore farms while decreasing those significant risks involved in the safety, technical, and environmental aspects. The paper has already been cited and read many times based on the stats from Elsevier (2022), Mendeley (2022), and ResearchGate (2022).

Section: Selecting appropriate End-of-life scenarios for offshore wind farms based on multi-criteria decision-making method.		
Novelty	Value	Scientific soundness
This work identifies and determines the optimum EoL strategy regarding the condition of the farm. The owner found it difficult to decide whether the repowering or decommissioning strategy for the end of the farm or beneficial to have a specified period as service life extension before any decision. The research introduces a methodological framework based on a comparative study of widely-applied Multi-Criteria Decision Making (MCDM) techniques.	In the first step, the main EoL strategies in the offshore wind farm have been specified based on the comprehensive literature review. The research investigated the most effective criteria through a literature review and brainstorming with experts. The questionnaire has been designed to gather the data, and then TOPSIS analysis as the MCDM approach involves determining the appropriate EoL approach. The result delivers an integrated evaluation of several economic, social, environmental, and technical criteria.	The research presents a methodological framework based on a comparative study of the Multi-Criteria Decision Making (MCDM) technique. Setting the privilege end-of-life scenario supports internal and external stakeholders maximize asset farms' profitability. The preferable selection of EoL scenarios decreases costs and enhances asset profitability in the offshore farm. The outcome would be beneficial for both the researchers and the owner of an offshore farm concerning the challenge of whether the repowering or decommissioning strategy for the end of the farm or beneficial to have a specified period as service life extension.

Section: Decommissioning vs Repowering of offshore wind farms – a techno-economic assessment.		
Novelty	Value	Scientific soundness
Comparative assessment between two of these EoL strategies, repowering and decommissioning through a techno-economic model.	Research developed a techno-economic computation framework base on LCOE to assess the consequence of key influencing factors from a deterministic and stochastic technique. It adopted the economic model of risk aversion to calculate the certainty equivalent of LCOE based on individually of the studied end-of-life scenarios. LCOE is computed based on the Capital expenditure (CAPEX), Operational and maintenance expenditure (OPEX), Decommissioning and disposal (D&D) or Repowering cost in order to encounter the optimal strategy. Furthermore, A plausibility assessment, as well as the shift from a deterministic to a stochastic computation to deal with considerable uncertainty regarding the number of variables that influence cost modelling, approved the suggested framework.	The study is attractive for researchers and academics. Outcomes of this work will be advantageous for the owner of OW farm to have a clear financial assessment associated with end-of-life scenario selection. The article has already been mentioned and reads multiple times based on the stats from Elsevier (2022), Mendeley (2022), and ResearchGate (2022).

Section: Comparative performance of Multivariate time series forecasting based on various deep learning models to consider effective planning of end-of-life strategies for offshore wind farms.		
Novelty	Value	Scientific soundness
This Planning and scheduling activities involved in the preferred end-of-life (EoL) scenario has become challenging. Major environmental parameters such as significant wave height can have a negative influence on the process of planning. In this research, a novel probabilistic methodology based on various models, including Long short-term memory (LSTM), Bidirectional long short-term memory (BiLSTM), and Gated recurrent unit (GRU), proposed to consider those main features as multivariate and univariate time series in the accuracy of forecasting significant wave height. This research reveals the value of feature selection in suggested multivariate or univariate time series wave height forecasting and claims that a strong correlation does not necessarily have a substantial causality of results accuracy.techniques.	In this research, a novel probabilistic methodology based on various models, including LSTM, BiLSTM and GRU proposed to consider those main features as multivariate and univariate time series in the accuracy of forecasting significant wave height. This research takes action regarding missing data and intervention to improve the quality of data and data consistency. Two separate sections have been assumed based on the various cases to understand better the role of feature selection.Pearson correlations were used to determine the correlations among features. This helps to determine which parameters have the highest impact on each other. It is vital to approve the accuracy of forecasting those proposed models. The root means square error (RMSE) and the mean absolute error (MAE) are selected as the model performance metrics to evaluate the accuracy.	Accurate forecasting of significant wave height prediction is essential for the planning and operating of maritime activities regarding hazard warnings and safety. Having reliable estimation of wave height as a vital parameter in wind farms provides this opportunity to have safer with less cost regarding the marine transportation, crew transfer, and decommissioning or repowering process. Characterizing waves helps to have reliable forecasting; however, it is difficult due to its stochastic nature. The uncertain, nonlinear, and non-stationary physical process of wave generation estimates wave height prediction challenging.

7.6 Future research

The optimal end-of-life strategy is a decision that should evaluate prices and risks and be supported by available data and a multi-criteria approach, considering influencing factors and available technological options. Due to the limited experience in wind farms having already reached the end of their nominal service life, further research on how such decisions could be better supported, e.g. through detailed integrity assessment frameworks, extended life cycle cost evaluation models or additional technological options.

Techno-economic assessment benefits from high-fidelity cost modelling for assessing the two scenarios, taking into account key influencing factors contributing to cumulative costs rather than informing decisions through a qualitative assessment. This topic is timely as the number of wind turbines approaching the end of their nominal service life is rapidly growing. Limitations of this work are the restricted literature on the techno-economic assessment of EoL scenarios, the scarcity of data related to service life extension and decommissioning processes, and the lack of accurate reliability data, which would authorise consideration of other methods. To this end, and to further advance the proposed concept, several additional topics can be investigated to create a more holistic impact assessment model:

The analysis can also include service life extension as an alternative scenario through a fully integrated techno-economic model and reliability failure data currently unavailable.

More representative modelling of stochastic variables, considering more data becoming available from the first full-scale wind farms to be decommissioned, can add further value to the current findings and serve the purpose of validating this approach.

