Decision-support for decommissioning offshore platforms.

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DECISION-SUPPORT FOR DECOMMISSIONING OFFSHORE PLATFORMS

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Above all, I am grateful to God whose grace enabled me to bring this great work to a successful end.

DEDICATION

This thesis is dedicated to the memory of my late sister Mrs Victoria Onyinyechi Okeke, who was called to eternity before the realization of a doctorate dream that she unwaveringly believed in.

ABSTRACT

An estimated 2,500 offshore decommissioning projects are expected to be completed between 2018 and 2040 with significant accompanying challenges.

In this research, a decision model for decommissioning offshore platforms is developed. The decommissioning decision model (DDM) aids logical determination of the optimal option for decommissioning a platform through a multicriteria decision analysis of the considered options with respect to safety, cost, environmental impact, technical feasibility, and public perception. It synthesizes information about a platform's features with expert opinion to identify the best option for decommissioning the platform from a list of available options. It also facilitates the progressive integration of historical data to replace subjective human opinion and improve the quality of decision-making as this becomes available.

A case-study approach was used to demonstrate the DDM's applicability with information from an industry survey of decommissioning practitioners. Five decommissioning options were considered for the case study platform, and these were evaluated with a hybrid of Likert scale and Analytic Hierarchy Process (AHP). Using this technique, the optimal option for decommissioning the case study was determined with a 60% efficiency savings in time taken to complete the analysis as compared to the traditional AHP process. Results showed that partial removal is the preferred option for the case study, and the platform features with high relevance to options selection are substructure weight, water depth and age. Moreso, respondents from the North Sea were observed to be more averse to leaving platform materials in place as compared to people from Offshore USA, Africa, and Asian Seas. These findings were seen to agree with literature and industry practice through a comprehensive validation process. Thus, evidencing the DDM's flexibility and robustness and making a case for its industry adoption.

After its validation, the DDM's capability to support integration of historical data was investigated with the aid of a prediction model for estimating the costs of using different options for decommissioning offshore platforms. This costing model was developed by applying machine learning regression to historical decommissioning cost data. The model predicts decommissioning options costs for five different scenarios with reasonable accuracy as indicated by an r-squared value of 0.935, implying that it is reliable for predicting decommissioning costs. It was used to predict decommissioning options costs for the case study. These costs were then integrated into the DDM to replace the input data for cost criterion as obtained from the survey.

The models developed in this research improve upon the existing works in decommissioning optimisation. Industry adoption of the decision model will result to significant reduction of time, resources and efforts spent in decision-making during decommissioning. By acting as an unbiased basis for justifying the choice of a decommissioning option for an offshore asset, the DDM mitigates the traditional conflict between stakeholders of decommissioning projects. The costing model aids early estimation of decommissioning costs for budgeting, asset trading and other preliminary cost evaluation purposes prior to detailed engineering cost estimation. Therefore, both models represent a significant contribution towards the advancement of the current offshore decommissioning practice.

Keywords: Decommissioning, Offshore platforms, AHP, Multicriteria decision analysis, Option selection, Decision model, Costing model, Machine learning.

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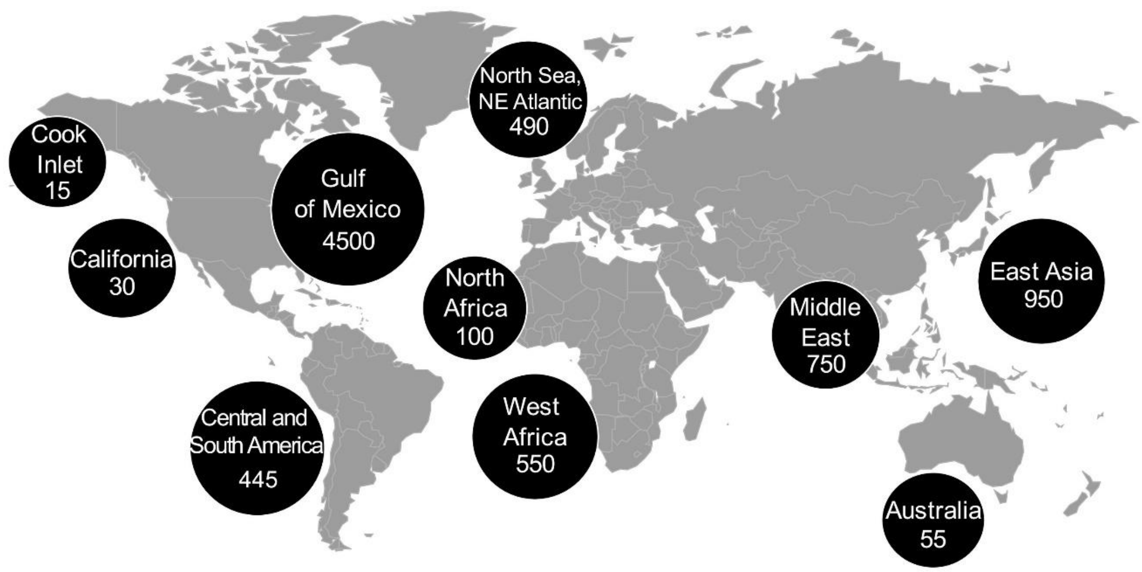
Chapter 1 : INTRODUCTION

1.1. Background

Offshore platforms that are used for petroleum exploration play a crucial role in meeting the global energy need. They are situated in locations across fifty-three countries worldwide as shown in Figure 1.1 and have an average life cycle ranging between 20-50 years (Statista 2018; Bernstein 2015). After this operational period and barring any life-extension strategy, the platform requires to be decommissioned.



* Numbers exclude pipelines and smaller subsea structures

Figure 1.1: Worldwide distribution of major* offshore oil and gas structures. (Sommer et al. 2019)

The decommissioning sequence comprises of all activities conducted from the cessation of production from the platform through to its final disposal. This process is more complex and capital-intensive for offshore platforms as compared to their onshore counterparts and its planning can take over two years.

The concept of decommissioning is broad and multi-faceted. Fam et al. (2018) performed an extensive review of decommissioning in several countries and pooled the findings together to describe decommissioning as a process which occurs in the final stage of the life cycle of an offshore structure, and entails closing the structure through methods which give due consideration to monetary costs, convenience to humans and wellbeing of the environment. In addition, Shen et al. (2017) explained that decommissioning is the process of planning, gaining approval, and implementing the removal, disposal, or reuse of an offshore hydrocarbon facility when its use is no longer beneficial. Decommissioning has also been described as a complex undertaking by the operator of an offshore hydrocarbon structure which involves planning and implementing the procedure for dealing with disused structure (Na et al. 2017). These perspectives on decommissioning provide insight to several aspects of the process including its timing, justification, and purpose.

Decommissioning can be defined as a process which entails all activities carried out at the end of the active lifetime of a platform, with the intent of remediating incurred adverse consequences, and preventing potential unwanted impacts which might arise from the operational use of the platform.

Offshore decommissioning is a dynamic and rapidly evolving aspect of the petroleum industry with varying legislations across different offshore regions. In the U.S. state of California for example, the regulations requiring the removal of all parts of offshore production facilities alongside any associated infrastructure has been relaxed to allow for reuse for other purposes after topsides removal (Bressler and Bernstein 2015). This contrasts with the more stringent regulations in the UK where it is rare to find an offshore platform that has been decommissioned by being converted to a different use (OGUK 2017). In Malaysia, the government has picked interest in reefing alternative for offshore platforms following the successful toppling of the BARAM-8 platform to create an artificial reef (Cheng et al. 2017). Bressler and Bernstein (2015) attributed the variations in decommissioning regulations to technological advances in aspects such as cutting and lifting capacity of machinery, but this has also been demonstrated to be strongly influenced by the attitude of the public (Jørgensen 2012). Moreso, the potential adverse impacts of decommissioning offshore platforms tend to be more severe than those of their onshore counterparts (Hall, João. and Knapp 2020).

According to International Energy Agency, IEA (2018), there has been a significant increase in global decommissioning activity levels. Factors driving this trend include the general drop in oil price and technological advancements (Palandro and Aziz 2018).

In the Gulf of Mexico, there has been a rapid increase in decommissioning activity such that, as of 2018, about 40% of all decommissioning in the region have taken place in the last ten years, and at rates which far surpass that of platform installation (Kaiser and Narra 2018). This mature basin in which production operations began in 1947, had 108 offshore structures decommissioned in 2017 whereas only one structure was installed in the same period (Kaiser and Narra 2018). In California alone, 27 offshore platforms are projected to require decommissioning before 2030 (Cantle and Bernstein 2015).

Another location experiencing a spike in decommissioning activities is the North Sea, a mature basin with an estimate of about 1,300 offshore platforms and a history of offshore exploration that dates to the early 1960s (OSPAR 2019). For example, an excess of six hundred decommissioning projects were estimated to have been completed in this location between 2016 and 2021 (Offshore Engineer 2016). The decommissioning-related financial burden to be borne by field operators and government in the UK is estimated to be approximately £40 billion by 2040 (Murray et al. 2018). Similarly, the estimated cost of decommissioning all the existing offshore assets in the UK Continental Shelf alone is currently estimated to be £51 billion (OGA 2019).

The IEA report quoted earlier forecasts that there will be over 2,500 offshore decommissioning projects between 2018 and 2040 as production platforms approach the end of their operational lifetimes. Furthermore, the nature of these projects is going to become increasingly complex, shifting from the conventional shallow water steel structures to larger and more technically challenging platforms in deeper water. This translates to higher costs especially as these diverse projects involve platforms which have individual unique characteristics (Kaiser and Narra 2018).

It is almost inevitable that the petroleum industry will be adversely affected by the offshore decommissioning challenge, especially in lieu of the exigent nature of this challenge. The situation is further complicated by several factors such as the rising concerns for environmental preservation, complexity and uniqueness of each project, high attendant financial burden, and stringent regulatory regimes. Indeed, a significant proportion of the global active offshore structures are either operating beyond or approaching the end of their design life (Ars and Rios 2017).

A report by IHS Markit predicts that the global yearly cost expended on decommissioning projects will increase from approximately $2.4 billion in 2015, to $13 billion per year by 2040, an increase of over 500% (Offshore Engineer 2016). The report also forecasts about two thousand offshore decommissioning projects between 2021 and 2040 with the total expenditure estimated at $210 billion.

Despite being capital-intensive, decommissioning projects deliver little or no return on investment as compared to other phases of an oil and gas field life cycle as shown in Figure 1.2. The figure shows the typical profitability of distinct phases of the lifecycle of a hydrocarbon asset. It indicates that the profitability of the field peaks after development but falls to zero at the decommissioning stage which occurs at the end of the lifecycle.

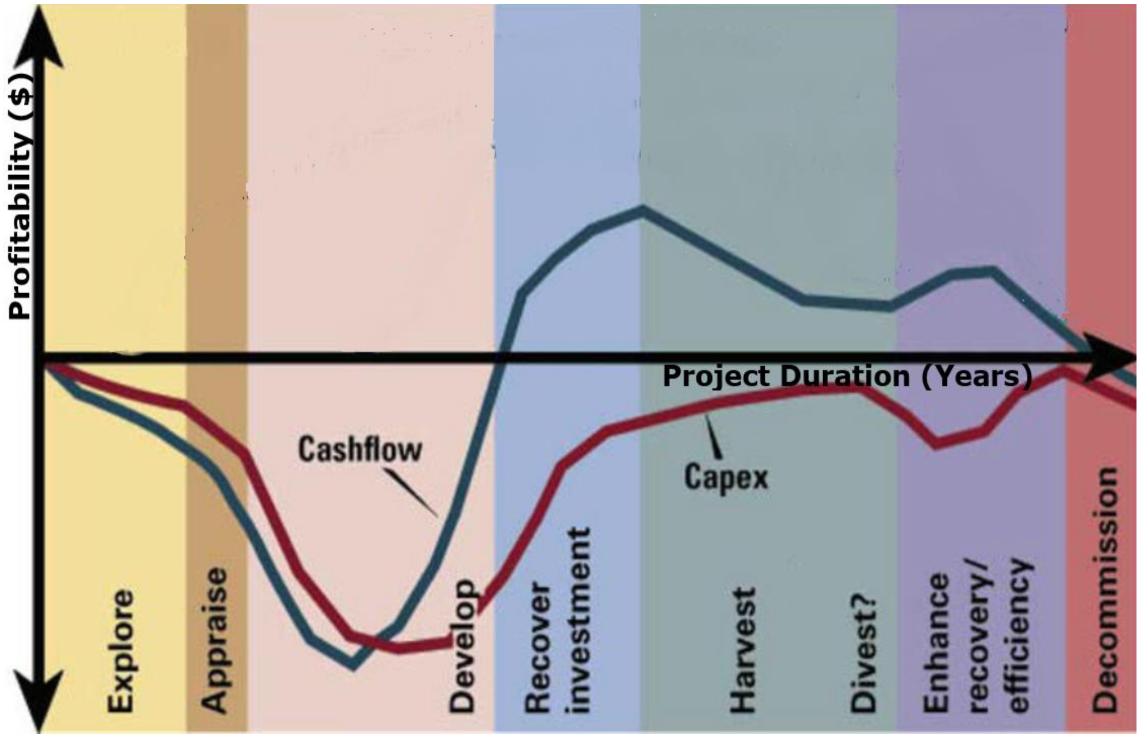


Figure 1.2: Typical stages in the life cycle of an oil and gas field (Adapted from Lakhal et al. 2009)

As stated in Offshore Engineer (2016) "*The effective decommissioning of offshore platforms, subsea wells, and related assets is one of the most important business challenges facing the oil and gas industry today and, in the future*". The huge costs and apparent adverse consequences that accompany decommissioning projects necessitate that these projects be optimised or executed as effectively as possible. Thus, there is a pressing need for innovations and tools to optimise decommissioning projects by improving the efficiency of carrying out these projects, and consequently driving cost savings.

1.2. Research Justification

There are several options for decommissioning a platform and using a suboptimal option for a decommissioning project can result to adverse consequences. Potential victims of these consequences include the asset owners (monetary loss, physical harm to employees, and reputational damage), environment (pollution, loss of fish stocks and marine communities, climate change), and public (loss of recreational site, tax, impairment to trawling and other fishing activities, lower navigational access). Thereby making decommissioning option selection a high-stake decision. This decision is often the prerogative of asset owners, although not exclusively, as external entities such as the government and the public are important stakeholders of the project. The government is responsible for approving the selected decommissioning option and this often requires that the asset owner can evidence that the option selection followed a thoroughly scientific and logical assessment process. The public typically expects return to a clear seabed after operations and have the potential to push back on even government-approved decisions if they perceive that the decision-making process is flawed (Owen and Rice 1999). Therefore, a "*robust and transparent decision-making process is essential in developing public trust and acceptance of any decommissioning solution that leaves materials in situ*." (Nuffel et al. 2022).

Platform decommissioning option selection represents a complex decision-making problem due to the existence of several decommissioning options and severe consequences that can arise from using a suboptimal decommissioning option for a project (Andrawus et al 2009; Guevara 1998). Hence, due diligence by project stakeholders in identifying a decommissioning option which results in the best outcome is important. This typically entails complex trade-offs between specified decision criteria to identify an option likely to result in the overall most positive outcome.

The challenge in dealing with such a multi-criteria problem arises primarily because the decision criteria often conflict with each other (Jørgensen 2012; Wilkinson et al. 2016; Shaw, Seares and Newman 2018). For example, the safest option might be one with the worst environmental impact or the cheapest option can also have a lot of associated safety risks. In addition, care must be taken to account for all influencing factors while arriving at a decision as an inadequate criteria/sub-criteria scope will likely result to backlashes from certain stakeholder groups and correcting these can be either expensive or impossible. For example, Shell suffered reputational damage during the Brent Spar controversy and eventually had to dismantle the Brent platform on land, resulting to an additional cost in the range of £20M to £80M (Owen and Rice 1999). The company appeared to have underestimated the strength of public perception when it decided that deep-sea disposal was the best option for decommissioning the structure after scientific studies (Jørgensen 2012). This highlights the need for a decision support tool in the form of a decision model which eases the complexities of decommissioning decision-making through a logical process. A decision model comprises a network of interconnected decisions, information and knowledge which represents a repeatable decision-making approach. It supports effective decision-making by providing a way to "*visualize the sequences of events that can occur following alternative decisions or actions in a logical framework, as well as the outcomes associated with each possible pathway*" (Kuntz et al. 2013).

Options selection has been identified as one of the key decision-making problems encountered when decommissioning an offshore platform, alongside selection of well abandonment technique and subsea structure decommissioning methodology (TSB 2016a; Vrålstad et al. 2019; Vidal et al 2022). Gourvenec (2018) suggests that the solution to this problem is likely to exist in the form of a consistent and reusable procedure for collecting and synthesizing decommissioning data in a streamlined manner and using a transdisciplinary approach. Accurate cost estimation is also crucial to the success of a decommissioning project and has a large bearing on the option that will be adopted. Resolving the current challenges with decommissioning project costing requires the combination of existing knowledge with mathematical techniques through bespoke cost estimation approaches (Ahiaga-Dagbui et al. 2017). Therefore, development of decision support for addressing these two issues translates to a significant contribution towards decommissioning projects optimisation.

1.3. Aim and Objectives

This research aims to develop decision support for assisting decision-makers to determine the best available option for decommissioning their offshore platform. To achieve this aim, the specific objectives are as follows:

i. To develop a decision model for identifying the best decommissioning option for an offshore platform with the aid of multicriteria decision analysis.

ii. To investigate the applicability of the developed decision model by using it to evaluate decommissioning options for a case study platform.

iii. To investigate the validity of the developed decision model and results obtained from its application to the case study platform.

iv. To develop a decommissioning options costing model and integrate this into decommissioning decision-making.

1.4. Research Context

Decommissioning projects, just like every other project, comprises of a planning and an execution stage. These can be optimised using two main approaches, namely the planning-focused approach and execution-focused approach. The execution-focused approach to decommissioning optimisation entails seeking out innovative ideas to improve the coordination of human resources and equipment during decommissioning. Key considerations when taking this approach include effective personnel safety measures, efficient scheduling of activities, waste management, environmental friendliness of workflow and technological advancements (Bemment 2001; Decom North Sea 2014; ABB 2015; Invernizzi et al. 2018; Hall, João and Knapp 2020).

The planning-focused approach, on the other hand, ensures that high-quality decisions and choices are made while planning at the early stages of the decommissioning project management. Optimised decision-making during planning is tantamount to the success of decommissioning projects. Key considerations of the planning-focused approach include budgeting, contractor (and equipment) selection, determination of project timeline, decommissioning option selection, and selection of a decommissioning methodology (Ferris and Tjea 2015; McCann, Henrion and Bernstein 2016; TSB 2016a; Cheng et al. 2017; Martins et al. 2020). This research adopts a planning-focused approach to decommissioning optimisation in that it is directed towards the decision-making stage of decommissioning project management.