Investigation of the sensitivity of each EoL alternative to critical influencing factors related to the deployment location, such as distance from the port, water depth and wind shear, can provide valuable insights into the most relevant strategies. The result of MCDM regarding EoL strategies in OW farms confirms the need for research to investigate the type of repowering strategies for the farm. Apart from this, the decision matrix and weight foundation are based on an expert view. A survey was conducted of 10 experts with seven to twenty years of effective practical experience and scientific background in the offshore renewable energy industries and marine environmental science. The survey participants contained: three offshore engineers, two academic renewable energy experts,two marine environmental scientists and two commercialisation experts with an energy economics background and one principal researcher with expertise in UK energy and resource law.

Currently, there is a lack of background regarding EoL strategies in OW farms, which negatively impacts the reliability of human decisions. The level of energy production based on the repowering strategy should be considered an essential factor. In the coming study, it is essential to provide the MCDM regarding optimal end-of-life strategy selection based on more quantitative criteria and compare the result with this research.

This work uses a novel probabilistic methodology based on multivariate and univariate time series forecasting of ML models, including LSTM, BiLSTM, and GRU, to forecast significant wave height accuracy. These ML models are appropriate frameworks to indicate complex systems due to using a dynamic behaviour of data based on their internal memories. The novel probabilistic methodology could be developed further by applying other ML models-based time-series methods to forecasting significant wave height. In addition, correlation analysis is implemented to avoid the irrelevant variables in meteorology and oceanography to unnecessarily increase the cost, running forecasting time of a prediction system and degrade its generalisation. Accurate forecasting is essential for the planning and operating of maritime activities regarding hazard warnings and safety. Having reliable estimation of wave height as a vital parameter in wind farms delivers this opportunity to have safer with less cost regarding the marine transportation, crew transfer, and decommissioning or repowering process.In future work, it is necessary to find a method to avoid irrelevant variables based on the causal analysis to improve the accuracy of the result.

Appendix: Comparative performance of Multivariate time series forecasting based on various deep learning models to consider effective planning of end-of-life strategies for offshore wind farms.

The distribution of selected features during the one, three, and twenty years studied is shown in Table 7 and figures 28 to 35. This helps to understand better the modification of those features regarding time and provides more clarification regarding ML model selection for forecasting.

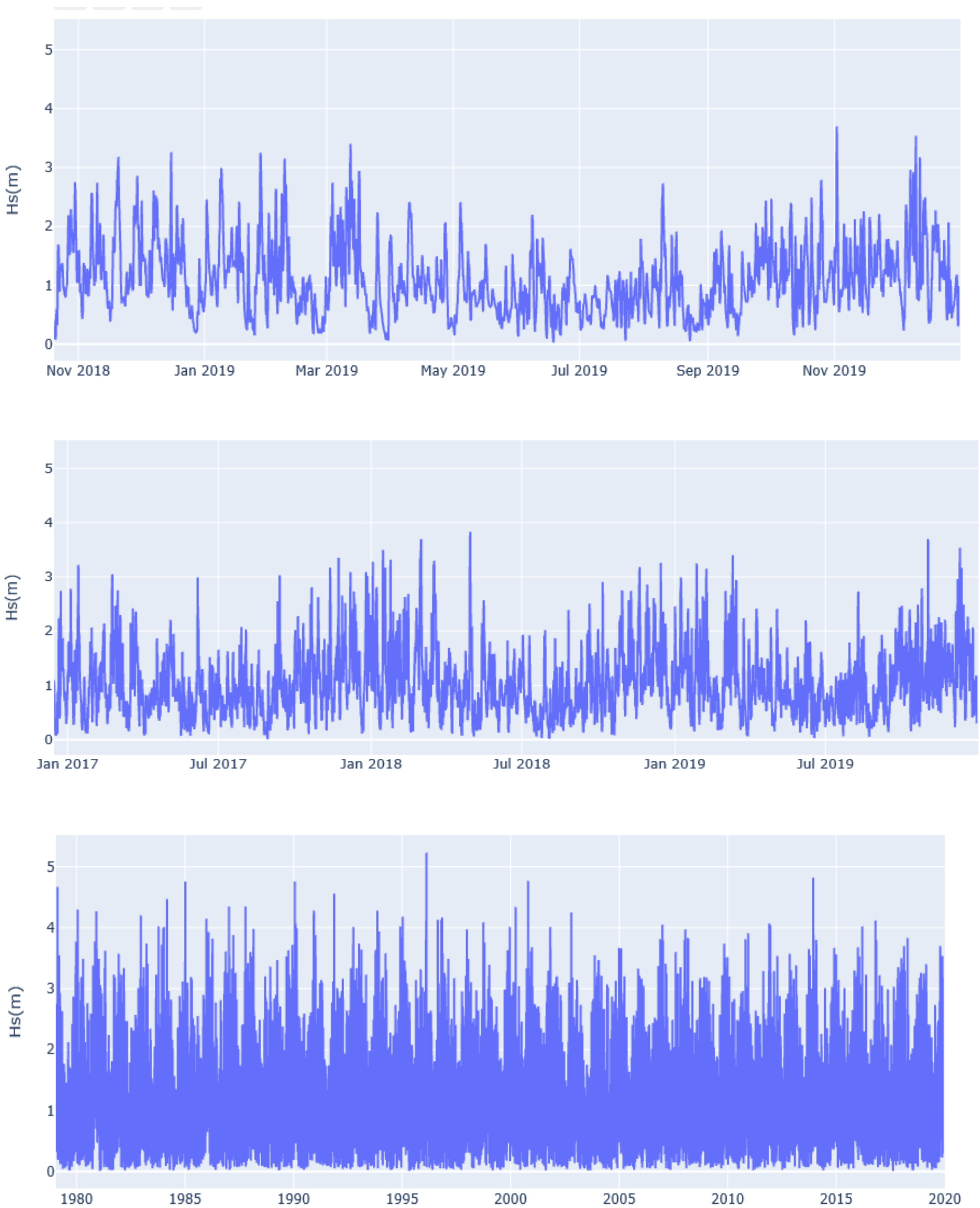


Figure 28.Distribution of significant wave height during the one, three, and twenty years period of studies.