In terms of scope, fixed steel jacket-type platforms were adopted as the primary focus of this research. This platform type comprises over 80% of the global offshore platforms and there is more flexibility around their decommissioning options as compared to other platform types (Sarhan and Raslan 2021; OGUK 2022). In considering the platform, the analysis focuses on the topsides and substructure as these are the largest components of the structure. Decommissioning options for fixed steel jacket-type platforms include complete/partial removal to land/sea, toppling in place as artificial reef, reuse in another location, and leaving in place and repurposing for alternative use.

1.5. Ethical Considerations

Ethical considerations are an essential aspect of any research which involves participants such as this research. According to Resnik (2015), ethics can be understood from two perspectives; first as the norms for conduct that distinguish between acceptable and unacceptable behaviour but also as a method, procedure, or perspective for deciding how to act and for analysing complex problems and issues.

Bell, Harley and Bryman (2022) classified ethical principles into harm to participants, lack of informed consent, invasion of privacy, and deception. These issues require consideration in every research but are particularly crucial when human beings or animals are the subject of the research and when personal data is involved because usage of information of such nature must comply with data protection regulations (Voigt and von dem Bussche

2017). However, the subject of this research is a theoretical case study platform and although expert opinion is obtained from individuals via the survey, no personal data were collected. Hence there were no attendant privacy or confidentiality issues.

The only ethical issue that was encountered during the conduction of this research related to the handling of information obtained from the online survey of decommissioning experts. The survey was structured such that the responses were anonymous, and explicit consent of the respondents was first obtained to ensure that no confidentiality rights were infringed upon. Furthermore, the questionnaire was hosted on a European Union General Data Protection Regulation compliant online platform with adequate protective measures taken to ensure privacy when analysing the data.

Lastly, precaution was applied in designing the survey questionnaire in line with the following guidelines from ALHababi (2015).

i. Participants must understand the goal of the research, purpose of the research, the nature of their involvement, length of time required, and what will be done with their responses.
ii. Participants must be explicitly informed that involvement is voluntary, and they can withdraw at any time.
iii. Privacy and confidentiality of data and participants must not be violated.
iv. Participants must not be deceived, and information must either be explicitly stated or implicitly defined.
v. The location of the research must be explicitly stated.

1.6. Thesis Structure and Organisation

This thesis report presents all aspects of the research conducted towards the achievement of the research objectives in ten chapters.

CHAPTER ONE: This chapter provides an overview of offshore decommissioning and justification for the research. It also highlights the research aim and objectives. Furthermore, it delineates the research by outlining its context and limitations. The chapter concludes by discussing the ethical considerations for the research.

CHAPTER TWO: The literature review chapter presents a detailed discussion of the current decommissioning practice in the offshore industry. It begins broadly by describing offshore structures and their components before narrowing into decommissioning of offshore platforms with particular emphasis on procedure, existing regulations, and options for carrying out such projects. This is followed by a critical review of existing works in evaluation of decommissioning options to identify the decision criteria to be adopted for options evaluation and establish the foundation for developing a decommissioning decision model. Finally, the application of a multi-criteria decision analysis technique called the Analytic Hierarchy Process (AHP) to offshore decommissioning is discussed.

CHAPTER THREE: Following the findings from Chapter two, this chapter outlines the plan and procedure for achieving the research aim and objectives. It presents the research approach, design, strategies, and data analysis techniques used in this work and the justification for their adoption.

CHAPTER FOUR: This chapter describes the development of the decommissioning decision model (DDM) using the methodology presented in Chapter three. It presents the model's general framework and detailed design for each of its four constituent phases. Lastly, the benefits envisaged from industry adoption of the decision model are highlighted.

CHAPTER FIVE: This chapter introduces the theoretical case study used in this research to demonstrate the applicability of the DDM developed in Chapter four. It examines the regional context of the case study platform and provides information about the platform's physical features. The chapter also presents the application of the DDM to the case study and the main results from evaluating decommissioning options for the case study platform using information from a survey of decommissioning practitioners as input. It concludes by discussing the use of the survey to prioritise and rank platform features in order of their relevance to decommissioning options selection.

CHAPTER SIX: This chapter investigates the validity of the DDM and results of its application to the case study as presented in Chapter five. The validation specifically examines the survey input data, model logical structure, and accuracy of model results. The outcomes of these endeavours are also discussed.

CHAPTER SEVEN: This chapter describes the integration of historical data into decommissioning decision-making. It discusses the use of mathematical modelling to relate decommissioning options costs to the prioritised platform features identified from the survey as reported in Chapter five. The chapter concludes by presenting a methodology for decommissioning options costing from historical data.

CHAPTER EIGHT: This chapter presents the development of a decommissioning options costing model from machine learning, secondary decommissioning cost data and prioritized platform features. After its development, the model is used to forecast the decommissioning options costs for the case study platform. This is then integrated into the DDM in replacement of subjective survey input data to improve accuracy.

CHAPTER NINE: This chapter presents the research conclusion and its wider impacts along with recommendations for future work.

Chapter 2 : LITERATURE REVIEW

Existing literature pertinent to formulating the research aim and objectives are reviewed in this chapter.

The chapter begins by describing offshore structures and the regulations and procedure for their removal. This is followed by a discussion of the options for decommissioning offshore platforms. Subsequently, the applicable decision criteria and key desirable capabilities of a fit-for-purpose decommissioning decision model is established from critically reviewing existing works in the domain of decommissioning options evaluation. The last section introduces a Multicriteria Decision Analysis technique called the Analytic Hierarchy Process and highlights its suitability for decommissioning decision-making.

2.1. Offshore Structures

An offshore structure or platform is a large marine facility with components which enable the production, processing, and storage of petroleum resources from reservoirs beneath the seabed. The main material composition of offshore structures is steel, though some older platforms have a base structure made of reinforced concrete. These structures are globally distributed. Since 1947, an excess of 7,500 platforms have been installed in several offshore locations across fifty-three countries and in water depths up to 1,850 meters (Manjunatha, Sathish and Sahana 2016; Statista 2018). Although the function, size, and configuration of these structures vary widely, and no general descriptions can encompass all platform types, most comprise of two major components namely topsides or deck, and substructure.

2.1.1. Types of Offshore Platforms

There are different types of offshore platforms as shown in Figure 2.1 and these are broadly classified as fixed or mobile depending on their mobility when in use (Bull and Love 2019). However, this research focuses on the decommissioning of fixed platforms because their removal presents the greatest difficulty, and they constitute most offshore installations in the world (Decom North Sea 2014).

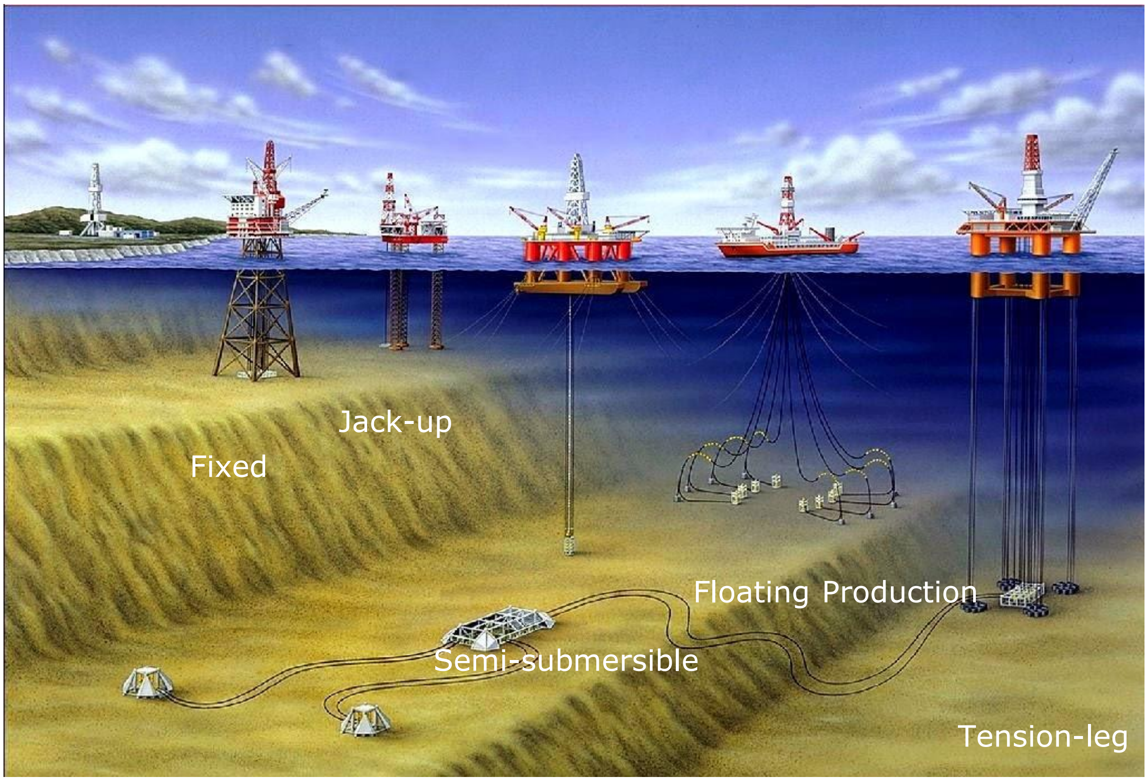


Figure 2.1: Types of offshore platforms (Adapted from Strukts 2012)

Fixed platforms are further sub-divided into fixed steel jacket platform and concrete gravity-based platforms depending on the material composition of their substructure or section which is anchored to the seabed (Lawrence and Fernandes 2022). Steel jacket platforms are drilled into the seabed using piles while gravity-based platforms rest on the seabed and are held in place by the weight of the structure.

The types of fixed platform and their main components, the topsides, and the substructure, are illustrated in Figure 2.2. These components are further discussed below.

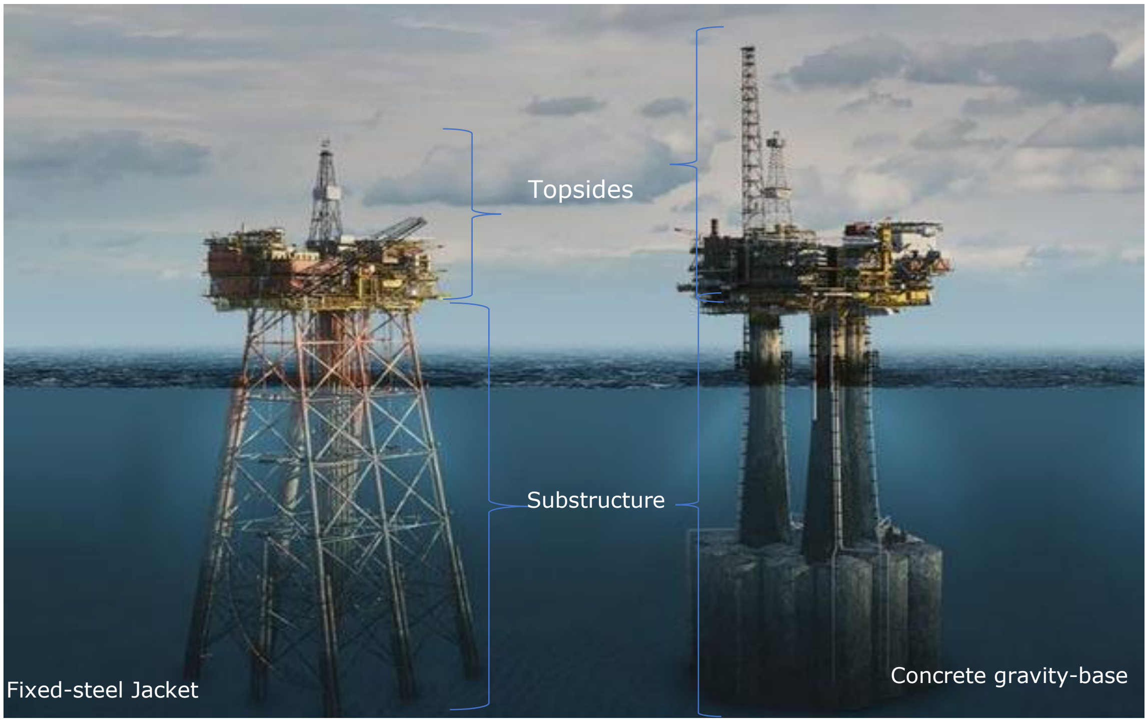


Figure 2.2: Components of an offshore platform (Adapted from Rachain 2017)

2.1.1.1. Topsides

Topsides comprise of all facilities which sit on the substructure of the platform and above the water level including the living quarters for accommodating rig personnel and the equipment used for drilling and processing hydrocarbon from the reservoir. It is made up of prefabricated modules which are assembled on either land or sea depending on the available offshore lifting capability.

The topsides of most offshore platforms weigh between 1,000 to 30,000 tonnes and their removal during decommissioning is a complex operation as shown in Figure 2.3. Nevertheless, this is a compulsory requirement in most offshore regions with well-defined decommissioning guidelines including the North Sea and Gulf of Mexico (Fam et al. 2018). The North-West Hutton topsides, which was one of the largest in the North Sea, weighed about 20,000 tonnes as at the time of its decommissioning (Jee 2014).

Figure 2.3: Removal of the Welland platform topsides (Nixon 2019)

2.1.1.2. Substructure

Substructure refers to the component that directly supports the topsides of an offshore platform. The design of a substructure is dependent on several factors including the environmental condition of its target location, water depth, capacity of the topsides it is to support, average sea wave heights, expected life span (Chandrasekaran 2018). The substructure of a fixed offshore platform can be classified as either concrete gravity based or steel-jacket type depending on the nature of its constituent material.

Concrete Gravity Base (CGB) structures are large, reinforced structures that have concrete as the main make-up material and rest firmly of the ocean floor primarily due to their own weight. The decommissioning of this platform component poses a greater challenge than that of their steel jacket counterpart due to their massive weights. Difficulties encountered in such decommissioning projects are often due to structural uncertainties, buoyancy, and manner of structural disintegration during removal operation.

Removal of CGB structures during decommissioning is not a compulsory regulatory requirement in some regions. The Oslo and Paris (OSPAR) regulation which applies to the North Sea region specifies that operators can apply for a derogation case during the decommissioning of gravity-based structures. The Maureen and Frigg platforms which were decommissioned in year 2000 and 2003 respectively are examples of recent decommissioning projects involving concrete gravity-based structures. In both cases, the platforms were left in place after removal of all toxic substances (Broughton, Davies and Green 2004).

Fixed-steel jackets primarily consist of a lattice with steel circular hollow sections which are securely welded together and rigidly fixed to the ground with the aid of steel piles. This platform component rests on the ocean floor and extends to 10-20 feet (3.1-6.2 metres) above the water surface. It comprises of open pipe columns, or legs, interconnected by tubular bracing members, which make the jacket a rigid space frame structure able to support the weight of the topsides.

Their sizes and weights vary depending on the water depth and the amount of deck work area required, however they are typically fabricated onshore in one piece and transported on a barge offshore, where they are installed. During jacket installation, tubular pilings are inserted through the legs of the jacket and driven into the ocean floor 200-400 feet (61-122 meters) to support the weight of the platform and resist the horizontal forces caused by current, wind, and waves. These pilings are connected to the jacket with a welded connection at the top of the jacket legs. Conductors extending from the deck are also installed through guides in the jacket and this component houses the wells that are drilled and completed to produce oil and gas from the underground reservoir.

A substantial proportion of global offshore structures have a steel jacket base (OGUK 2018; Sarhan and Raslan 2021) with about 50% of all offshore platforms in the North Sea belonging to this category (ABB 2015). Figure 2.4 is an illustration of the Murchison jacket, the heaviest decommissioned steel jacket in the world to date with a weight of 27,600 tonnes and height of 166 meters above the seabed.

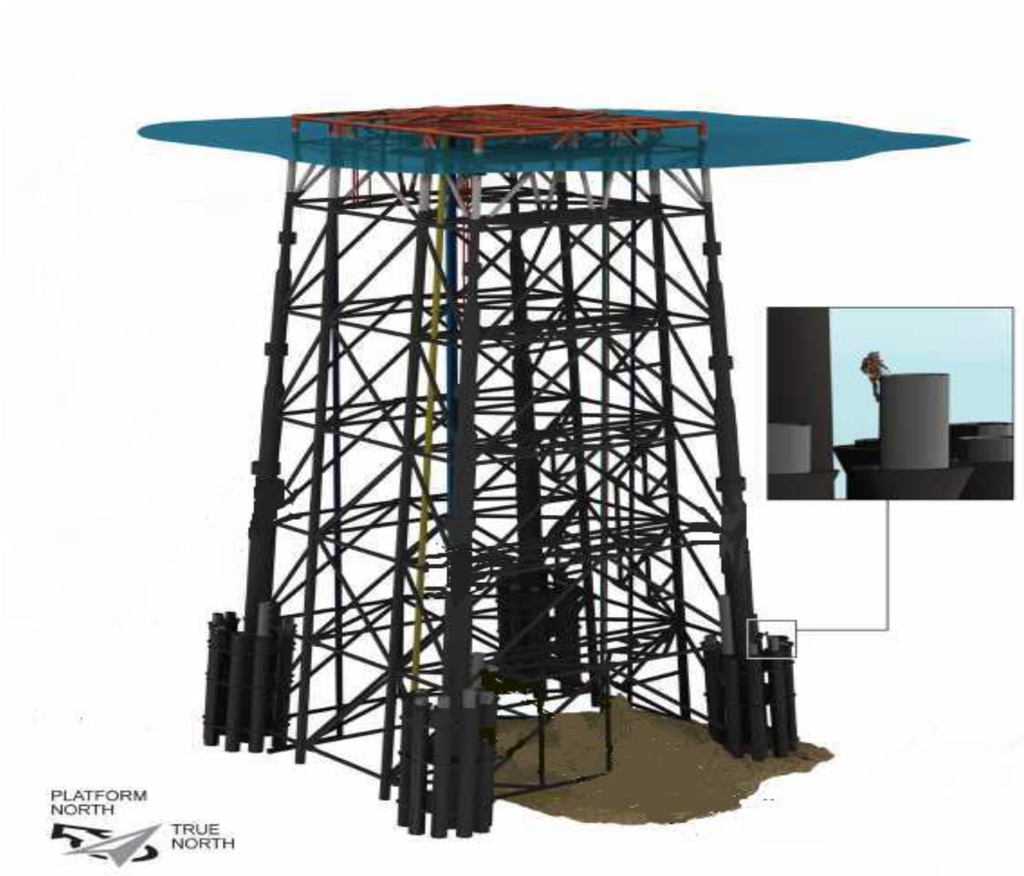


Figure 2.4: Schematics of Murchison platform (Adapted from CNRI 2013)

The decommissioning of offshore platforms is a major operation which can span from 2 years for smaller structures up to 15 years for much larger structures in deep-water. This large scale of decommissioning projects necessitates that adequate care is taken to follow the correct procedure in their execution.