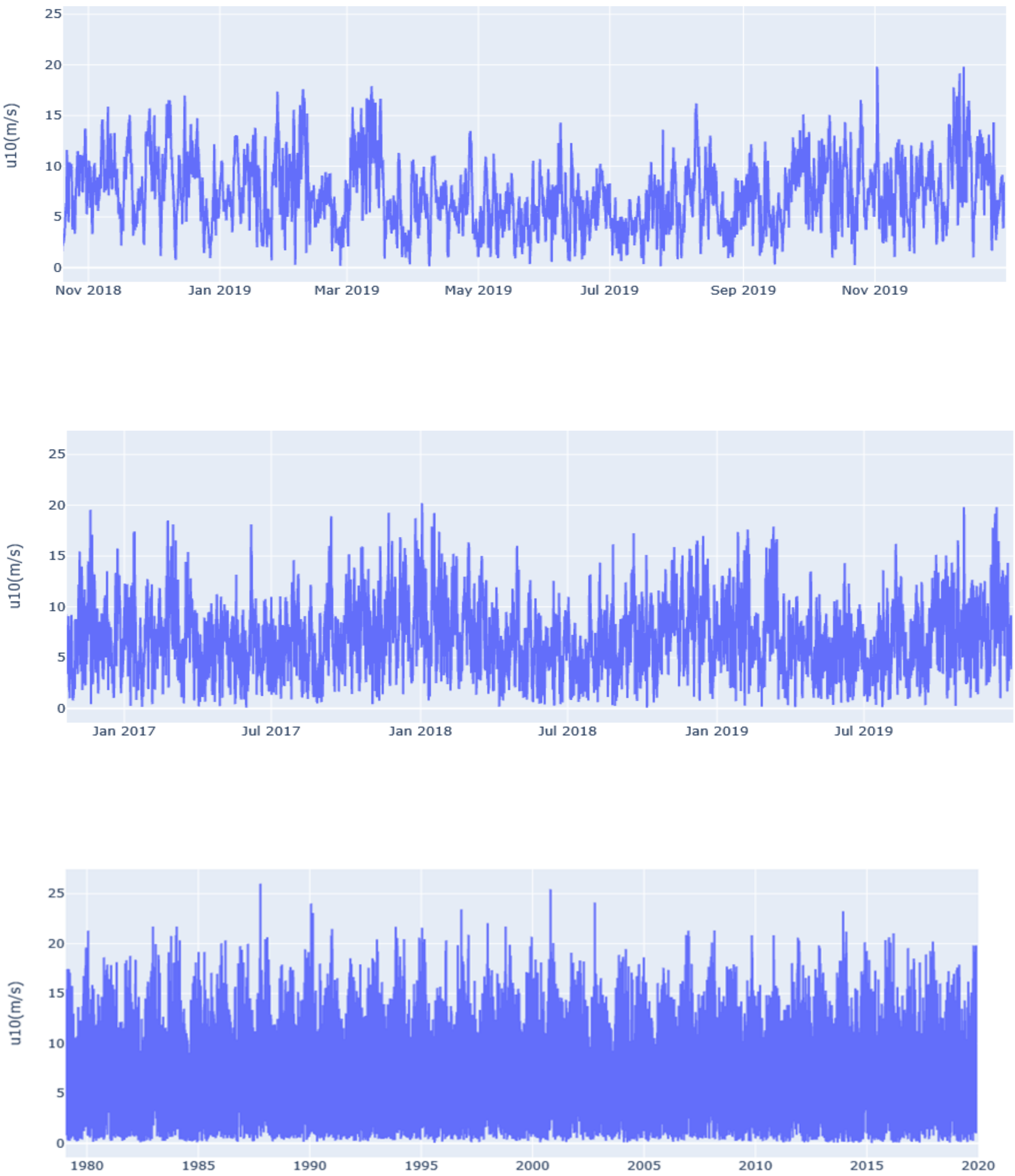
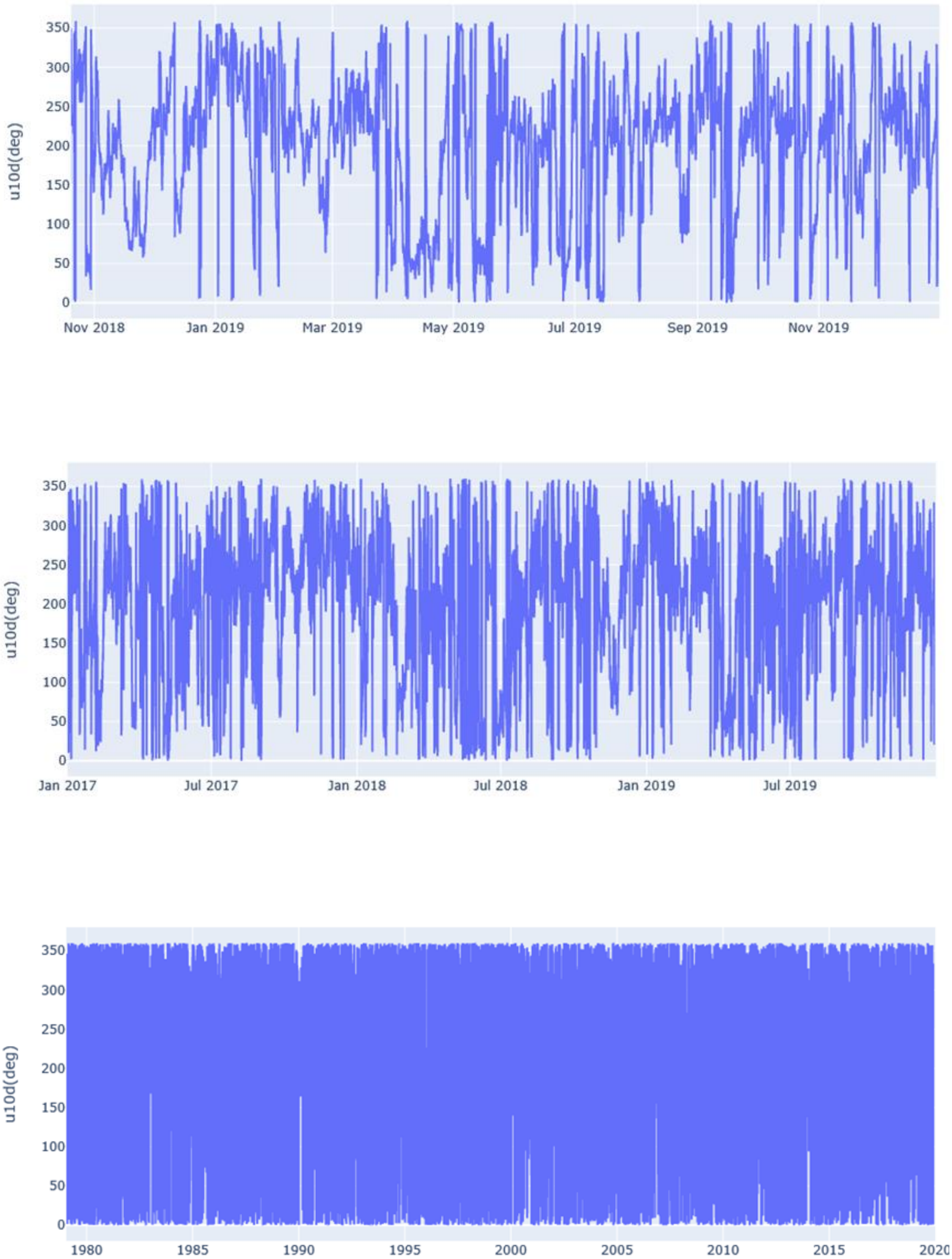