2.2. Offshore Decommissioning Procedure

The procedure for decommissioning offshore platforms can vary across projects depending on the platform's unique characteristics and the governing legislative framework amongst other factors (Byrd, Miller and Wiese 2014).

Notwithstanding these variations which exist in terms of scale, scope, and complexity, decommissioning projects follow a similar procedure.

In general, the major stages of any decommissioning project can be summarised from (Byrd, Miller and Wiese 2014; Saeed 2016; Fam et al. 2018; OGUK 2022) and include

i. Initial analysis and planning
ii. Regulatory approval
iii. Cessation of production
iv. Well plugging and abandonment
v. Platform preparation
vi. Pipeline abandonment
vii. Components' removal
viii. Site clearance and remediation
ix. Post decommissioning monitoring.

The nature of the last four stages depends on the decommissioning option selected for executing the project. Thus, adequate planning and documentation is required for the entire process. This is achieved using a decommissioning program; a document which details the field operator's intended project plan for decommissioning a platform and is submitted to the regulatory body for approval 2-5 years before the commencement of decommissioning operations (Bureau Veritas 2018).

Additionally, the selected option for decommissioning a fixed-steel jacket must be approved by the applicable regulatory regime in the location where the platform is situated before it can be used for executing the project. Thus, it is imperative to understand the nature of government regulations that are relevant to offshore decommissioning projects.

2.3. Decommissioning Regulations

There are a wide range of national, regional, and global legislations that govern the decommissioning of offshore structures as shown in Table 2.1. Among these are fifteen regional conventions that apply to the environmental protection aspect of offshore decommissioning of which the Oslo and Paris Convention (OSPAR) is the convention overseeing the protection of the marine environment in the North Sea region (Saeed 2016).

Table 2.1: Offshore decommissioning legislations (Adapted from IOGP 2017)

Global	**Regional**	**National**
United Nations Convention on the Law of the Sea	OSPAR Convention	United Kingdom Petroleum Act, Energy Act, etc.
London Convention and Protocol	Helsinki Convention	United States of America National Fishing Enhancement Act
International Maritime Organisation Guidelines	Bucharest Convention	Norway Petroleum Activities Act, Pollution Control Act, *etc.*
Geneva Convention on the Continental Shelf	Barcelona Convention	*etc.*
	Abidjan Convention	
	etc.	

The reader is referred to IOGP (2017) for further details of the relevant decommissioning legislations as this information is outside the remit of this research. Nonetheless, a brief explanation of some of these regulations are provided below.

2.3.1. International Maritime Organisation (IMO) Guidelines and Standards

The IMO global standards were established in 1989 and require complete removal of all offshore structures installed at shallow water depth (<100 meters) and having a substructure weighing below 4,000 tonnes (Al-Ghuribi et al. 2016). Partial removal is permitted for heavier structures in greater depths with the condition that not less than 55 meters of clear water is provided, and the site is clearly marked to avoid potential adverse interference with navigation (Fam et al. 2018). The guidelines also specify that structures can remain on the sea, if permitted by the State, depending on the technical feasibility, potential environmental impact, cost, risks, and potential for reuse associated with its decommissioning, as determined from a case-by-case evaluation (Chandler et al. 2017).

2.3.2. Oslo and Paris (OSPAR) Convention

The OSPAR convention was established in 1992 as a merger between the Oslo Convention for the Prevention of Marine Dumping from Ships and Aircraft and the Paris Convention on Prevention of Marine Pollution from Land-based Sources (Saeed 2016). It came into force in 1998 and covers fifteen European countries including the United Kingdom and a maritime area containing about 1,400 offshore installations as shown in Figure 2.5. This convention serves as the framework for protecting and conserving the North-East Atlantic which includes the North Sea (Enright and Boteler 2020).

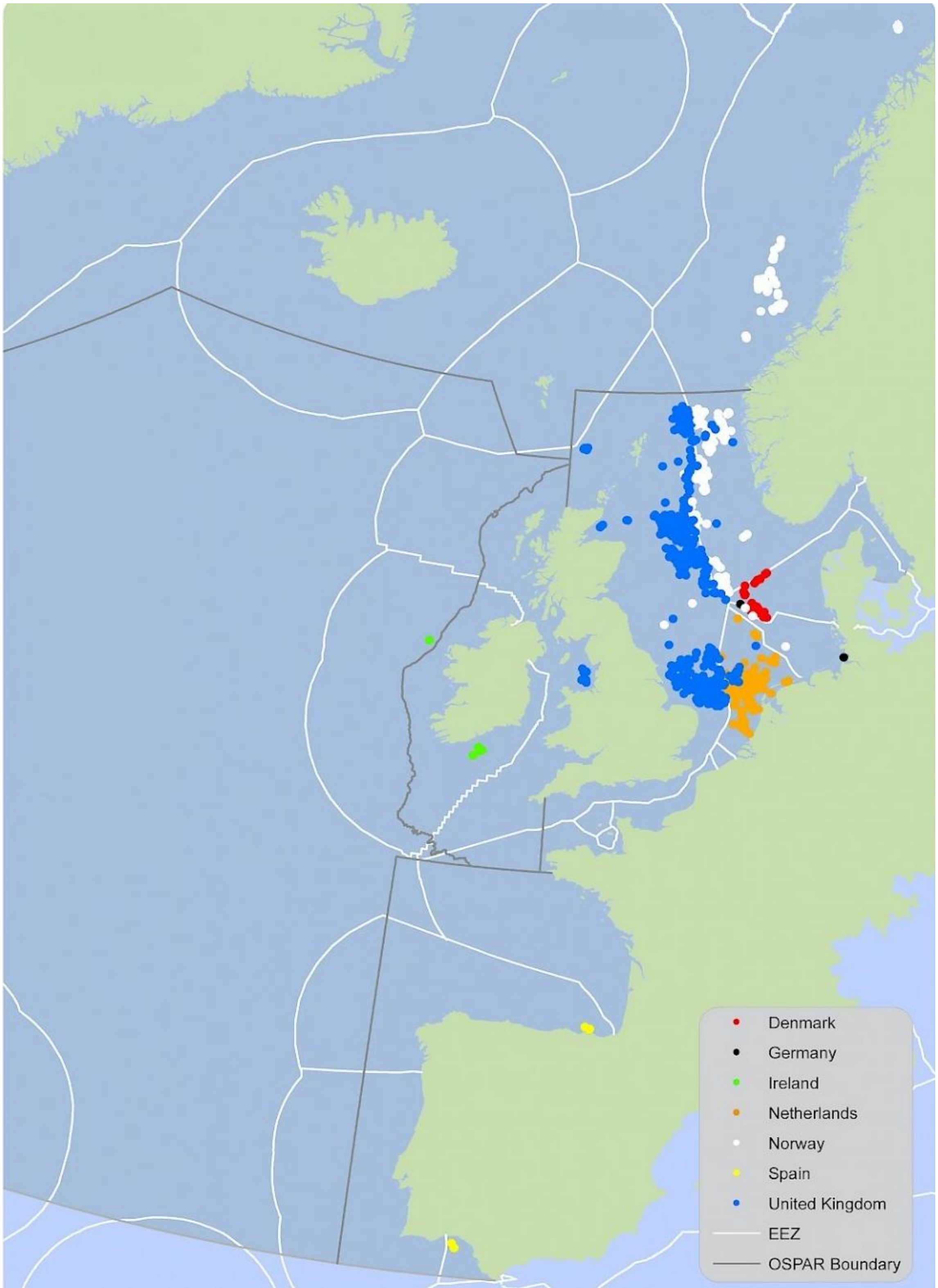


Figure 2.5: Distribution of offshore installations in the OSPAR region (OSPAR 2019)

In July 1998, the OSPAR Decision 98/3 act which bans the disposal of offshore structures at sea was adopted by OSPAR member countries (OSPAR 1998). Decision 98/3 is generally thought to have been shaped by the Brent Spar incident of 1995 in which Shell was prevented by an environmental activist group from decommissioning a platform with deep sea disposal option even though the decommissioning plan had been approved by the UK government (Lau 2018).

The act specifies that

i. The topsides of all installations must be returned to shore.

ii. All steel installations with a jacket weight less than 10,000 tonnes in air must be completely removed for re-use, recycling, or final disposal on land.

Individual countries can decide to be more stringent in their decommissioning legislation than the regional legislations to which they are a party. For example, the UK government stipulates that toppling and dumping of offshore installations is prohibited in its waters even though Decision 98/3 allows the disposal of concrete installations at a licensed deep-water site (BEIS 2018).

From the above, it can be deduced that regulatory requirements are structured to ensure that operators make dedicated efforts to properly decommission their offshore facilities. McCann, Henrion and Bernstein (2016) observed that regulatory requirements encapsulate a host of issues including '*potential residual risk to animals and ecological processes from remaining debris; potential interference with natural ecosystem processes and potential risk of long-term pollution*'.

2.3.3. The United Nations Convention on the Law of the Sea (UNCLOS)

The United Nations Convention on the Law of the Sea (UNCLOS) is an international treaty which was adopted in 1982 and came into force in November 1994 (Nordquist 2011). It is a widely accepted legislation which specifies the rights and responsibilities of countries in relation to their use of water bodies, and institutes guidelines for responsible exploration and management of natural resources in the marine environment (IOGP 2017). UNCLOS is currently ratified by 167 United Nations member states and the European Union as shown in Figure 2.6.

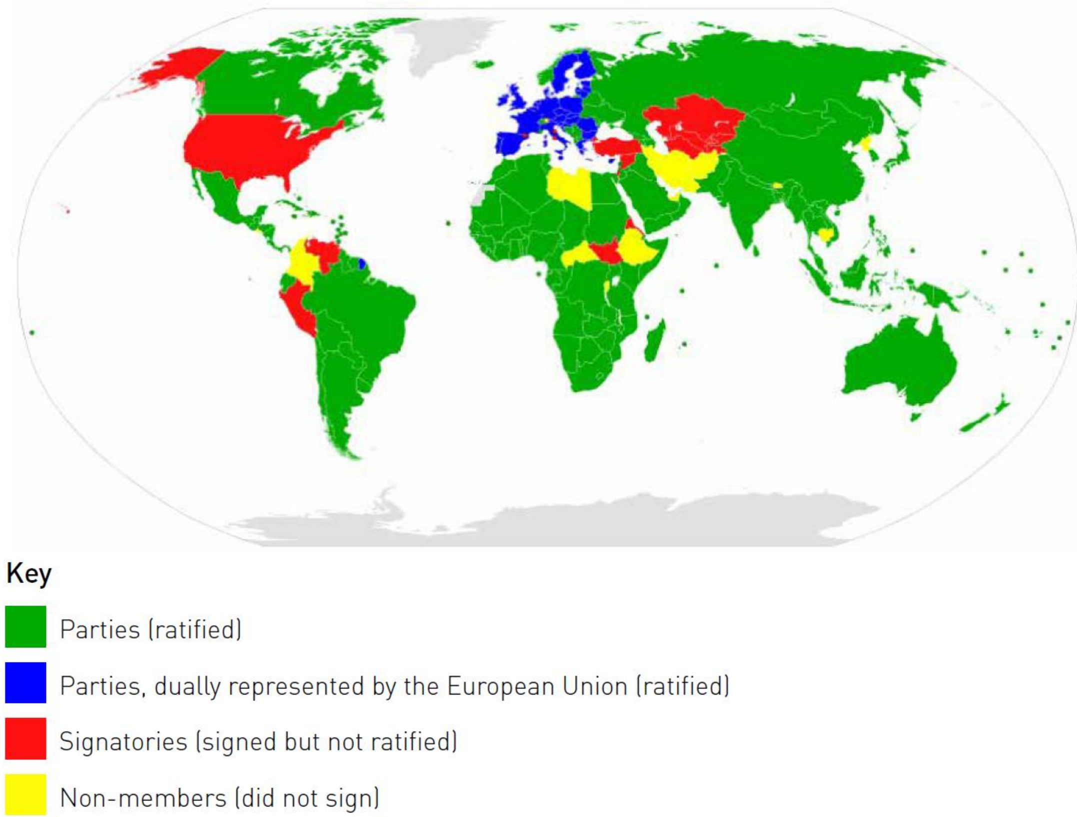


Figure 2.6: Status of countries with respect to UNCLOS adoption (IOGP 2017)

UNCLOS is the first legislation to make provision for leaving some part of the structure behind on decommissioning (Fam et al. 2018). Article 60(3) of the treaty addresses the decommissioning of disused offshore structures without specifying their complete removal and mandates appropriate publicity on details of any incompletely removed structures, thus failing to impose an absolute obligation to remove offshore structures and consequently establishing the possibility of partial removal (IOGP 2017; Trevisanut 2020). The article also makes it compulsory for participating countries to comply with generally accepted decommissioning standards such as the IMO Guidelines which were originally soft laws (Klabbers 2017; Fam et al. 2018). This was achieved by explicitly specifying that these standards are to govern decommissioning operations in countries that are a party to UNCLOS.

There is no mention of pipelines or cables removal in UNCLOS but article 210 of the legislation accentuates protection and preservation of the marine environment by requiring countries to prevent, reduce and control pollution of the marine environment which results from dumping (IOGP 2017; Fam et al. 2018).

Having explored decommissioning regulations that oversee decommissioning projects, the different decommissioning options for executing these projects will be discussed in the subsequent section.

2.4. Decommissioning Options

The availability and acceptability of a decommissioning option depends on the condition and location of the offshore platform and applicable legislation (Truchon et al. 2015). Some characteristics of a platform that can be used to infer its condition include the type of construction, size, structural integrity, and distance to shore (APPEA 2016).

Several options exist for decommissioning an offshore platform, but these can broadly be grouped into three main options namely leave in place, partial removal, and complete removal.

2.4.1. Complete Removal

Complete removal entails the entire removal of the offshore structure and remediation of the disturbed site. This is the default decommissioning option in regions such as the North Sea where the prevalent view is that complete removal of the platform will result to minimal negative impact on the marine environment and allow the ecosystem to return to its original conditions (Sommer et al. 2019). It is popularly accepted as the decommissioning option that best mitigates environmental and safety risks (Fowler et al. 2014; Al-Ghuribi et al. 2016). This notion is captured in the precautionary principle which mandatorily requires, as much as is reasonably possible, the cleaning up of the ocean after all human activities (McCann, Henrion and Bernstein 2016).

However, Fowler et al. (2018) notes that regulations that mandatorily require structure removal usually exist only as a legacy of past policy and have been a historical subject of conflict. There are scenarios where regaining the previous condition is impossible or not preferable. For such cases, removal of platforms may result to the loss of biological species and associated ecosystem and functions, thus having a detrimental impact on the environment (Lusseau, Paterson and Neilson 2016). Furthermore, complete platform removal is likely to always be the most financially expensive option and involves industrial activities which can cause environmental disturbance, generate substantial atmospheric emission of non-eco-friendly gases such as carbon, and result to loss of fish stocks (Fowler et al. 2014; Cantle and Bernstein 2015).

2.4.2. Partial Removal

Partial removal involves dismantling the installation and leaving some of the base matter in place. For regions under the IMO regulation, the part of the structure left in place must be such as to allow for at least 55 meters of clear water in order not to jeopardise the safety of other sea users. The removal of offshore platforms is usually a complex engineering activity due to their weight and size. Therefore, operators might opt to settle for this option due to technical difficulties and huge associated costs of complete removal (Chandler et al. 2017; Fam et al. 2018).

McCann et al. (2017) analysed decommissioning options for Platform Harmony in the GOM and their results indicated that partial removal is better than complete removal if assessed only based on cost and environmental impact. The authors concluded that the choice between complete and partial removal is primarily dependent on how much importance the governing legislation places on strict compliance to lease agreement as compared to financial and environmental implication of the operation.

2.4.3. Leave in Place

Leaving the platform in place is a decommissioning option which is often permissible in areas where there is considerable emphasis on conserving the marine environment. This option usually entails removal of the topsides and installation of navigational aids which is maintained for as long as the structure remains in place. For locations with calm water conditions, the components of the platform can act as an artificial reef and support entire ecosystems of living organisms (Macreadie, Fowler and Booth 2011). An offshore platform can also be left in place for the purpose of acting as a haven for threatened species, feeding site for predators, and breeding site for fish biomass including overfished species such as Sebastes paucispinis (Claisse et al. 2014; Coolen 2017; Fowler et al. 2018). Hence, this option is permissible in such regions as the Gulf of Mexico where mechanisms exist through which platforms serve as valuable ecological habitats that support localised food webs (Truchon et al. 2015). However, there might be stipulated maintenance and asset integrity requirements for platforms decommissioned using this option to mitigate any envisaged negative impacts.

Furthermore, the platform can be adapted to serve a different purpose depending on its condition. Several alternative uses of disused offshore structures have been proposed such as

- Renewable energy hub for power generation from wind, wave, and/or solar energy
- Hub for space exploration
- Site for aquaculture projects
- Site for CO_2 sequestration or gas storage
- Prison or Military training facility.
- Recreational facility such as hotel, tourism site, etc

However, these reuse alternatives do not eliminate the ultimate need for removal because the platform will eventually lose its structural integrity over time (McCann et al. 2017). Additionally, the decision to leave a structure in place is extremely controversial and has been the subject of debate in most parts of the world (Jørgensen 2012; Fowler et al. 2014).

2.5. Review of Decommissioning Options Evaluation

Globally, a wide range of approaches exist for analysing the risks, benefits and trade-offs involved in selecting a suitable decommissioning option. The set of criteria used to evaluate decommissioning options is critical to the quality of decision-making as it forms the basis for judgement. It should cover all known aspects of the decommissioning operation and have criteria which are individually holistic, independent, and assessable with either data or expert judgement (Fowler et al. 2014).

Stakeholders in the assessments of the suitability of any chosen decommissioning option includes government representatives, operating companies, and the public (Bressler and Bernstein 2015). Owing to the difference in values and perspectives of these stakeholders, the decision to adopt an option for the decommissioning operation often involves complex and contentious trade-offs (Fowler et al. 2014; McCann, Henrion and Bernstein 2016). This requires a holistic evaluation of all the available decommissioning options with reference to some accepted decision criteria (Al-Ghuribi et al. 2016; Ahiaga-Dagbui et al. 2017). For any given structure, the suitability of a decommissioning option is dependent on its unique characteristics and immediate environment, hence no single decommissioning options will be optimal for all scenarios. As a result of this, decommissioning requires consideration on a case-by-case basis in which the most suitable option is chosen based on the structure’s unique decommissioning requirements and outcome of a formal assessment (Ekins, Vanner and Firebrace 2006).

In regions with well-developed decommissioning regimes such as the Gulf of Mexico and the North Sea, there are frameworks used by operators to formalise the process for decommissioning options assessment. These frameworks contain sets of criteria that are deemed relevant to a decommissioning project and can be implemented using decision-making approaches. They were investigated in this research work to identify the criteria that are relevant to choosing the option for decommissioning an offshore platform.

2.6. Decommissioning Options Assessment Frameworks

These are frameworks typically designed by the government body responsible for overseeing decommissioning projects in the region where the offshore structure is situated. The three most widely used assessment frameworks are Comparative Assessment, Net Environmental Benefit Analysis and Best Practical Environmental Option (Sommer et al. 2019).

2.6.1. Best Practical Environmental Option

Best practicable environmental option (BPEO) is a systematic procedure which involves the examination of all reasonable decommissioning options with specific reference to technical feasibility, environmental, risk and safety, costs, and public acceptance (Sommer et al. 2019). It is commonly practiced in Malaysia and other countries in the Asian region.

BPEO provides a structured evaluation of decommissioning options by considering the project in five sections: jackets, cutting methods and depth, offshore pipelines, onshore pipelines, and seabed deposits. This evaluation is conducted at a high level to determine the removal option that best suits the platform under consideration through a clear decision-making process (Kanmkamnerd, Phanichtraiphop and Pornsakulsakdi 2016). The assessment is done both qualitatively and quantitatively with the findings utilised by both operators and regulators. BPEO also provides auditable traces to support decisions which is based on environmental considerations.

However, there is limited guidance on the methodology used to conduct BPEO and its application is not well documented, thus it is prone to being misinterpreted (Palandro and Aziz 2018). Furthermore, there is likely to be challenges with adapting the assessment for scenarios where there is need for a more detailed analysis due to its limited documentation and standardisation.

2.6.2. Net Environmental Benefit Analysis

Net Environmental Benefit Analysis (NEBA) is a framework for evaluating and quantitatively ranking the decommissioning options for a platform by considering ecosystem values and weighing the associated costs and net environmental benefits. The net environmental benefit of a decommissioning option depends on how much adverse/beneficial impact will potentially result from executing the project with the option, the duration required for the ecosystem to recover its baseline conditions, and the final condition afterwards.

Use of NEBA requires adequate definition of the assessment scope, and ecological service areas (and metrics) that will independently represent aspects of the impact being assessed. The general methodology is to develop a NEBA model unique to the platform in which assessment results are presented as mean scores that reflect the difference between the service gains and service loss for each evaluated option as evaluated through the service areas (Kanmkamnerd, Phanichtraiphop and Pornsakulsakdi 2016; Palandro and Aziz 2018). NEBA is typically adopted in regions such as the Gulf of Mexico where all or part of the structure may be left in place provided that the operators can demonstrate that leaving the platform in place is more beneficial to the environment than removing it. It is also utilised in scenarios where there is a requirement to gain a more detailed understanding of how the decommissioning options will affect the environment. For example, the decommissioning options for the Bongtok platform in Thailand was assessed using NEBA despite the BPEO assessment results (Sommer et al. 2019).

Nevertheless, the efficiency of NEBA as a decision-making tool is limited in that it is entirely based on environmental considerations. In the light of the multi-faceted nature of decommissioning decision-making, NEBA alone is insufficient for making a balanced judgement. Therefore, the framework is not sufficiently robust in terms of the set of criteria it considers.

2.6.3. Comparative Assessment

Comparative Assessment (CA) is the assessment framework used in the UK Continental Shelf. It is a detailed process for assessing the impact of decommissioning options with reference to five main criteria as shown in Table 2.2. Conducting this assessment is a mandatory requirement before a structure can be considered for derogation in the UKCS (OGUK 2015). The default option when using CA is that all installations will be completely removed as dictated by decision 98/3 (OSPAR 1998).

Table 2.2: Main Decision Criteria and Sub-criteria used in Comparative Assessment

Assessment Criteria	**Matters to Be Considered**
Safety	Risk to personnel
	Risk to other users of the sea
	Risk to those on land
Environmental	Other environmental compartments (including emissions to the atmosphere)
	Energy/Resource consumption
	Other environmental consequences (including cumulative effects)
Technical	Risk of major project failure
Societal	Fisheries impact
	Amenities
	Communities
Costs (Economic)	Cost estimates

As can be seen from Table 2.2, CA considers a more robust set of criteria in comparison to BPEO and NEBA. There are publicly accessible reports of its implementation and a worked guidance example to make it easier to use (Genesis and Catalyze 2015; GOV.UK 2022). In addition, it is flexible and can be applied to decommissioning decision-making across a wide range of complexities by being used alongside a multi-criteria decision analysis model (Ferris and Tjea 2015).

Nevertheless, a critical evaluation of CA reveals that its use can be subjective in scenarios where the assessment criteria indicate that differing options are most suitable for the decommissioning project e.g., societal consideration showing that complete removal is the best option whereas technical feasibility favours partial removal. The availability of several sub-criteria for each of the main criteria also means that operators can choose to focus on those sub-criteria that favour a decommissioning option that is more convenient for them. More so, the Environmental Impact Assessment (EIA) used to evaluate the environmental criterion in CA often overlooks the potential ecosystem values of plants and animals which might have been developing at the base of the platform since its operational lifetime (Sommer et al. 2019). This undermines any positive environmental impact that the jacket may have by acting as a habitat. For example, during the decommissioning of the Murchison platform it was decided that no further investigation will be conducted even though the EIA had revealed the presence of fish biomass and large volumes of marine growth (CNRI 2013).

Despite these issues, the CA framework is superior to BPEO and NEBA due to its robust criteria set, well-defined process and flexibility of application which makes it adaptable to different regions and range of complexities. Further, its superiority over other assessment frameworks has been acknowledged by several authors (Palandro and Aziz 2018; Tung 2020).

Therefore, the decision criteria of the CA framework were adopted for evaluating decommissioning options in this research work with some modifications:

i. The societal criterion is replaced with public perception due to the relevance of public opinion to decommissioning decision-making as demonstrated in the Brent Spar controversy (Jørgensen 2012).

ii. The scope of the environmental criteria is broadened to facilitate a more complete evaluation that duly considers the ecosystem values of offshore platforms.

iii. Additional sub-criteria from extensive literature review are included to the list of sub-criteria for Technical Feasibility and Cost criteria in Table 2.2.

2.7. Decision Criteria

Following the review of assessment frameworks in the preceding sections, five decision criteria were adopted for the assessment of decommissioning options. These are Safety, Environmental Impact, Technical Feasibility, Cost, and Public Perception. Further description of these criteria is subsequently presented.

2.7.1. Safety

Safety is a primary consideration in offshore decommissioning. It is a crucial aspect of the planning and implementation of all stages of the project irrespective of the size and location of the platform. Most regulatory regimes require operators to re-appraise the safety condition of the facility to be decommissioned before the work can be started. This is necessary because decommissioning activities present new and different hazards from those arising from the normal operation of the platform (Tsimplis, Dbouk and Weaver 2019).

Safety considerations significantly dictate the suitability of a decommissioning option because the anticipated level of risk will vary depending on the selected course of action. Using this criterion to evaluate a decommissioning option requires an assessment of the safety risk to all personnel involved in the project as well as individuals who are likely to be exposed to risk from the successful completion of the work if decommissioning is executed with the option (SHELL 2017).

A study of eight offshore decommissioning projects by Bemment (2001) revealed that leaving an offshore platform in place, or reusing it, is the overall safest decommissioning options and there are higher safety risks associated with complete removal options when compared to partial removal. Further analysis of the results also suggested that the risks associated with partial removal and toppling in place are similar. This is because leaving the platform in place only requires its effective monitoring whereas its removal involves various levels of hazardous activities such as those listed in Table 2.3.

Table 2.3: General safety concerns during decommissioning operations (OGUK 2017)

Area of Concern	Potential Source of Risk
Lifting	The substantial number of lifts and the uncertainties surrounding load paths and structural integrity
Diving	Significant diver intervention may be required to support extensive subsea cutting and lifting operations
Cutting	The thickness of the sections to be cut and number of cuttings required all increase the risk to personnel.
Hazardous substances	Legacy materials of construction and operations, as well as poisonous chemicals and other harmful products released during decommissioning activity, such as from hot work during dismantling
Integrity	Hidden flaws and structural degradation in aged facilities can lead to unforeseen safety threats.
High levels of manual activity	High numbers of personnel can be involved at all stages of the project, onshore and offshore, performing extensively manual tasks. The number of hours personnel spend offshore loosely correlate with the likelihood of harm.
Transportation	Accidents can happen while either loading the dismantled parts of the platform onto a sea vessel or unloading it onshore.
Disposal	Safety issues can arise from the burial, reuse or recycling of steel and other materials that make up the platform

Safety can be measured either quantitatively, semi-quantitatively or qualitatively depending on the level of estimated risk, available data, and the complexity of the analysis (HSE UK 2013). Quantitative risk assessment methods such as annual Potential Loss of Life and Fatal Accident Rate yield more precise outputs however qualitative assessments can be used for cases where there is insufficient safety data.

2.7.2. Environmental Impact

The environmental impact of a decommissioning option is a major factor that determines its suitability. Most legislations require operators to evaluate the environmental consequences of decommissioning their offshore platform hence this criterion is considered in BPEO, NEBA and CA. Though the scope and implication of findings from environmental assessments typically differ depending on the decommissioning context.

There has been significant research in understanding the positive and negative environmental implications of decommissioning an offshore structure (Fowler et al. 2014, 2018; Truchon et al. 2015; Sommer et al. 2019). The ecosystem within which a platform exists can vary from the cold deep-sea environment of the North Sea to tropical shallow waters e.g., Southeast Asia. These differences in environmental factors lead to significant differences in the nature of the biological communities that develop around the platform over time.

While most environmental studies have focused on understanding the relationship between marine ecosystems and offshore platforms which remain in the sea over time (Heery et al. 2017; Shaw, Seares and Newman 2018), adequate knowledge of the consequences of removing these platforms is yet to be established (Fowler et al. 2018). This can be attributed to the fact that the removal of offshore structures is a new practice when compared to how long ago the installation of these structures began.

Fowler et al. (2014) observed that the environmental implications of decommissioning options are likely to be examined less elaborately in regions where complete removal is mandatory than in regions where a range of decommissioning options is permissible. Consequently, there is a higher tendency to disregard aspects of the ecosystem which require further investigation while evaluating the environmental impact of decommissioning a North Sea platform when removal is compulsory. The EIA (Environmental Impact Assessment) which is conducted as part of decommissioning planning in the UKCS provides good insight into the changes that will occur in the environment because of using a decommissioning option, however it is often criticised for being overly simplistic and placing less importance on the continuity of the marine ecosystem that forms around the base of the platform during its operating lifetime (Anifowose et al. 2016; OPRED 2019). This inconsistency in depth and scope of environmental assessment highlights the need for cooperation between decommissioning stakeholders to better understand the influence of offshore platforms on the marine environment.

A GOM-based environmental analysis by Truchon et al. (2015) indicated that environmental aspects which are most sensitive to the choice of decommissioning option are trophic interactions, dispersal, support of rare species and biodiversity. Similarly, Fowler et al. (2014) identified the most deterministic environmental aspects of decommissioning to be alteration of hydrodynamic regimes, habitat damage from scattering of debris, and smothering of soft-bottom communities. Other aspects of the environment that require consideration during decommissioning include energy usage, atmospheric emissions, and other forms of environmental pollution.

2.7.3. Technical Feasibility

The technical feasibility of a decommissioning option refers to the likelihood of using the option to successfully decommission an offshore platform. Technical feasibility is usually assessed qualitatively based on expert opinion from industry specialists which can be obtained through technical workshops or engineering studies organised by the owner of the platform to be decommissioned. It depends on many factors including existing technology and industry experience, physical condition of the platform, and proposed project execution plan.

A good understanding of the likelihood of completing a decommissioning project in a desired manner with the aid of a selected decommissioning option is crucial when evaluating how that option compares to others. Several existing works have addressed aspects of the relationship between technical feasibility and the suitability of decommissioning alternatives. For example, Andrawus, Steel and Watson (2009) listed technical feasibility as one of the criteria for assessing the suitability of a decommissioning option. Similarly, Na et al. (2017) highlighted logistic requirements such as availability of sea vessel for hire and feasibility of technology as a decision criterion in his analytic hierarchy process (AHP) model for evaluating decommissioning options. Also, Cheng et al. (2017) observed that it is often the case that only one vessel is used to carry the removed parts of the platform and further proposed a semi-automated 4D/5D Building Integrated Modelling approach to aid the efficient scheduling of activities during decommissioning project execution. These works demonstrate the relevance of technical feasibility, or aspects of it, to the selection of a suitable decommissioning option for a project.

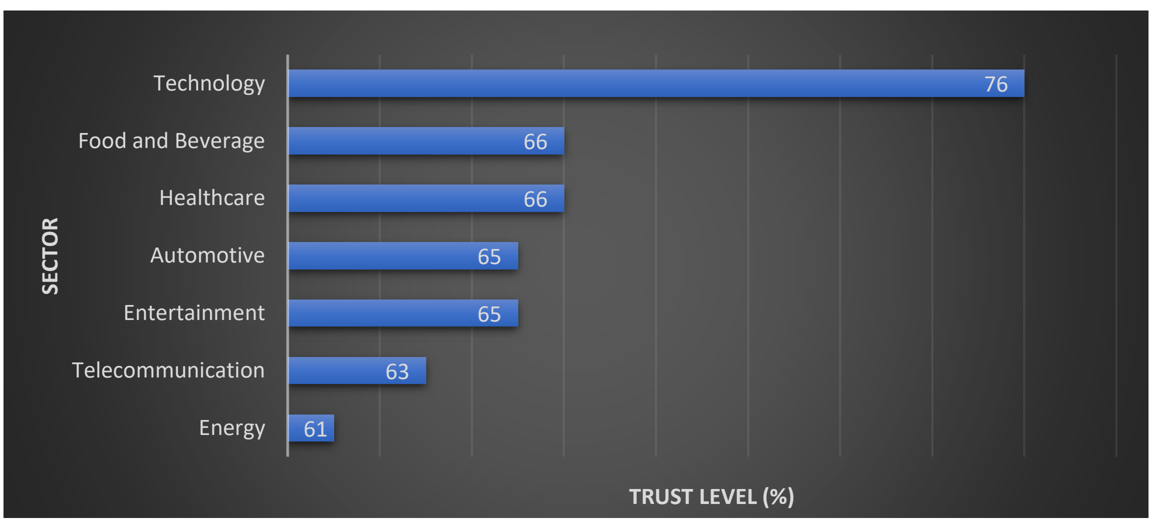
According to OGUK (2017), the main aspects of technology that influences the selection of a decommissioning option are offshore and subsea cutting and offshore lifting. Hence, the technical feasibility of a decommissioning option depends on the activities involved when using that option for the decommissioning project as determined from either engineering and technical studies or experience from past projects. Assessment of technical feasibility is achievable because most of the machinery (vessels and equipment) required for executing decommissioning projects, unless they are newly developed or emerging technology, will already have a track record. Technical data which comprises such records is likely to include equipment capabilities, environmental working envelope and station keeping methods, crew size, experience of executing similar activities and possible operational issues.

Aspects of technical feasibility that were considered by BP while assessing decommissioning options for the Brent Field include complexity of option, novelty of equipment and procedure, reliability of equipment and vulnerability to weather issues (SHELL 2017). Further, the UK decommissioning guidelines suggests risk of major project failure, technology demands, availability, and track record as some of the sub-criteria for technical feasibility (OGUK 2015). Nonetheless, strategic engagement with the decommissioning supply chain and other operators is an integral part of understanding existing and new technologies and techniques, and consequently adequately assessing the technical feasibility criterion.

2.7.4. Public Perception

Public perception refers to the beliefs and opinion of the masses about how a decommissioning project should be carried out. The diversity of people who make up the public is vast and includes the academia, fishermen, pressure groups, local community, and the media. Since the 1980s, the public has played an increasingly important and influential role in determining the appropriateness of decision that affect the society especially when there is a consensus opinion by its members (Almond and Esbester 2016). However, effectively communicating technical issues about the project to the public usually poses a challenge because of their limited understanding of the industry concepts.

The low-trust relationship between the public and the energy sector is historic as evidenced by the findings from the global study conducted by Edelman Intelligence (2019) and shown in Figure 2.7. The energy sector's 61% public trust level is the lowest when compared to the trust levels of Telecommunication, Healthcare, Technology, and other sectors.



*Data used for this survey spreads across five years (2015-2019)

Figure 2.7: Global public trust levels for different commercial sectors (Adapted from Edelman Intelligence 2019)

The result in Figure 2.7 primarily applies to the Oil and Gas industry because this is the core of the energy sector. Suggestions about how to manage public trust during decommissioning projects are subsequently briefly discussed.

2.7.4.1. Management of Public Opinion During Decommissioning

A decommissioning plan that meets the regulatory requirements can still be rejected if it is deemed by the public to be unacceptable. The Brent Spar controversy of 1995 demonstrates the dire consequences that can result when operators fail to effectively engage the public while making decisions pertaining to their decommissioning projects (Smith et al. 2019). Greenpeace, the environmental group that led the Brent Spar protest, also compelled the Norwegian government to reject a proposal by Esso to decommission the Odin jacket by toppling in situ to form an artificial reef. Additionally, plans to dump components of the North-East Frigg platform in the Norwegian Sea failed due to public opposition. In the end, both the Odin jacket and the Frigg platform were returned to shore for other uses (Shaw 1999). Following these incidents, operators have begun to increasingly incorporate public opinion in the decision-making process during decommissioning of their offshore assets (SHELL 2017).

The modalities for managing public opinion and exchanging knowledge that pertains to offshore decommissioning are outlined in the literature (Cvitanovic et al. 2015; Wilkinson et al. 2016). Ignoring public opinion can mar the success of a decommissioning project by generating avoidable conflicts (Wilkinson et al. 2016). On the other hand, an approach that embraces cultural differences of all stakeholder groups can expedite the engagement process and ensure a smooth interaction between the parties involved (Cvitanovic et al. 2015).