Figure 29.Distribution of Wind speed during the one, three, and twenty years period of studies.

Figure 30.Distribution of wind direction during the one, three, and twenty-year period of studies.



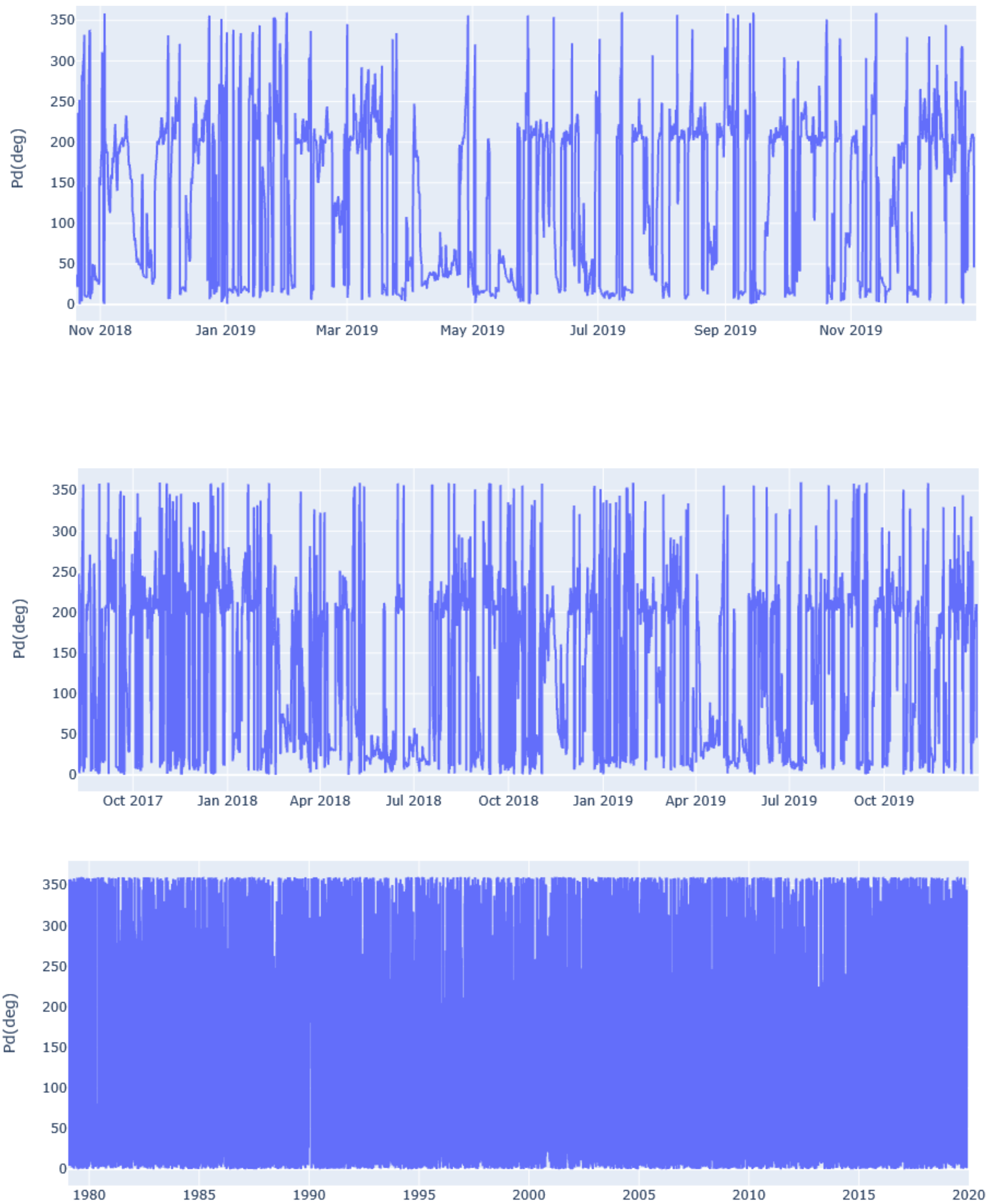


Figure 31.Distribution of peak wave direction during the one, three, and twenty years period of studies.