The results from a public survey in Australia indicated that protection of the environment is of highest priority to the public during decommissioning (Shaw, Seares and Newman 2018). Based on this, the public is more likely to favour the complete removal of an offshore platform over the option of leaving it in place despite the higher costs that this would incur. Though this stance can be shifted if people are convinced about the benefits of leaving the platform in place as demonstrated in California's adoption of rigs-to-reef programme (McCann et al. 2017).

Nevertheless, both operators and the public are likely to benefit from further research into the development of decision models. Such models can be used by both technical and non-technical personnel to determine the most suitable decommissioning option for an offshore structure with a significant degree of confidence.

2.7.5. Cost

This refers to the financial burden that will be incurred by using a decommissioning option for a project. Accurate cost prediction is important to all stakeholders of the decommissioning project (Baxter 2016; Fowler et al. 2018). However, the costs of decommissioning projects are often difficult to estimate due to the rapidly evolving nature of cutting and lifting technology (Cheng et al. 2017). In addition, determining the future costs of decommissioning projects is fraught with significant uncertainties. For example, the UK Oil and Gas Authority disclosed in 2019 that it expected 49% of the decommissioning cost estimates by operators in the region to be accurate to within -20% to +100% (NAO 2019). These uncertainties are mainly because operators will not incur majority of the costs for many years, by which time decommissioning technology, supply chain prices, and environmental regulations could all have changed significantly. Also, there is potential for some offshore assets to be reused for carbon capture usage and storage, for example, rather than being removed at end-of-life. Discounting is another possible means of reducing uncertainty in decommissioning cost estimation. But the dynamic nature of the supply chain and permissible decommissioning options make it challenging to determine appropriate discount rates for reducing decommissioning costs into a long-term cash flow.

Offshore decommissioning costs vary across different regions due to several factors which include typical structure weights, weather and climatic conditions, depths per region and proximity to shore. Additionally, the type of asset, existing legislative requirements and adopted decommissioning strategy can significantly contribute to cost variations in offshore decommissioning projects. The disparity in project costs is huge, ranging from \$2 million for a simple fixed steel structure in shallow water situated in the GOM up to about \$2 billion for a gravity-based platform weighing over 200,000 tonnes installed in deep-water in the North Sea (Eke et al. 2021).

Cost data of decommissioning projects is usually withheld by companies and treated as confidential information. In the UKCS, yearly cost estimates are compiled by the Oil and Gas Authority from information obtained through a nation-wide operators' survey (OGA 2021). However, these are presented as high-level summaries which do not show the actual project costs.

2.7.5.1. Existing Works in Decommissioning Cost Analysis

Several research works have been directed towards the subject matter of decommissioning cost analysis and a chronicled review of these works provide a sound foundation for making contributions to the research area.

Ekins, Vanner and Firebrace (2006) conducted a material and energy flow analysis for the decommissioning of a large fixed offshore structure in the North Sea which included estimation of the financial expenditures of undertaking the project under different scenarios. The authors considered three decommissioning scenarios; leave in situ, shallow disposal, and complete removal to shore. The costs of completely removing the platform's topside and jacket were first obtained on a confidential basis from an operating company which had performed intensive studies on the offshore asset for the purpose of drafting a decommissioning programme. These costs were then multiplied by factors corresponding to the cost proportions for removal observed from the decommissioning cost estimate of a previous project to estimate costs of shallow disposal. The authors assumed that the leave in-situ scenario would attract no expenditure. Using this method to estimate the costs of different decommissioning options for a platform is beneficial when there is limited data available such as when cost of only one option is known. However, more accurate results are only achievable if there is a means to obtain cost proportions of the activities that are involved in using the other options under consideration. Furthermore, the cost proportions are likely to be inaccurate if the platform being decommissioned has varying attributes like configuration, weight and location as compared to the platform from which the parallels are being drawn.

In a similar work, Proserv Offshore (2009) conducted a decommissioning cost estimation study in the US Gulf of Mexico on behalf of the Minerals Management Service, an agency of the United States Department of the Interior that manages the nation's petroleum and other mineral resources in the outer continental shelf. Kaiser and Liu (2014) translated the cost data reported Proserv Offshore, with the aid of basic regression analysis, into generalized functional relations for estimating the costs of the various stages of decommissioning for 53 deep-water structures in the Gulf of Mexico. Different decommissioning stages and the platform features that serve as input to their cost estimation models in their work are shown in Table 8.1.

Table 2.4: Platform Features used for cost estimation (Kaiser and Liu 2014)

Decommissioning Stage	**Platform Feature used as Cost Factors**
Well plugging and abandonment	Water depth, number of wells, rig/rig-less method
Conductor severance and removal	Water depth, number of conductors
Pipeline decommissioning	Water depth, diameter, length, and volume
Umbilical and Flowline removal	Water depth, length
Riser removal	Water depth
Fixed Platform removal	Water depth, number of piles

Use of a parametric cost estimation technique like regression analysis is beneficial for reducing statistical data into a more compact form. It also provides an indication of the major factors that influence the project cost and the nature of these influences. However, basic regression analysis has been criticized for being too simplistic and inadequate for capturing finer details of complex systems such as decommissioning projects (Maxwell 1975).

Application of machine learning regression analysis is likely to perform better than basic regression analysis when solving such problems.

In a related study, TSB Offshore leveraged on information collected from over ten years of experience and collaboration with field specialists in the GOM to develop algorithms for estimating the costs of the various tasks involved in decommissioning (Byrd, Miller and Wiese 2014). These estimates were then coded into a proprietary database software tool called the Platform Abandonment Estimation System (PAES). The tool receives the general descriptive information about the structure and produces an initial estimate of its decommissioning cost which can be further customized by a knowledgeable cost engineer. Figure 2.8 shows the variation of decommissioning costs with depth for a 4-piled platform as generated by the PAES tool.

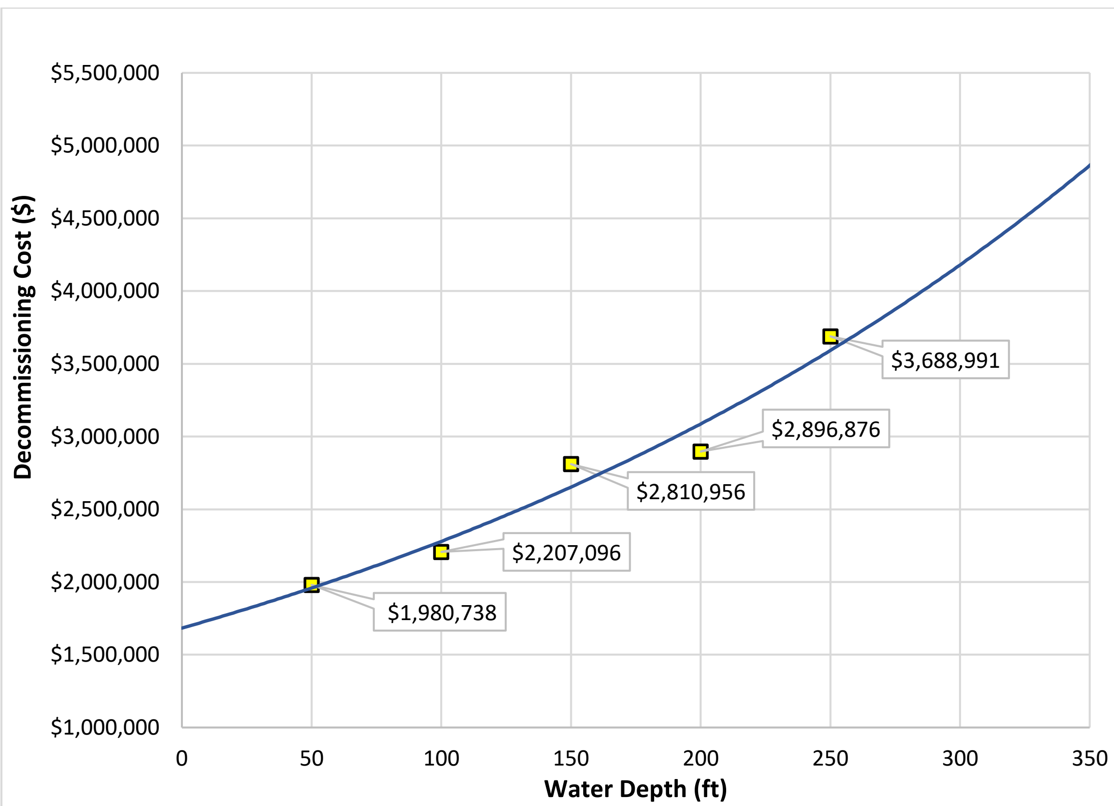


Figure 2.8: Complete removal cost variation with depth for a platform (Adapted from Byrd, Miller and Wiese 2014)

The accuracy of results from PAES is high and the primary source of discrepancies has been identified to be the quality of input information. Nevertheless, there are several limitations to using PAES. The costing algorithms used for its development are kept confidential hence the tool can be regarded, to a considerable extent, as a black box that provides little insight into the cost elements of decommissioning. Furthermore, the tool only provides cost estimates for decommissioning with the Complete Removal option with no consideration for other options.

In the North Sea region, the Living North Sea Initiative (LiNSI) conducted a study in 2015 to estimate jacket removal costs for all platforms in the North Sea and assess the potential cost savings for alternative decommissioning options (LiNSI 2015). The man-hours and equipment directly involved in the process of jacket decommissioning were used as basis for their analysis. In addition to complete removal of jackets, their partial removal to 25 metres (depth of GOM rigs-to-reef programme) and 55 metres (cut-off depth from IMO guidelines) were considered. The analysis results were presented as cost ranges for distinct categories of jackets based on size and location. The LiNSI study shows that there is value to be realised from decommissioning options cost analysis in that it can provide project stakeholders with information for decision making and be used as input to government policy development. However, a limitation of this work is that it only focused on jacket structure and no consideration was given to other parts of the platform such as topsides and conductors, hence it is insufficient for estimating the full decommissioning project cost. Also, the use of cost ranges, though beneficial from the aspect of increasing the likelihood of obtaining accurate estimations, makes it challenging to determine the cost of decommissioning an individual platform. Hence, use of the cost estimates for assessing the cost of decommissioning an asset is limited.

In a related work, Bressler and Bernstein (2015) used the Bureau of Safety and Environmental Enforcement cost estimates for complete removal of oil and gas platforms in offshore California (TSB 2016) to develop estimates for partially removing the platforms in a bid to compare both decommissioning options. Partial removal is defined in Bressler and Bernstein (2015) as removal down to 85 feet below mean sea level with the upper jacket section left on the seabed beside the remaining portion as an artificial reef. The cost for this decommissioning option was estimated by identifying the differences in the option's engineering procedure as compared to complete removal option and quantifying the change in cost due to these differences with inputs from engineers. Their results indicate that partially removing twenty-seven platforms will result to a 56% savings on the cost of their complete removal. However, it is difficult to verify the accuracy of their results as the platforms are yet to be decommissioned. Nevertheless, there is agreement between the authors and Smith and Byrd (2020) on the decommissioning phases where cost differences are likely to exist. This knowledge is adopted when deriving Partial Removal costs in this research. Further, the cost dataset they used is a reliable basis for estimating the costs of decommissioning with Complete Removal, especially as it intended to be updated at five-yearly intervals to account for changes in market conditions of the decommissioning industry (TSB 2016b).

Decommissioning options cost analysis as performed by Bressler and Bernstein (2015) is more detailed and precise than that of LiNSI (2015) in that it makes use of exact cost values for the considered platforms. It also identifies the key platform attributes that determine the cost difference between complete and partial removal costs to be size and water depth of the structure. However, only one variant of the partial removal options was considered unlike the study by LiNSI (2015) which considered three variants, and replicating their analysis is challenging as this was performed using a proprietary software called PLATFORM®. Therefore, the work can be improved by expanding the cost analysis to a larger number of partial removal options and presenting the results in a readily accessible format with the aid of appropriate mathematical tools and techniques.

Ahiaga-Dagbui et al. (2017) interviewed individuals involved with decommissioning projects in the UKCS and found that error margins as high as 40% in forecasted versus actual budget figures was common. Similarly, a study of 40 decommissioning projects from 1994 to 2005 revealed that actual costs were typically about 12% higher than estimated costs (Henrion, Bernstein and Swamy 2015). The North-West Hutton decommissioning project cost £230 million at completion, a deviation of approximately 50% from the predicted value of £154 million (Jee 2014). These results interpret to complexities in decommissioning costing and highlight the need for innovation in this project aspect.

Having defined the decision criteria, the next step is to review existing decision-making approaches for evaluating decommissioning options with reference to these criteria to determine which will be most suitable for a decommissioning project.

2.8. Review of Approaches to Optimising Decommissioning Options Evaluation

The application of mathematical and statistical techniques to decommissioning is understudied in comparison to other aspects of the offshore platform life cycle (Nishanth, John and Whyte 2016; Ahiaga-Dagbui et al. 2017). However, remarkable progress has been made in this area within the last decade due to the global increase in the number of platforms that require decommissioning and availability of data as more experience of implementing such projects is gained.

Kaiser and Narra (2018) observed that there have been significant collaborative efforts to share knowledge from decommissioning projects. Several independent publications which describe offshore decommissioning operations in several regions are now available in the public domain (APPEA 2016; Bureau Veritas 2018). Government is working towards cost reductions by promoting the sharing of decommissioning knowledge amongst operators (Bernstein 2015; OGA 2021). A web-based tool called Late Life Planning Portal was launched by Decom North Sea in 2017 to foster cooperation of regulators, operators, and supply chain towards the improvement of decommissioning practice (Decom North Sea http://decomnorthsea.com/l2p2). These developments have resulted to rapid growth in decommissioning knowledge, thus fostering research in this domain. There has also been increased efforts towards optimising the decision-making process of evaluating decommissioning options to determine the best option for carrying out a decommissioning project.

The approaches that have been proposed for evaluating decommissioning options can be broadly categorised into quantitative and mixed approaches depending on the nature of criteria they handle.

2.8.1. Quantitative Approaches

This comprises of decision-making approaches which only deal with quantifiable information about aspects of the decommissioning project to minimise subjectivity and bias in the obtained results (Nicolette, Travers and Price 2014). Quantitative approaches are desirable when measurable data is available and can be readily acquired. They yield results which can be clearly communicated, verified, and reproduced. However, the application of quantitative approaches to the evaluation of decommissioning options is limited by the unavailability of data to quantify several criteria used in assessing decommissioning options. Quantitative metrics is not fully developed for such criteria as technical feasibility and public perception. Hence, most studies that utilise this approach tend to focus on a few decision criteria. Furthermore, obtaining the required data for these models may be expensive and involve complex data gathering processes.

2.8.1.1. Ecosystem-Based Management Assessment

Truchon et al. (2015) developed an ecosystem-based management approach for evaluating decommissioning options for offshore platforms by analysing all interactions within the ecosystem where the platform is situated. In their work, a remotely operated video (ROV) study was conducted on a deep-water fixed-steel jacket platform in the GOM to obtain data which was then used to rank three decommissioning options based on their ecosystem services. The obtained results, which is factual and based on empirical data, indicated that leaving the jacket in the marine environment is the best option. However, repeating this technique for another platform will be expensive and the model has limited scope as it primarily considers the environmental criterion of decommissioning. Thus, it can only serve as supporting evidence for a more thorough evaluation of options.

2.8.1.2. Building Information Model

Similarly, Cheng et al. (2017) proposed the use of 4D/5D building information modelling (BIM) technology for evaluating decommissioning options by visualizing the schedules, cost and resources involved in the project implementation. This approach is useful for project management consideration of decommissioning and can help to reduce non-productive time, monitor costs, and track resource utilization. However, it does not show which option is best for a given offshore platform and no consideration is given to safety, environment, and other aspects of the project. Thus, it appears to be an over-simplification of decommissioning projects.

The use of quantitative approaches for options evaluation is favoured by advancements in ROV and other technologies that can be used to measure the structural and environmental condition of offshore platforms. At present however, their exclusive use is inadequate for complete evaluation of decommissioning options because other criteria that are difficult to quantify are also of equal or even greater importance to stakeholders (Fowler et al. 2014; McCann, Henrion and Bernstein 2016).

2.8.2. Mixed Approaches

This comprises of decision-making approaches which are developed for evaluating decommissioning options by considering both qualitatively and quantitatively assessed criteria. They are typically developed using information from platform data analysis and discussions with decommissioning experts. Mixed approaches are particularly effective in handling decision-making issues like those encountered during decommissioning in which it is required to both incorporate the objectives of different stakeholder groups and handle a wide range of data types (Cinelli, Coles and Kirwan 2014; Govindan and Jepsen 2016). Most research into decommissioning options evaluation falls into this category due to its suitability in dealing with cases involving either unquantifiable or missing data.

2.8.2.1. Material and Energy Flow Analysis

One of the first works in this domain was the use of material and energy flow analysis to assess the performance of two decommissioning options as compared to the leave in-situ option for a large North Sea fixed steel jacket platform (Ekins, Vanner and Firebrace 2006). Twelve aspects of decommissioning were considered and data for the analysis was obtained from the owners of the considered platform on a confidential basis, with values inferred from two past decommissioning projects when unavailable. The results showed some useful relationship between aspects of partial and complete removal options which can be extended to other platforms. In addition, the wide range of issues incorporated into the model makes it useful as a reference point for future works. However, the information required for the analysis is only available from extensive platform studies which are carried out just before decommissioning, and often withheld from the public by operators in a bid to protect their reputation. Thus, it cannot be easily replicated for other platforms.

2.8.2.2. Net Present Value Analysis and Weighted Evaluation

Andrawus, Steel and Watson (2009) leveraged on the knowledge of decommissioning experts to develop a hybrid technique which combines weighted evaluation (WE) and net present value (NPV) analysis for evaluating decommissioning options. The authors used this approach to evaluate four decommissioning options for platform Hidalgo by assessing the financial and non-financial impacts of the options as shown in Figure 2.9.

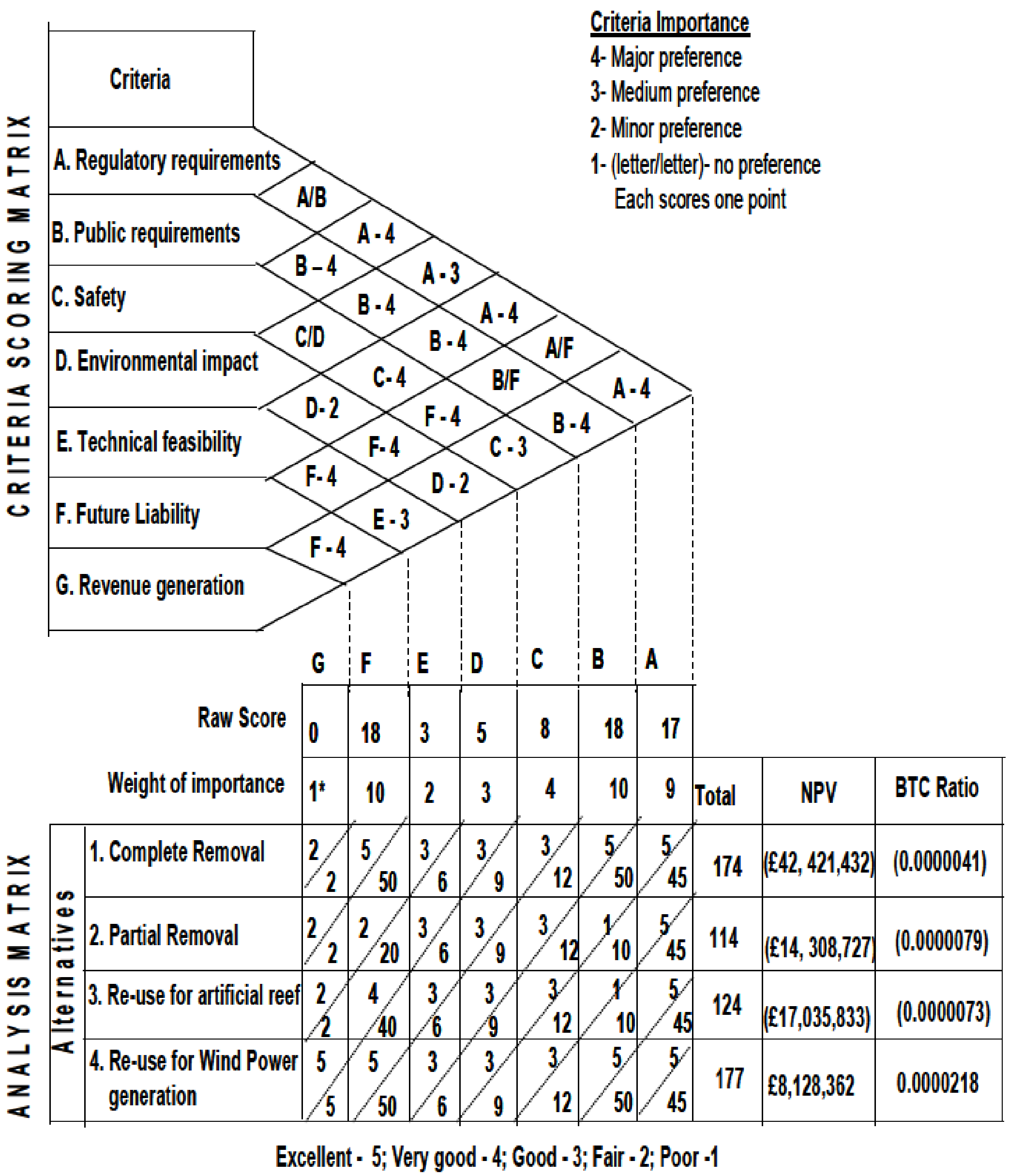


Figure 2.9: Decommissioning options evaluation for Hidalgo platform (Andrawus et al. 2009)

WE is a variant of a multicriteria decision analysis (MCDA) technique known as the Analytic Hierarchy Process (AHP). It involves pairwise comparisons of criteria to determine their weights and scoring of decommissioning options based on their individual performance with reference to these criteria. The scores from WE are divided by the NPV values of the assessed options to obtain a benefit-to-cost ratio which is then used to rank the options. This procedure is mathematically represented by equations 2.1 and 2.2.

$$A_i = \bigvee_{i=1,n} \sum_{j=1}^{m} W_j . S_{ij} \qquad (2.1)$$

$$BTC_i = \bigvee_{i=1,n} \frac{A_i}{NPV_i} \qquad (2.2)$$

Where A is the weighted score of a decommissioning option, W is the weight of importance of a criterion and S represents the performance rating of the option with reference to a criterion. BTC and NPV are respectively the benefit-to-cost ratio and net present value of the decommissioning option.

This approach improved on the work of Ekins, Vanner and Firebrace (2006) by utilising the experience gained by industry to develop a more reproducible analysis, and clearly highlighting the importance of public perception to decommissioning options assessment. Furthermore, the use of expert opinion also implies that the results will be more accurate as more decommissioning experience is gained despite the inherent subjective nature of human judgement. However, the analysis cannot be performed without actual decommissioning cost figures, and it is not clear how the discussions with decommissioning experts was synthesised to obtain the criteria weights and performance scores. Some of the decision criteria also appear to have been double counted, for example, future liability appears to refer to aspects of safety and cost. Hence, the approach can be improved by using the CA criteria, using cost figures in a relative format like the other criteria, and better structuring the process of collecting expert opinion.

2.8.2.3. Multi-Criteria Approval

Fowler et al. (2014) proposed the use of an MCDA technique called Multi-criteria Approval (MA) for evaluating decommissioning options through the judgement of decommissioning experts. MA involves the assignment of 1 and 0 as scores of decommissioning options depending on their performance against the decision criteria and ranking of each option based on the summation of its scores across all criteria. The method was applied to the evaluation of decommissioning options for an offshore platform in California and the results indicated that leaving the platform in place was the best option. The work further points to the relevance of criteria weights and viability of using expert opinion in evaluating decommissioning options. However, MA is overly simplistic in that it is an outright pass/fail analysis that provides little insight into the relative performance of the assessed options. Furthermore, performing a full assessment of decommissioning options with all criteria used in their work is a challenging task, requiring over thirty judgements by each of the experts.

2.8.2.4. Multi-Attribute Utility Theory

McCann et al. (2017) also proposed the use of an MCDA technique called Multi Attribute Utility Theory (MAUT) for evaluating decommissioning options for twenty-seven platforms in California. MAUT is based on utility theory (Keeney 1968) and involves independent determination of each criteria score. Information for the analysis was obtained from extensive data studies of the considered platforms. Their work was widely accepted and influenced the state of California to adjust its regulatory policy to accommodate a reefing decommissioning option.

Furthermore, quantitative values like cost were scaled by interpolation as shown in Equation 2.3 to be easily comparable and the criteria weights was made variable to suit the preference of decommissioning stakeholders. Thus, it allows for sensitivity analysis.

$$U_i = \frac{X_i - X_{worst}}{X_{best} - X_{worst}} \qquad (2.3)$$

Where for element i, U_i is the scaled value, X_i is the actual value, X_{best} is the best possible value, and X_{worst} is the worst possible value.

However, criteria used are mainly environment-focused and do not account for other aspects of decommissioning such as safety and technical feasibility. Also, MAUT is data-intensive and requires extensive data gathering before it can be applied to decommissioning due to the complexity of such projects.

Data gaps were still reported by the authors despite evaluating only two decommissioning options for the twenty-seven platforms over a 20-year period (Bernstein 2015). Hence, it is expensive to replicate in other regions with much higher number of platforms.

2.8.2.5. Analytic Hierarchy Process

Na et al. (2017) proposed the use of AHP to evaluate the decommissioning options for a platform based on the platform's structural parameters and optimal project planning. The information used for the analysis was obtained by interviewing decommissioning experts and mathematical steps were taken to reduce inconsistencies in their responses. This approach is well structured and minimises error in collating expert opinion.

However, the aspects of decommissioning considered are limited with no consideration for either environmental impact or public perception, and criteria weights are fixed as shown in Figure 2.10. In practice, criteria weights are variable because they represent the preferences of the stakeholders evaluating the decommissioning options. Hence, the analysis can be more robust if other criteria are incorporated, and the weightings made flexible.

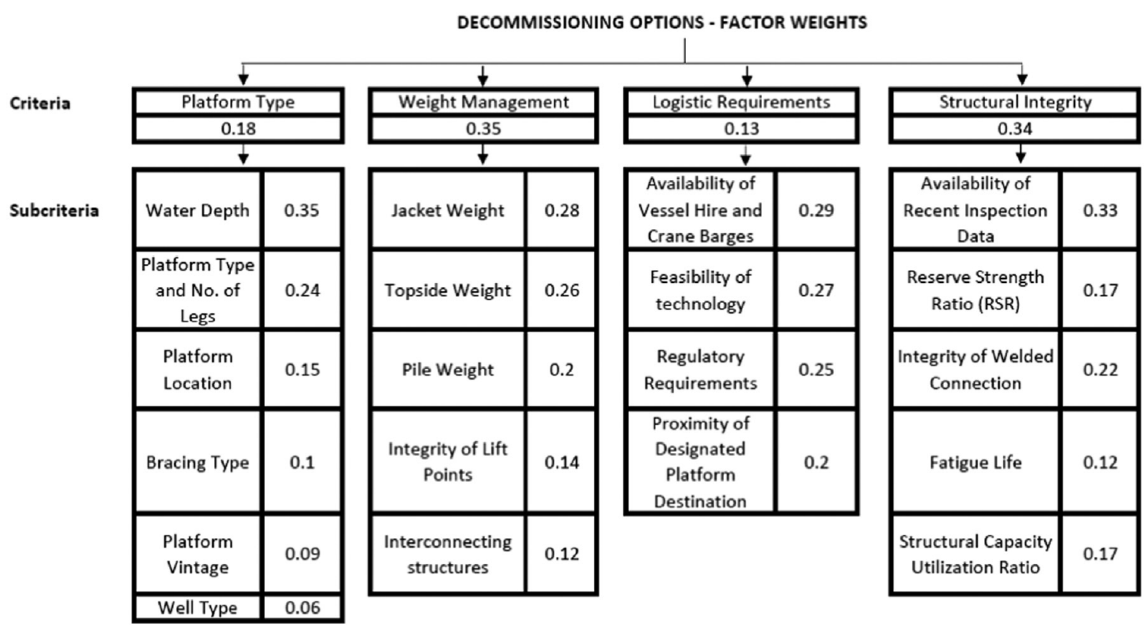


Figure 2.10: Weights of decommissioning decision criteria and sub-criteria (Na et al. 2017)

The learnings from the review of these research endeavours in optimising the evaluation of decommissioning options forms the basis of developing an improved decision model for decommissioning decision-making. This tool will capture the identified strengths and minimises the weaknesses of previous works.

In addition, it will be useful to understand how changing platform characteristics and environmental condition will affect the result of evaluating decommissioning options. This is because proper understanding of this relationship is key to developing a reusable tool which can be easily adapted to different platforms and regions.

A summary of the reviewed approaches to evaluating decommissioning options is shown in Table 2.5 with their considered decision criteria presented as a subset of the decision criteria adopted in this research.

Table 2.5: Existing approaches to optimising decommissioning options evaluation

Technique Used	Approach Type	Criteria Considered	Source	Strengths	Weaknesses
Material and energy flow analysis, financial flow analysis	Mixed	Safety – Health and safety. Environmental – Relative energy use and emissions, rate of recovery of materials from present structure, clear seabed, conservation of stocks of non-renewable resources, impacts on the marine environment, impacts of resource extraction, impacts of landfill. Public perception – Jobs in the UK, impacts on the fishing industry, impacts on fish stocks and other marine life. Economic – Financial expenditures.	(Ekins, Vanner and Firebrace 2006)	Wide range of decision criteria.	Does not account for the safety of personnel and technical feasibility of each option. Difficult to replicate due to difficulty of obtaining required data.
Net Present Value (NPV) analysis and Weighted Evaluation (WE)	Mixed	Safety – Safety, future liability. Environmental – Environmental impact. Technical – Technical feasibility. Public perception – Public requirements. Economic – Revenue generation.	(Andrawus, Steel and Watson 2009)*	Easy to replicate. Wide range of decision criteria. Criteria is weighted.	Expert opinion poorly structured. Actual cost figures required. Some criteria not independent
Multi-criteria decision analysis (Multi-criteria Approval)	Mixed	Safety – Health and safety. Environmental. Public perception – Socioeconomic, additional stakeholder concerns. Economic – Financial.	(Fowler et al. 2014)	Easy to replicate, Wide range of decision criteria.	Difficult to compare similar options because there are only two scoring outcomes. Large number of judgements required
Ecosystem-based management (EBM) Assessment	Quantitative	Environmental – Habitat extent and structural complexity, biodiversity, trophic interactions, dispersal, spawning, secondary production, benthic	(Truchon et al. 2015)	Based on empirical data and minimizes bias. Detailed analysis of environmental	Limited range of decision criteria. Difficulty of obtaining required data for some criteria.

		production, rare species. Public perception – aesthetic values, marine harvested species (commercial), marine harvested species (recreational), biomedical.		impact of options.	
4D and 5D building information modelling (BIM)	Quantitative	Technical – Schedules. Economic – Cost, resources.	(Cheng et al. 2017)	Based on empirical data and minimizes bias. Supports project management	Limited range of decision criteria. Difficulty of obtaining required data for assessing some criteria.
Multi-criteria decision analysis (Multi-Attribute Utility Theory)	Mixed	Safety – Compliance. Environmental – Impact on marine mammals and birds, benthic impacts, air quality, water quality. Economic – Economic costs. Public perception – Marine resources and fish biomass, ocean access impacts.	(McCann et al. 2017)	Wide range of decision criteria. Criteria is weighted	Limited number of considered options (complete removal and partial removal). Difficulty of obtaining required data for some criteria.
Multi-criteria decision analysis (Analytic Hierarchy Process)	Mixed	Safety – Structural integrity. Technical – Platform type, weight management, logistic requirement. Economic – Weight management.	(Na et al. 2017)	Expert opinion is structured. Easy to replicate.	Limited range of decision criteria

*Regulatory requirements considered as a criterion by authors but not included in table.

The use of expert opinion to support the evaluation of decommissioning options is a prevalent theme in the reviewed works. Figure 2.11 presents the number of criteria considered in each of the reviewed works on decommissioning options evaluation and groups these based on whether expert opinion is used or not. It is deduced from the figure that usage of expert opinion is more prevalent when a wide range of decision criteria is considered.

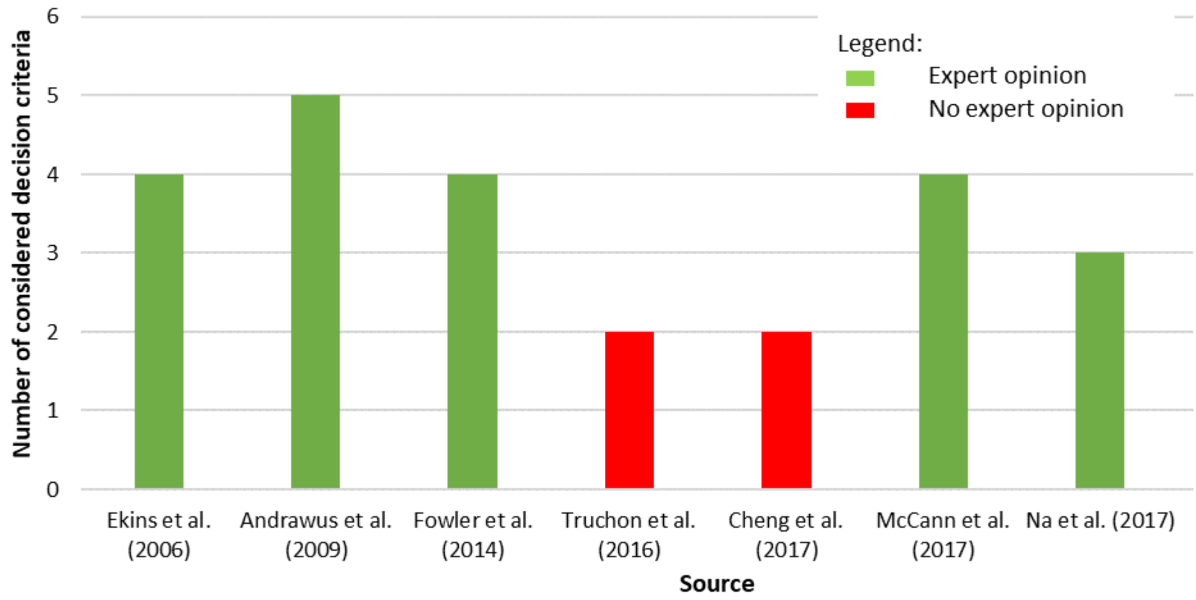


Figure 2.11: Prevalence of the use of expert opinion in evaluating decommissioning options.

Lack of empirical data relating to offshore decommissioning has been identified as a major challenge to optimising decommissioning options evaluation, hence use of expert opinion seems justifiable (Macreadie, Fowler and Booth 2011).

On the other hand, Fowler et al. (2014) observed that human judgement is inherently subjective and can be influenced by

i. Historical controversies such as the Brent spar saga in the North Sea
ii. Communication inefficiencies due to language differences and interpretation of the criteria
iii. Cultural background, extent of training and prior experience of the experts
iv. Personal interests of parties involved.

Therefore, it is important to progressively replace expert opinion by integrating decommissioning data into the decision-making approach as these become available.

The conducted literature review provides rich insights into key desirable capabilities of a robust decommissioning decision model. Firstly, the model must be able to account for both qualitative and quantitative criteria. Secondly, for the purpose of minimising subjectivity of human judgement, caution must be applied when the use of expert opinion is unavoidable by gathering these opinions systematically and with the aid of a well-structured technique that is easy to understand. Lastly, multi-criteria decision analysis is best suited for developing the model due to the multifaceted nature of decommissioning.

Concisely, the established desirable capabilities of a robust decision model for determining the optimal option for decommissioning an offshore platform are:

i. Broad range of decision criteria and ability to accommodate qualitative and quantitative data for evaluating options with respect to these criteria.

ii. Clarity and structure in use of expert opinion when required, and capability for replacing expert opinion with actual decommissioning project data as this becomes available.

iii. Use of Multi-Criteria Decision Analysis

2.9. Survey Application to Offshore Decommissioning

Surveys are a widely used research tool for collecting human opinion. Collis and Hussey (2013) describe a survey as the elicitation of information from respondents with the aid of either questionnaires, interviews, or both, and for the purpose of generalising from a sample to a population. Surveys are a viable workaround to challenges with data scarcity. Despite the existence of drawbacks to the use of surveys such as insufficient sample size and risk of bias from either the developer or the respondents, the method is a valid means of exploring a wide range of issues such as those inherent in decommissioning.