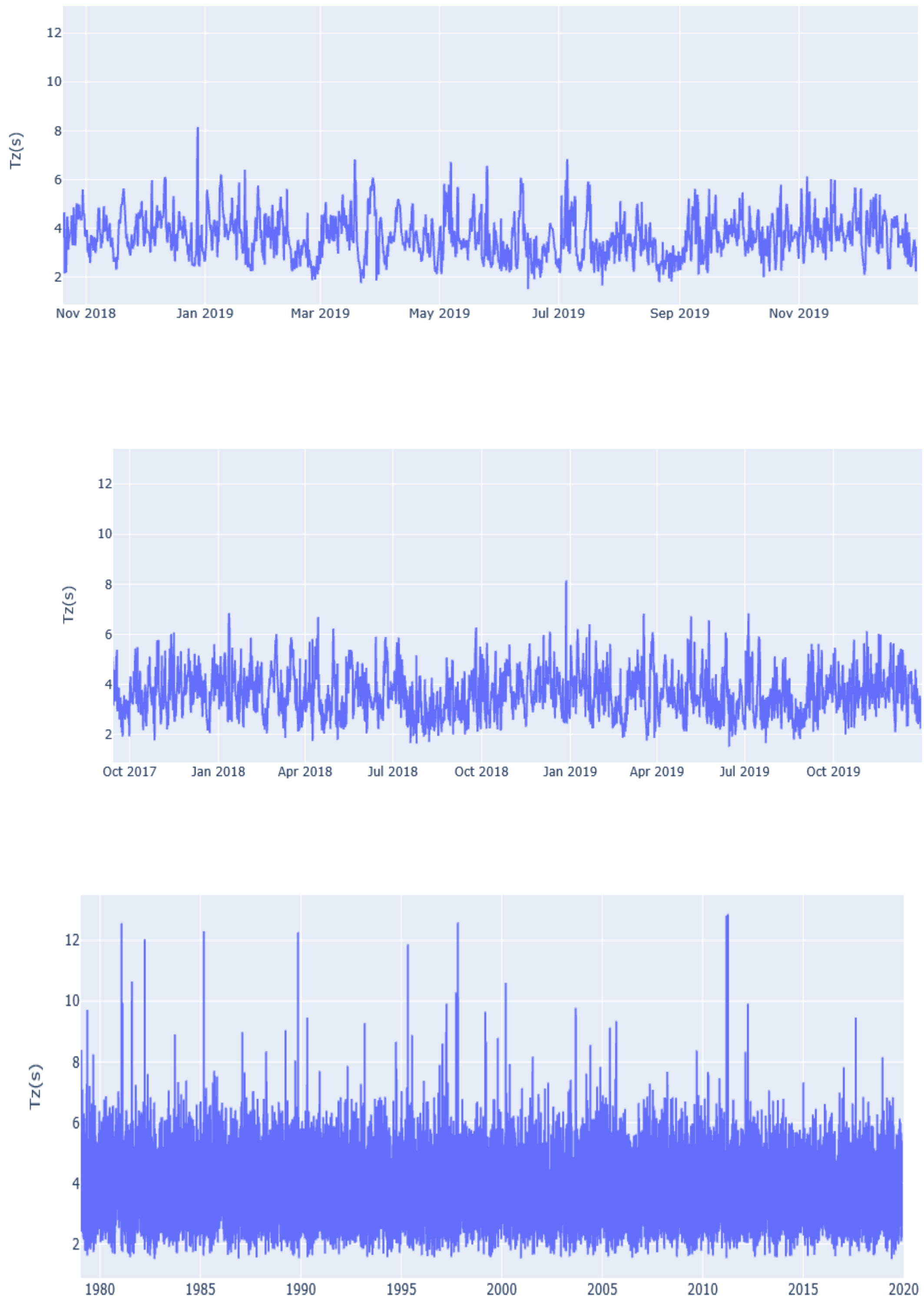


Figure 32.Distribution of zero-crossing wave period during the one, three, and twenty years period of studies.