The use of surveys in offshore decommissioning studies is gradually becoming commonplace in recent times, particularly since the 20th century (Bernstein et al. 2010; Fowler et al. 2014, 2018; Na et al. 2017; Capobianco et al. 2021). This trend is driven by the steady increase in the decommissioning knowledge of professionals in the energy sector as more projects are executed globally (Tung and Otto 2019; Kumar et al. 2021; Kaiser 2022). It is also supported by the growing realisation that sound decommissioning decisions must incorporate both quantitative and qualitative information (Fowler et al. 2014; McCann et al. 2017). Further, paucity of decommissioning data is a challenge to research in offshore decommissioning because the domain is multifaceted and still emerging. Hence it was deemed necessary to make use of experts' opinions, with the aid of a survey of decommissioning practitioners, to capture comprehensive information for supporting the analysis in this research work.

A questionnaire is a survey instrument for data collection which comprises of either close-ended, open-ended, or both types of questions, and typically include a series of items which reflect the research aims (Ponto 2015). Adequacy of design is the most controversial issue associated with using survey questionnaires (Harlacher 2016) due to its strong influence on the accuracy of measuring respondents' perceptions. Therefore, standard questionnaire design guidelines must be followed in developing survey questionnaires.

2.10. Multi-Criteria Decision Analysis

MCDA encompasses all mathematical modelling techniques used to solve complex decision problems in which it is required to consider several criteria to determine the best alternative or course of action. It has been successfully applied to decision-making problems in such industries as engineering, resource management and healthcare (Hamurcu and Eren 2019; Stojčić et al. 2019). Literature reviews of MCDA and their merits/demerits have been extensively covered in the literature (Velasquez and Hester 2013; Kumar et al. 2017; Mardani et al. 2017; Sriram et al. 2022). Hence, MCDA has widespread acceptance across several industries.

MCDA is readily applicable to solving the decision-making problem of selecting an optimal option from a list of options for decommissioning an offshore platform if the problem is conceptualised as a multicriteria problem in which the goal is to determine the optimal decommissioning option from a list of options. Moreso, knowledge of decommissioning options for offshore platforms and the decision criteria for their evaluation is already well-established. Therefore, in this research, the AHP MCDA technique is applied to solving the multi-criteria problem of evaluating decommissioning options for an offshore platform to determine which is best for its decommissioning.

Further information about the AHP technique and the procedure for its application is provided below.

2.10.1. Analytic Hierarchy Process

AHP aids comprehensive decision-making by logically structuring the decision elements according to their hierarchy and showing the relationship between criteria and the possible alternatives through the aid of pairwise comparison matrices.

A hierarchy is simply a stratified system of arranging the components of a multicriteria decision-making problem such that each component, except for the top one, is subordinate to one or more components. AHP handles the complexities of decision-making by reducing the task to basic pairwise comparisons and using the results to develop overall priorities which then enable the ranking of the alternatives. This technique, which was developed by Saaty (1977), involves relative measurement and is thus suitable for scenarios when absolute measurements are not obtainable. Hence it can be used to effectively handle MCDA involving both qualitative and quantitative criteria with ease (Ishizaka 2019).

Islam and Saaty (2010) identified several uses of the AHP technique, and these include

i. Simplified representation of a complex problem

ii. Measurement/allocation of criteria weights

iii. Determination of optimal choice among alternatives

iv. Measurement of consistency in human judgement

v. Prediction of future outcomes

vi. Resolution of conflicts by clear analysis

vii. Framework for forward/backward planning

viii. Supporting tool for other decision-making techniques such as Cost Benefit Analysis and MAUT.

Usage of the AHP technique is further promoted by the availability of user-friendly computer software such as Decision Lens, Super Decisions and Expert Choice which aid the decision-maker in evaluating the mathematical aspects of the technique (Mu and Pereyra-Rojas 2018). The AHP approach involves applying rational and intuitive thinking to the determination of the best option from several alternatives by evaluating these with respect to a set of criteria. It is also very flexible in that it can accommodate the subjectivity of human judgements by making provision for managing inconsistencies.

With the aid of AHP, a decision-maker can structure the decision-making problem visually in the form of an attributes hierarchy as shown in Figure 2.12. The decision aim is the main objective or aim of the decision-making process, and the criteria are the factors to be considered in making the decision. The last level of the hierarchy shows the options available for the decision-maker to choose from.

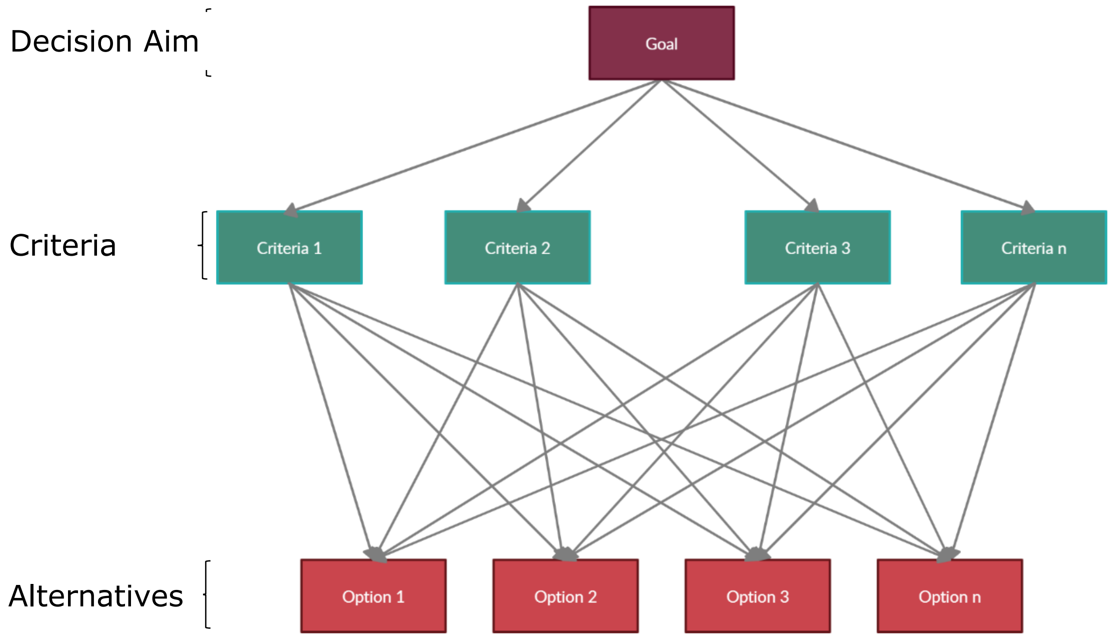


Figure 2.12: AHP decision hierarchy structure (Adapted from Mu and Pereyra-Rojas 2018)

In addition to the three major hierarchy levels, there might be a need to include sub-criteria which further compartmentalise aspects of the criteria and improve the objectivity of the options comparisons as shown in Figure 2.13. However, comparisons must only be between elements at the same hierarchy level to make sense. For example, a criterion cannot be directly compared with the sub-criterion of another criterion. Also, usage of sub-criteria is not compulsory because some criteria (such as criteria 3 in Figure 2.13) are standalone in nature.

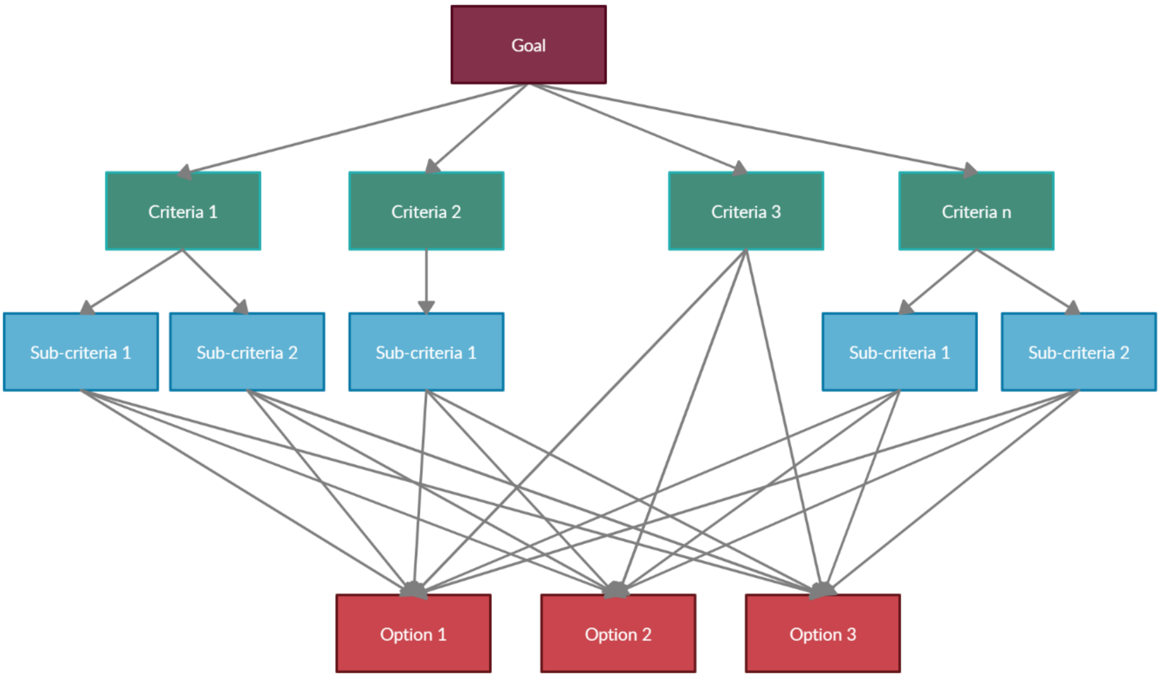


Figure 2.13: Modification of AHP hierarchy to incorporate decision sub-criteria.

Elements at the same hierarchy level are compared in pairs to assess their relative preference with respect to each of the elements at the immediate higher level. The comparisons are also made with respect to a single element i.e., sub-criteria comparison is made with reference to the parent criterion, criteria comparison is made with reference to the main goal, and alternatives are compared with reference to each sub-criterion.

To standardise the AHP process of paired comparison judgments, Saaty (1977) developed the scale shown in Table 2.5 for translating verbal description of relative importance to numbers which then aid the hierarchical ranking of the decision elements according to their relative importance.

Table 2.6: AHP Relative Importance Scale (Saaty and Vargas 2012)

Intensity of Importance	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective
2	Weak importance	

3	Moderate importance	Experience and judgment slightly favour one activity over another
4	Moderate plus importance	Experience and judgment strongly favour one activity over another
5	Strong importance	
6	Strong plus importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
7	Very strong or demonstrated importance	
8	Very, very strong importance	The evidence favouring one activity over another is of the highest possible order of affirmation
9	Extreme importance	
Reciprocals of above	If activity *i* has one of the above nonzero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	A reasonable assumption
Rationals	Ratios arising from the scale	If consistency were to be forced by obtaining n numerical values to span the matrix

Saaty's scale is easy to use, and its effectiveness has been validated through theoretical justification and numerous successful applications by different authors (Saaty and Vargas 2012).

2.10.1.1. Application of AHP to Multicriteria Decision-Making Problems

AHP has been successfully applied to decision problems in several fields including engineering, economics, medicine, and policy-formulation (Velasquez and Hester 2013; Kumar et al. 2017). It has also been applied to the problem of site-selection for energy projects (Merrouni et al. 2018; Ozdemir and Sahin 2018), transportation planning (Islam and Saaty 2010; Moslem 2020), economics (Sharma 2018) and construction (Salem, Salman and Ghorai 2018) with satisfactory results.

Other fields where AHP has been successfully applied include government, business, industry, healthcare, shipbuilding, and education (Sharma 2018) and these examples clearly demonstrate the interdisciplinary applicability and versatile nature of the technique.

Moreso, the use of AHP to solve Petroleum Engineering problems is detailed in the literature. A form of Fuzzy-AHP was used to conduct risk assessments for the upstream oil and gas industry and evaluate the risks involved in investment activities (Chang et al. 2006). White et al (2014) combined AHP and a geometric database to solve the complex problem of pipeline routing decisions in the offshore Arctic environment. AHP was employed to validate the results obtained from using Quality Function Deployment process to determine the optimal subsea processing technology for marginal field development (Ohanyere and Abili 2015).

AHP has been successfully applied to decision-making in the nuclear industry which shares similarities to offshore structures in terms of financial scale of projects, being situated in relatively isolated locations, and tendency to cause harm to people and environment (Wan, Yongling and Junjie 2016; Bai, Liu and Chao 2017; Invernizzi et al. 2018). It has also been used in combination with other Operations Research tools such as Digital Mock-up System and Data Envelopment Analysis to facilitate management of nuclear reactors decommissioning projects with satisfactory results (Kim and Song 2009; Ho and Ma 2018).

2.10.1.2. Application of AHP to Offshore Decommissioning

The inherent ability of the AHP technique to produce meaningful results even in the absence of quantitative data makes it particularly appealing for solving decision-making problems in the offshore decommissioning problem domain due to the paucity of data in this area (Fowler et al. 2014).

For example, Andrawus, Steel and Watson (2009) utilised pairwise comparison in weighted evaluation technique which combined consideration of financial and non-financial criteria in evaluating decommissioning options for a platform. Similarly, Na et al. (2017) determined the AHP technique to be the MCDA method most suited for decommissioning planning and management. Their work focused on platforms in the South China Sea and only addressed the structural and technical aspects of decommissioning. Nevertheless, it was recommended as a starting point for the development of more robust decision-making approaches that incorporate financial as well as environmental aspects of decommissioning projects. The present research builds on their work in that the AHP technique is applied to decommissioning options evaluation with consideration for a wider suite of criteria and sub-criteria.

Furthermore, a merit of the AHP technique is its ability to enable efficient group interaction and decision-making (Saaty and Peniwati 2013). This feature makes it particularly suitable for addressing the MCDA problems that arise during decommissioning planning because these issues typically require collective inputs from stakeholders across several departments. In addition, a robust review by Martins et al. (2020) suggests that AHP is the MCDA technique with the most widespread use in solving decommissioning problems within the oil and gas industry.

Asset owners in the UKCS whose fields are at the end-of-life stage are required to submit a decommissioning programme (DP) which details the intended workflow for decommissioning the platform and associated facilities. Preparation of a DP entails considerable data-gathering which necessitates the conduction of platform-based technical studies. To ensure conciseness and robustness, the report is furnished with information from other supporting documents as illustrated in Figure 2.14.

Figure 2.14: Main documents and supporting studies for Murchison decommissioning (CNRI 2012)

Elaborate documentation is particularly important for platforms that are candidates for derogation as there is a legal requirement for the platform operator to justify the decision to leave any part of the platform structure behind (BEIS 2018). A comparative assessment report is one of the primary supporting documents for a DP and the AHP technique has been applied to various degrees in developing this report for several decommissioning programs (CNRI 2012; Repsol 2017, 2020; Xodus Group 2017, 2018, 2020). Hence, it is beneficial to further understand this MCDA technique and its effective adoption for solving the decision problem of evaluating decommissioning options.

2.11. Summary

The review of existing literature in this chapter has set the stage for the research by providing a rich understanding of offshore decommissioning. The different alternatives for decommissioning offshore platforms were grouped into three main options i.e., complete removal, partial removal and leave in place. Through a critical review of previous works in decommissioning options evaluation, five decision criteria were adopted for evaluating decommissioning options. These are safety, environmental impact, technical feasibility, cost, and public perception. Next, a review of decommissioning cost analysis was performed, and this highlighted the need for improvements to current decommissioning options costing approaches. Through this critical review, the AHP technique was identified as the MCDA technique most suited for developing a robust decommissioning decision model. It was also established that such a model must ensure structured use of expert opinion and replacement of this with actual decommissioning project data when it becomes available. These insights guided formulation of the research objectives as stated in Chapter one and will also be used to furnish an adequate methodology for this research in the next chapter.

Chapter 3 : RESEARCH METHODOLOGY

This chapter discusses the research techniques and tools used to achieve the aim and objectives of this research as stated in Chapter one. The research approach and design are presented in section 3.1 and section 3.2 respectively. Section 3.3. outlines the research methods and strategy used for data collection. The main data analysis techniques used in this research are subsequently described in section 3.4. Finally, a summary of the chapter is presented in section 3.5.

3.1. Research Approach

The key differences between the three main research approaches to investigating the aims and objectives of a research are shown in Table 3.1.

Table 3.1: Differences between deductive, inductive, and abductive research approaches (Adapted from Saunders, Lewis and Thornhill 2020)

	Research Approach		
Key Aspect	**Deductive**	**Inductive**	**Abductive**
Logical inference	When the premises are true, the conclusion must also be true.	Known premises are used to generate untested conclusions.	Known premises are used to generate testable conclusions.
Generalisability	Generalising from the general to the specific.	Generalising from the specific to the general.	Generalising from the interactions between the specific and the general.
Use of data	To evaluate propositions or hypotheses related to an existing theory.	To explore a phenomenon, identify themes and patterns and create a conceptual framework.	To explore a phenomenon, identify themes and patterns, locate these in a conceptual framework and test this through subsequent data collection and so forth.
Theory	Theory falsification or verification.	Theory generation and building.	Theory generation or modification; incorporating existing theory where appropriate, to build new theory or modify existing theory.

Based on this information, the deductive research approach was identified to be the most adequate for this research work. The research begins by using information from reviewing literature and existing knowledge about options evaluation to develop a decision model for identifying the optimal decommissioning option for an offshore platform. This is followed by investigating the applicability of the developed model with the intent of either confirming or contradicting the performance of the model depending on the obtained outcomes.

3.2. Research Design

The design adopted for this research comprises of a synthesis of quantitative and qualitative research methods and utilises multiple data analysis techniques including AHP, machine learning, sensitivity analysis and data scaling. The novelty of this methodological approach lies in its unique combination and application of existing research elements to the optimisation of offshore decommissioning decision-making to facilitate objective analysis and unlock valuable insights. Hence, the research design is innovative, and its outcome represents an advancement of the existing body of decommissioning knowledge.

A schematic flowchart showing the logical steps followed in this research is presented in Figure 3.1. The figure illustrates the general plan of action used to accomplish the research aim and objectives.