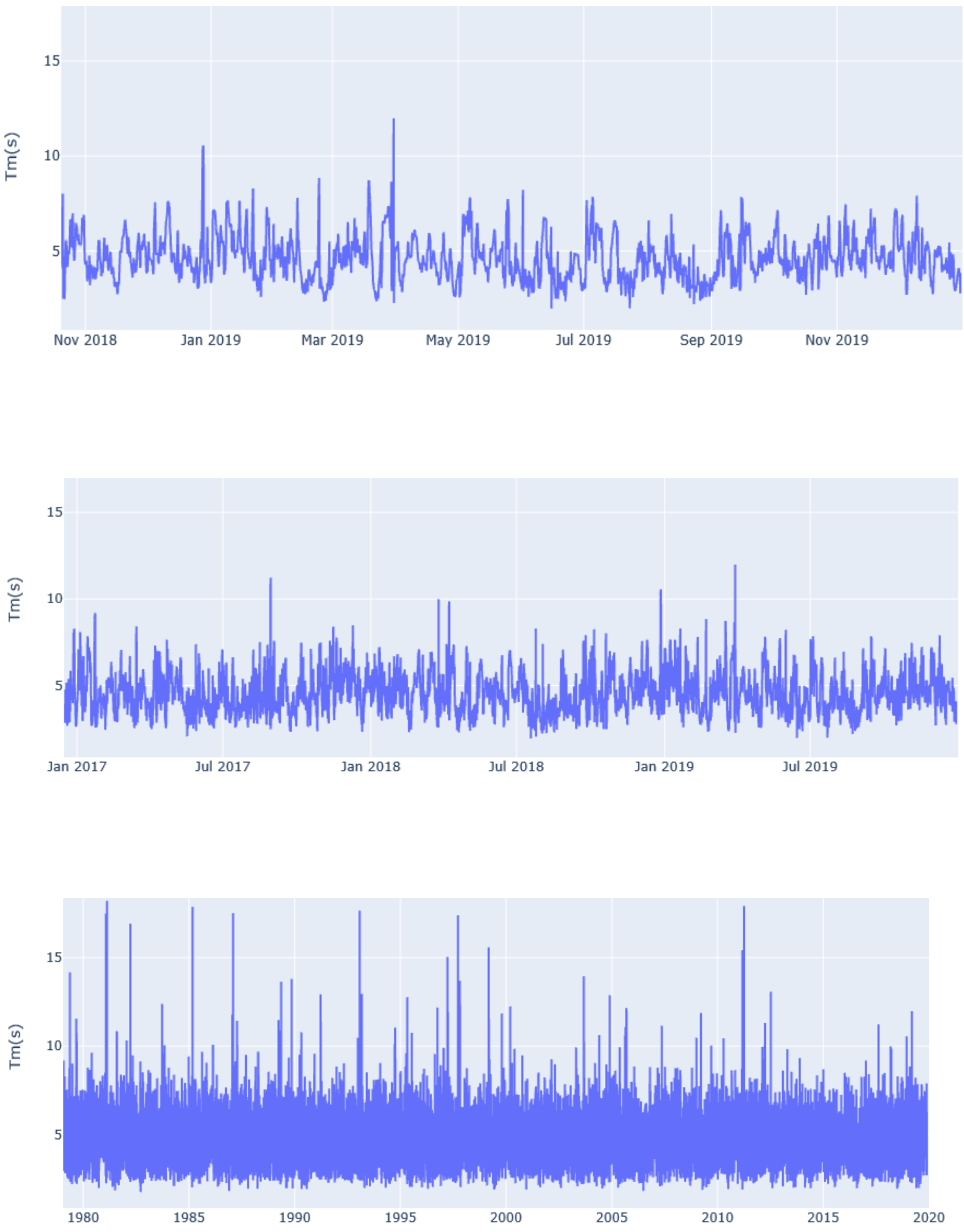


Figure 33.Distribution of mean wave period during the one, three, and twenty years period of studies.

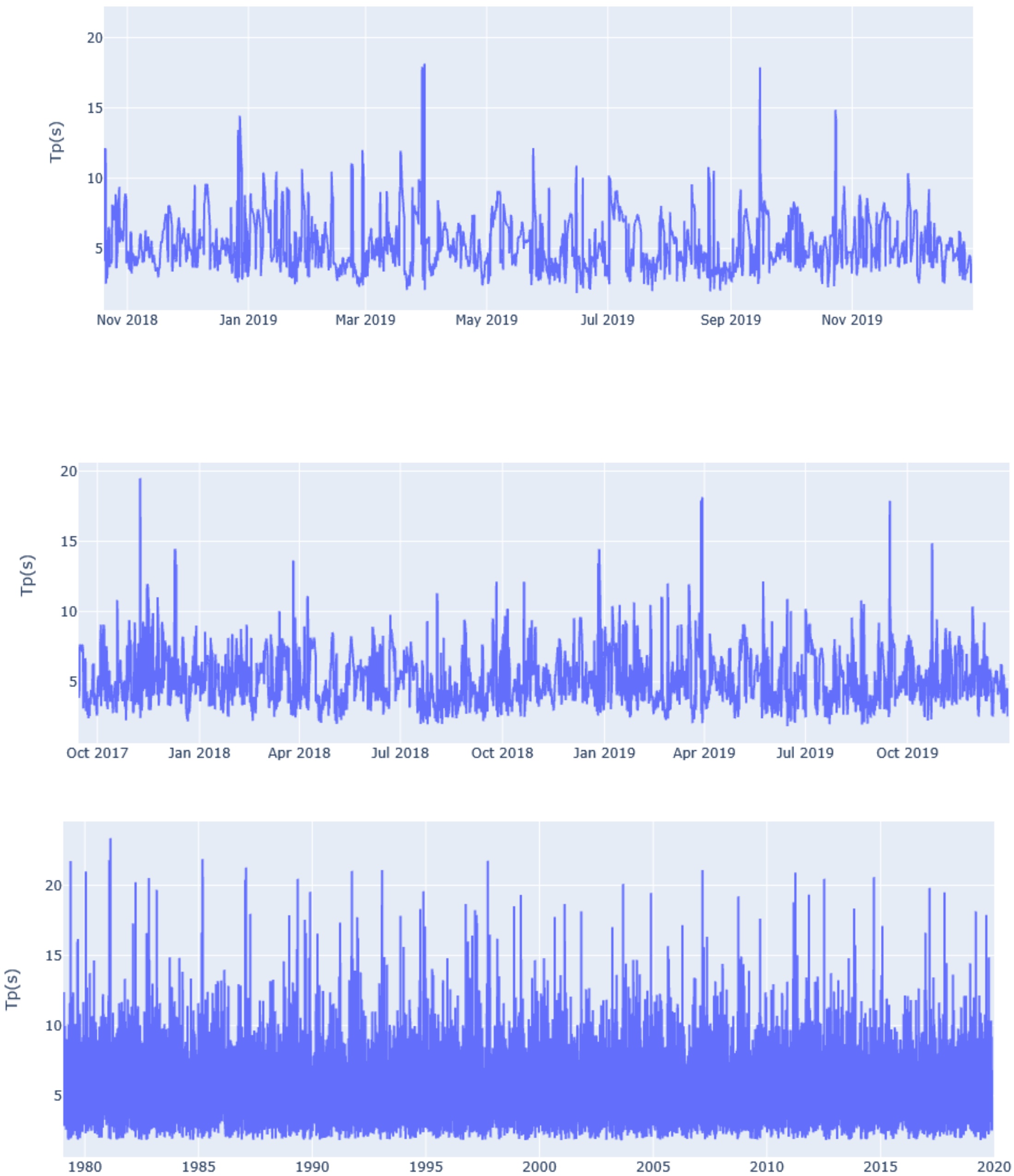


Figure 34.Distribution of peak period during the one, three, and twenty-year period of studies.

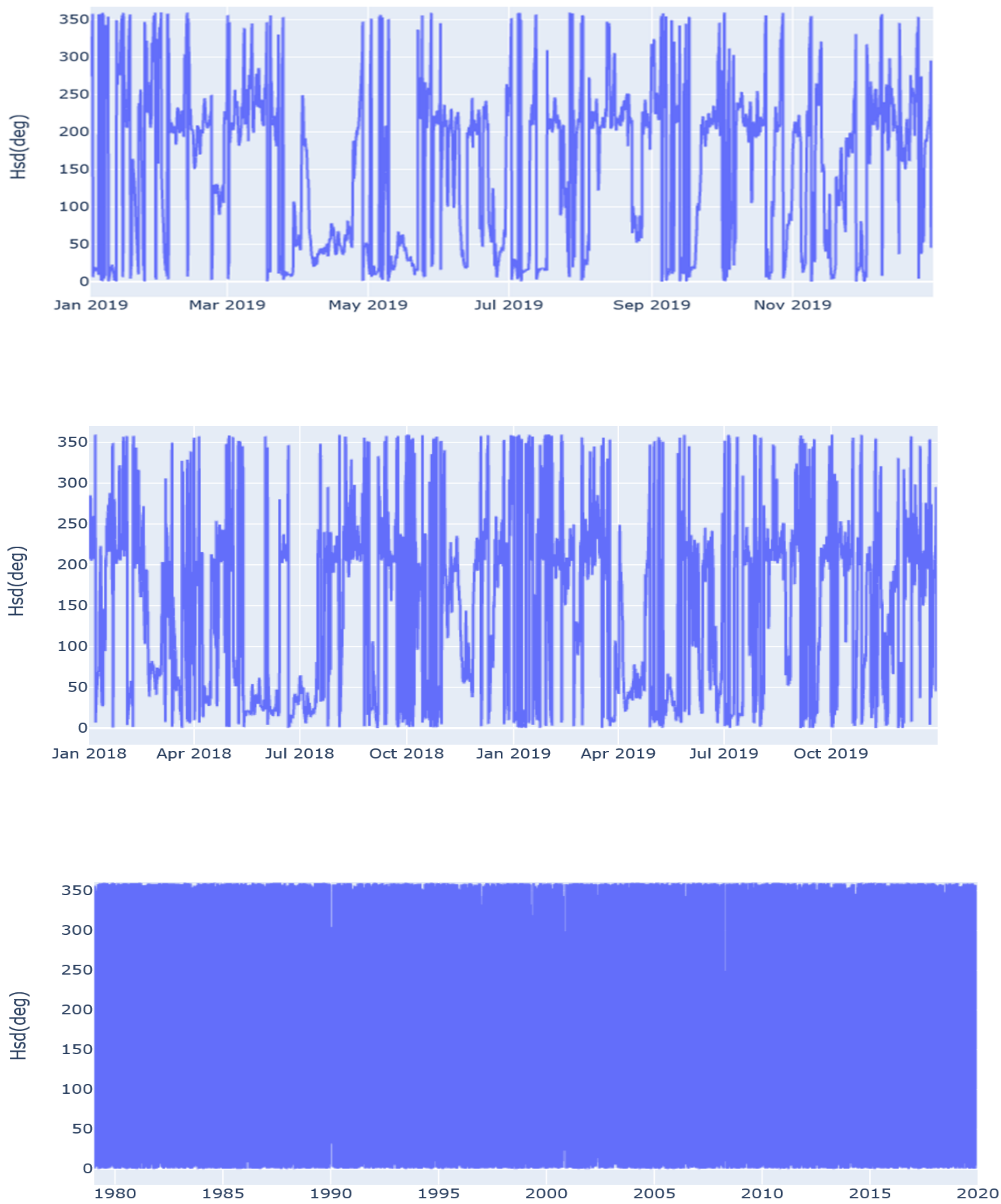


Figure 35.Distribution of mean wave direction during the one, three, and twenty years period of studies.

Figures 28 to 35 illustrate the change in those essential features based on each year's season. The winter and spring months show a high increase in those selected parameters. The figures confirm that these features do not change much from year to year between 3 and 20 years.

Appendix: Process of the TOPSIS method

Weightage	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Weather conditions	Type and number of turbine and foundation	Availability of data for residual life estimation of subsystems
	8	5	7	10	5	9	5	8	4	3	8

Matrix	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Type and number of turbine and foundation	Weather conditions	Availability of data for residual life estimation of subsystems
Partial Decommissioning (internal Cut)	5	5	6	5	3	8	7	6	7	5	3
Full Decommissioning	8	4	9	3	3	7	7	6	5	6	5
Repowering	3	8	8	8	6	6	5	7	7	6	7
Service life extension +Full Decommissioning	8	6	5	4	7	7	9	5	6	6	8
Service life extension +Partial Decommissioning	4	7	6	6	7	8	9	5	8	5	8

Matrix	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Type and number of turbine and foundation	Weather conditions	Availability of data for residual life estimation of subsystems
Partial Decommissioning (internal Cut)	25	25	36	25	9	64	49	36	49	25	9
Full Decommissioning	64	16	81	9	9	49	49	36	25	36	25
Repowering	9	64	64	64	36	36	25	49	49	36	49
Service life extension +Full Decommissioning	64	36	25	16	49	49	81	25	36	36	64
Service life extension +Partial Decommissioning	16	49	36	36	49	64	81	25	64	25	64
Total	178	190	242	150	152	262	285	171	223	158	211
Square Root	13.34166406	13.78404875	15.55634919	12.24744871	12.32882801	16.18641406	16.88194302	13.07669683	14.93318452	12.56980509	14.52583905

Normalised Matrix	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Type and number of turbine and foundation	Weather conditions	Availability of data for residual life estimation of subsystems
Partial Decommissioning (internal Cut)	0.374765844	0.362738125	0.385694608	0.40824829	0.243332132	0.494241651	0.414644214	0.458831468	0.468754671	0.397778642	0.206528517
Full Decommissioning	0.599625351	0.2901905	0.578541912	0.244948974	0.243332132	0.432461444	0.414644214	0.458831468	0.334824765	0.477334371	0.344214195
Repowering	0.224859507	0.580381	0.514259477	0.653197265	0.486664263	0.370681238	0.296174439	0.535303379	0.468754671	0.477334371	0.481899874
Service life extension +Full Decommissioning	0.599625351	0.43528575	0.321412173	0.326598632	0.567774974	0.432461444	0.53311399	0.382359556	0.401789718	0.477334371	0.550742713
Service life extension +Partial Decommissioning	0.299812676	0.507833375	0.385694608	0.489897949	0.567774974	0.494241651	0.53311399	0.382359556	0.535719624	0.397778642	0.550742713

Normalised Weight	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Weather conditions	Type and number of turbine and foundation	Availability of data for residual life estimation of subsystems
Type	8	5	7	10	5	9	5	8	4	3	8
Type	64	25	49	100	25	81	25	64	16	9	64
Total	22.84731932										
Normalised Weight	0.350150488	0.218844055	0.306381677	0.43768811	0.218844055	0.393919299	0.218844055	0.350150488	0.175075244	0.131306433	0.350150488

	Marine ecosystem and Habitat colonisation	Greenhouse gas (GHG) emissions	Technological Obsolescence	NPV	Training crew and suitable types of equipment	Safety of personnel and marine life	Removal legislation and guidelines	Availability and types of Vessel	Type and number of turbine and foundation	Weather conditions	Availability of data for residual life estimation of subsystems
Partial Decommissioning (internal Cut)	0.131224443	0.079383082	0.118169761	0.178685422	0.05325179	0.194691324	0.090742421	0.160660062	0.082067338	0.052230895	0.072316061
Full Decommissioning	0.209959109	0.063506466	0.177254641	0.107211253	0.05325179	0.170354909	0.090742421	0.160660062	0.058619527	0.062677073	0.120526768
Repowering	0.078734666	0.127012931	0.157559681	0.285896676	0.106503581	0.146018493	0.064816015	0.187436739	0.082067338	0.062677073	0.168737476
Service life extension +Full Decommissioning	0.209959109	0.095259699	0.098474801	0.142948338	0.124254177	0.170354909	0.116668827	0.133883385	0.070343433	0.062677073	0.192842829
Service life extension +Partial Decommissioning	0.104979555	0.111136315	0.118169761	0.214422507	0.124254177	0.194691324	0.116668827	0.133883385	0.093791244	0.052230895	0.192842829
Negetive / Posetive	N	N	P	N	P	P	P	P	P	P	P
V+	0.078734666	0.063506466	0.177254641	0.107211253	0.124254177	0.194691324	0.116668827	0.187436739	0.093791244	0.062677073	0.192842829
V-	0.209959109	0.127012931	0.098474801	0.285896676	0.05325179	0.146018493	0.064816015	0.133883385	0.058619527	0.052230895	0.072316061

Alternatives	Si+	Si-	Pi	Rank
Partial Decommissioning (internal Cut)	0.181136981	0.157028366	0.464353806	5
Full Decommissioning	0.175240651	0.215830118	0.551895296	2
Repowering	0.206011658	0.190710787	0.480715899	4
Service life extension +Full Decommissioning	0.172399384	0.211040479	0.550387426	3
Service life extension +Partial Decommissioning	0.144636638	0.206475353	0.58806124	1

Appendix: Create GRU model in python

```
def create_gru(units):
    model = Sequential()
    # Input layer of forecasting of significant wave height model1
    model.add(GRU (units = units, return_sequences = True,
                 input_shape = [X_train1.shape[1], X_train1.shape[2]]))
    model.add(Dropout(0.2))
    # Hidden layer of forecasting of significant wave height model1
    model.add(GRU(units = units))
    model.add(Dropout(0.2))
    model.add(Dense(units = 1))
    #Compile forecasting of significant wave height model1
    model.compile(optimizer='adam',loss='mse')

    return model
model_gru = create_gru(64)
```

Appendix: Create LSTM in python

```
def create_model(units, m):

    model = Sequential()

    # First layer of LSTM Model for forecasting of significant wave height

    model.add(m (units = units, return_sequences = True,

                input_shape = [X_train2.shape[1], X_train2.shape[2]]))

    model.add(Dropout(0.2))

    # Second layer of LSTM Model for forecasting of significant wave height

    model.add(m (units = units))

    model.add(Dropout(0.2))

    model.add(Dense(units = 1))

    #Compile model for forecasting of significant wave height

    model.compile(loss='mse', optimizer='adam')



    return model

model_lstm = create_model(64, LSTM)
```

Appendix: Create BiLSTM model in python

```
def create_bilstm(units):
    model = Sequential()
    # Input layer for forecasting of significant wave height Model 3
    model.add(Bidirectional(LSTM(units = units, return_sequences=True),
                            input_shape=(X_train3.shape[1], X_train3.shape[2])))
    # Hidden layer for forecasting of significant wave height
    model.add(Bidirectional(LSTM(units = units)))
    model.add(Dense(1))
    #Compile model3 for forecasting of significant wave height
    model.compile(optimizer='adam',loss='mse')
    return model


model_bilstm = create_bilstm(64)
```

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