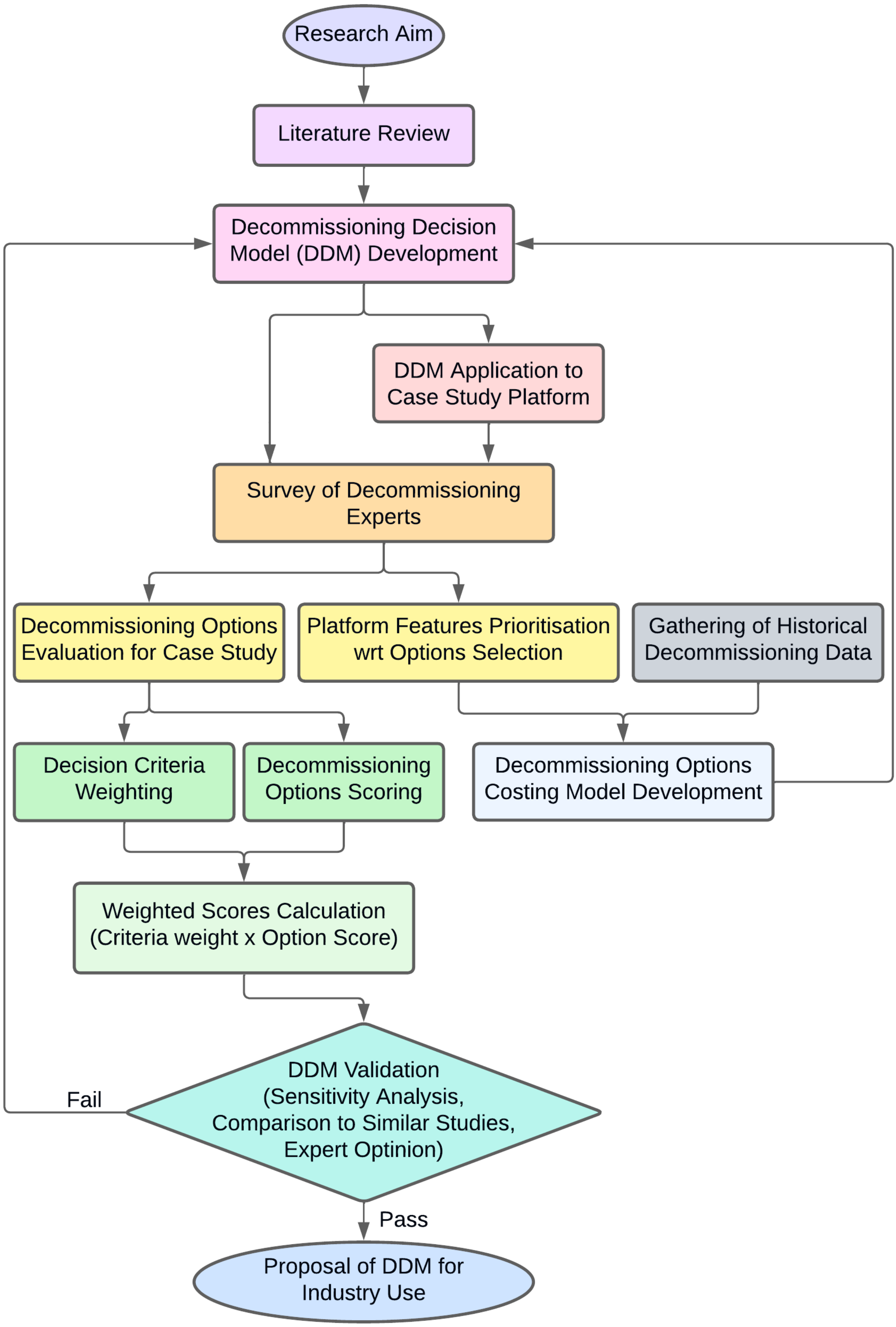


Figure 3.1: Research design

The research aim is to develop decision support to aid decision-makers in determining the best available option for decommissioning their offshore platform. This was initiated by a review of existing literature that is pertinent to offshore decommissioning to establish the theoretical foundation of the research.

Literature review in Chapter two of this thesis investigated the concept of offshore decommissioning and existing approaches for identifying the best option for decommissioning a platform with focus on their strengths and weaknesses. This provided an understanding of the main options for decommissioning offshore structures as well as the key considerations for choosing an option for a given project. The review identified flaws in the existing approaches such as limited scope of considered decision criteria, results ambiguity, excessive human bias in judgement, inability to combine qualitative and quantitative data, and inability to integrate historical data and emerging knowledge into options analysis as more decommissioning projects are completed. These findings were used to furnish the desirable capabilities of a robust decision model. Also, the key decision criteria that determine the suitability of a decommissioning option for a project were identified. A decommissioning decision model (DDM) which captures these learnings was subsequently developed in Chapter four.

After its development, the DDM's functionality and applicability to decommissioning projects was demonstrated by using the model to solve the problem of decommissioning options evaluation for a case study platform. Evaluation of the considered decommissioning options was facilitated by a survey of decommissioning experts. Analysis of the survey responses involves weighing the decision criteria, scoring the considered decommissioning options based on their expected performances in terms of each criterion, and combining the calculated weights and scores to obtain weighted scores for each option. The options were ranked based on their weighted scores, a value which indicates the level of expected desirable outcome from using the option for the decommissioning project. Following this, the DDM was validated and modified if the results were unsatisfactory, otherwise it was proposed for industry use.

A requirement of the DDM is the capability to support integration of historical data. To demonstrate this, the decommissioning survey was also used to identify platform features that have the highest influence on the selection of a decommissioning option. Machine learning regression was then applied to these features in combination with secondary historical data to develop a mathematical model for predicting the costs of decommissioning options. Finally, the costing model was used to predict the costs of using different options for decommissioning the case study and these costs were transformed into input for the DDM.

3.3. Research Methodology

The main methods and data analysis techniques used for achieving the aim and objectives of this research are mapped to the research objectives in Table 3.2.

Further description of these research elements is subsequently provided.

Table 3.2: Research Methodology

Research Objectives	Associated Tasks	Research Method	Data Analysis Technique
1. To develop a decision model for identifying the best decommissioning option for an offshore platform with the aid of multicriteria decision analysis.	a. Critically assess the existing approaches for evaluating decommissioning options for offshore platforms to identify their limitations.	Literature Review	-
	b. Develop a novel decommissioning decision model with information from 2(a) and multi-criteria decision analysis.	Literature Review	AHP, Machine Learning, Sensitivity Analysis
2. To investigate the applicability of the decision model by using it to evaluate decommissioning options for a case study platform.	a. Establish the relative importance of the factors considered in decommissioning options selection for a case study.	Case Study, Survey	Likert-AHP
	b. Evaluate decommissioning options for the case study platform.	Case Study, Survey	Likert-AHP
	c. Perform sensitivity analysis of the results for the case study.	Case Study	Sensitivity Analysis
3. To investigate the validity of the developed decision model and results obtained from its application to the case study.	a. Compare model results for the case study with results from similar works in literature.	Literature Review	-
	b. Validate the decommissioning decision model.	Survey	-
4. To develop a decommissioning options costing model and integrate this into decommissioning decision-making.	a. Review existing decommissioning cost estimation techniques to identify their limitations.	Literature Review	-
	b. Develop an improved approach for predicting the costs of decommissioning offshore platforms.	-	Machine Learning
	c. Integrate the outcome of 4(b) into the developed decision model.	-	Data Scaling

3.3.1. Case Study

Case study research strategy entails extensive examination of a single instance of a phenomenon in its real-life context for the purpose of generating an in-depth understanding (Crowe et al. 2011; Ridder 2017). This strategy was identified in this research as the most viable medium for generating the primary data for analysis. Case study implementation is achieved in four stages (Stake 1995; Hancock and Algozzine 2021), namely definition of the phenomenon of interest, selection of case study, data collection, and analysis, interpretation, and reporting of findings. These stages were followed in Chapter five of this thesis to investigate the applicability of the decommissioning decision model after its development i.e., objective 2.

3.3.2. Survey

A survey of decommissioning practitioners enabled the capturing of comprehensive information for supporting the analysis in this research work. This method was used for achieving parts of objective 3 and objective 4.

3.3.2.1. Survey Questionnaire Design

A copy of the decommissioning survey is attached to appendix 2 of this thesis. It comprises twenty-four questions distributed into three main sections as follows: Demographics (five questions), Comparisons and Judgements (eleven questions), and Additional Information (eight questions).

1. Demographics

The demographics section contained questions for understanding the defining characteristics of participants, namely their offshore region of operation, level of education, years of decommissioning-related experience, affiliation to decommissioning, and the aspect of decommissioning that they were most knowledgeable about. Based on these characteristics, the survey respondents were classified into distinct groups to understand the degree of diversity in the responses and extent of representation for each group.

2. Comparisons and Judgements

In this section of the questionnaire, the respondents were first provided with a factual description of the features of the case study to be decommissioned. Using this information and their knowledge of decommissioning, they proceeded to compare several alternatives with the aid of a predefined Likert scale and based on five decision criteria. The section is sub-divided into two parts namely Criteria and Sub-Criteria Weighting, and Decommissioning Options Scoring.

2A(I). Criteria Weighting

The survey questions are posed to solicit for qualitative responses and with the aid of a Likert scale, these qualitative responses are converted to their quantitative equivalents to make it possible to perform numerical calculations (see Table 3.3). This 5-point scale has been derived from the preference scale recommended for AHP analysis by Saaty (Asadabadi, Chang and Saberi 2019). A discussion of the effect of using other measurement scales for AHP analysis can be found in the literature (see Hossain, Adnan and Hasin (2014)).

Table 3.3: Conversion from qualitative to quantitative scales for criteria and sub-criteria weighting

Qualitative Response	Equivalent Quantitative Value
Least Important	1
Less Important	3
Moderately Important	5
Highly Important	7
Extremely Important	9

To harmonise differences in the opinion of participants to the questions in this section, responses to each question were aggregated into single consensus values by taking the geometric mean. These aggregated values are the input for Likert-to-AHP calculations to determine criteria weights.

2A(II). Sub-Criteria Weighting

As discussed in Chapter two of this thesis, decision criteria typically comprise key aspects or sub-criteria that capture all the important considerations within them. These sub-criteria had previously been explored by the researcher and a decision was made to explicitly include them in the survey as the tendency of participants being oblivious or only partly aware of these sub-criteria exists. Moreso, thorough knowledge of the interrelationship between the sub-criteria of a criterion is valuable to project stakeholders, especially when gathering data to inform decision-making in that this knowledge will influence effective allocation of resources and streamlining of efforts to focus on relevant data. With these in mind, the survey investigated sub-criteria weighting for two main reasons. These were to

i. Explicitly inform the participants about the key aspects of the decision-criteria and subsequently increase their likelihood of making good judgements when completing the survey.
ii. Further understand the decision criteria by investigating the relative importance of their constituent sub-criteria.

2B. Decommissioning Options Scoring

After establishing the weights of all decision criteria (and sub-criteria), the expected performance of decommissioning options for the case study platform with respect to each criterion was determined in the form of options ratings. To achieve this, the previously explained steps were repeated using responses to questions referring to options evaluation or scoring with reference to safety, environmental impact, technical feasibility, cost, and public perception.

The Likert scale used for scoring decommissioning options is shown in Table 3.4. This scale was also derived from the Saaty scale but differs from the scale for criteria weighting in that different adjectives are used for describing the rating alternatives in alignment with the wording of the questions.

Table 3.4: Conversion from qualitative to quantitative scales for decommissioning options scoring

Qualitative Response	**Equivalent Quantitative Value**
Worst	1
Poor	3
Average	5
Good	7
Best	9

Having determined the priorities for criteria weights and performance scores for the decommissioning options, the final step in the options evaluation was to combine both values into weighted scores for each evaluated option.

3. Additional Information

In the third section of the survey, participants were requested to suggest possible additional sub-criteria to be considered in the decision-making. The survey structure is restrictive due to the nature of the issues it addresses. However, making provision for respondents to include any additional information provides an opportunity for the survey to capture information that the author might not have considered during its design.

Also, survey participants were asked to give their opinion about the relative relevance or priority of platform features to options selection. Offshore platforms have distinctive features e.g., topsides weight and platform age. Knowledge of platform features which are most relevant to decommissioning considerations will aid the development of parametric decommissioning models which can feed into the DDM developed in this research. Eight main platform features are presented in this part of the survey and the participants qualitatively provide their judgement about the relevance rating for each of these. The platform features include:

- Topsides weight
- Substructure weight
- Water depth
- Platform age
- Distance from land
- Jacket weight
- Piles weight, and
- Number of piles

Prioritisation of these platform features was achieved by first converting each of the qualitative relevance ratings ascribed to them by the survey participants to quantitative values as shown in Table 3.5 to enable numerical calculations.

Table 3.5: Conversion from qualitative to quantitative scales for relevance rating

Qualitative Response	Equivalent Quantitative Value
No Relevance	1
Low Relevance	3
Moderate Relevance	5
High Relevance	7
Extremely high Relevance	9

Decommissioning-related work experience is regarded as the strongest indicator of the expertise of respondents since the decommissioning industry is still at an infancy stage (Birchenough and Degraer 2020). Hence, the prioritisation values were aggregated by calculating the Weighted Geometric Mean based on the years of decommissioning-related work experience of respondents as shown in Table 3.6. This implies that the opinions of individuals with more years of work experience weighed more than those of individuals with less work experience, as the former are assumed to be more knowledgeable on the subject. Note that conversion scales in Table 3.5 and Table 3.6 are adaptations of the Saaty scale.

Table 3.6: Assignment of Weights to Participants' years of work experience

Years of Work Experience	Assigned Weight
0 – 3 years	1
4 – 7 years	3
8 – 11 years	5
12 – 15 years	7
>15 years	9

3.3.2.2. Distribution of Survey Questionnaire

The target participants for the survey comprised individuals that are experts in decommissioning and people who had engaged with previous decommissioning projects as members of stakeholder groups. After its design, the survey questionnaire was uploaded to a website platform with its address link distributed to the target participants via personal emails, online groups, and social media networks. Online surveys are advantageous over offline surveys due to their ability to reach many target participants in less time, and with less manpower, and less expenses involved (Sinclair et al. 2012; Mondal et al. 2018). Hence, their adoption for this research.

The decommissioning survey was hosted on the JISC Online Survey tool, a web-based tool designed for academic research, education and public sector organisations (https://www.onlinesurveys.ac.uk/). The tool is easy to use, GDPR (General Data Protection Regulation) compliant, and ISO 27001 certified. It also has functionality for exporting the responses data to external tools such as Excel and SPSS. This made it an excellent choice for hosting the survey because, as part of the data analysis, follow-on AHP calculations were performed on the collated response data using Excel Software.

3.3.2.3. Pilot Survey

The pilot version of the online survey was conducted for a duration of two months in the period between November 2021-December 2021. This trial run was necessary for checking the appropriateness of the survey in terms of ease of comprehension, and time taken for completion, and for timely identification of any errors in the questions or their structuring.

There were thirty-three participants to the pilot survey and their feedback informed several changes to the original survey design including:

i. Clarification of the ethical statement in the first page of the survey to clearly highlight that any personal information will be kept anonymous.
ii. Removal of a question in the demographic section about respondent's current role in the offshore industry as this information was seen to be irrelevant to the analysis goal.
iii. Addition of a question to the demographic section for capturing the specific areas of decommissioning that a respondent is most knowledgeable about.
iv. Explicit explanation of the problem hierarchy to make it more understandable to the respondents and minimise ambiguities in interpretation of the information.

v. Adoption of a theoretical offshore platform in the POCS California region instead of Hidalgo platform as the case study to avoid ethical issues which would likely arise with the asset's owners if a real-life platform were to be used as the case study.

vi. Restriction of responses to questions in the Criteria and Sub-Criteria weighting sections such that respondent cannot assign the same rating to more than two elements at the same level. This restriction was to encourage critical reflection by the respondent in making judgements. An explanation of this rule is provided in the introduction of the section.

vii. Removal of Employment, Ocean Access, Recreational Use, And Tax Concessions as sub-criteria of the Public Perception criterion.

viii. Explicit description of the endpoint of removed portion of the platform by including a footnote to the Decommissioning Options illustration figure to clarify that all removed portions are taken to land for recycling/disposal.

Implementing these key changes to the content and structure of the pilot survey led to developing an improved version which then served as the main survey. Thus, effectively serving the purpose of questions and presentation validation prior to carrying out the main survey (Ball 2019).

After collection, numerical analyses were performed on the survey data using Excel software following its importation from JISC Online Survey Platform. AHP calculations constituted most of the analyses and the formulars for implementing the technique were coded into Excel software by the researcher before data importation in line with the procedure described in Burge (2014).

The next section details the data analysis techniques employed in this research.

3.4. Data Analysis Techniques

3.4.1. AHP Methodology

The methodology for implementing AHP as identified from literature (Islam and Saaty 2010; Ohanyere and Abili 2015; Mu and Pereyra-Rojas 2018; Ozdemir and Sahin 2018) is described below.

1. Decomposition: Define the elements of the AHP model including the goal or main objective of the process, criteria or factors that matter to the decision-maker, sub-criteria which highlight aspects of the criteria, and the alternatives or options that the decision-maker must choose from. These are used to develop the hierarchical structure which helps the decision-maker to gain a clearer understanding of the problem and nature of the desired solution. For more complex problems, experts are consulted at this stage to ensure that all relevant criteria and alternatives have been captured.

2. Prioritisation: Develop pairwise comparison square matrices, also called judgement matrices, for each set of elements in the same level except for the top element. For each matrix E, use the Saaty preference scale to assign values to the matrix cells as shown in Equation 3.1, where Eij is the value of the cell in the ith row, mth column of matrix E and represents the preference of the element in the ith row over the element of the jth determinant when both are compared with reference to their parent element. For example, a value of 1 indicates that the elements being compared contribute equally to the objective while a value of 9 indicates that the contribution of one element is significantly more important than the other.

$$E = \begin{bmatrix} E_{11} & \cdots & E_{1n} \\ \vdots & \ddots & \vdots \\ E_{n1} & \cdots & E_{nn} \end{bmatrix} \tag{3.1}$$

$$E_{ii} = 1,\ E_{ji} = \frac{1}{E_{ij}},\ E_{ij} \neq 0$$

Where n represents the number of elements in the comparison matrix.

The number of judgements or comparisons required to populate a matrix with n number of elements via pairwise comparisons was determined by Belton and Stewart (2002) to be given by Equation 3.2.

$$Number\ of\ judgements, J = \frac{n(n-1)}{2} \quad (3.2)$$

3. Synthesis: From the values in each judgement matrix, generate a priority vector which shows the weights of importance of all elements in the matrix. The priority vector, also called the eigenvector, can be estimated as the average of normalised columns as shown in Equations 3.3 and 3.4 (Shapira and Goldenberg 2005; Mu and Pereyra-Rojas 2018; Wang et al. 2020). This involves summing the values in each column to obtain column totals, normalising each cell by dividing its value with its column total, and taking the average value of each row.

$$Priority\ vector, P = \begin{bmatrix} P_i \\ \dots \\ P_n \end{bmatrix} \qquad (3.3)$$

$$P_i = \frac{1}{n} * \sum_{j=1}^{n} \frac{E_{ij}}{\sum_{k=1}^{n} E_{kj}} \qquad (3.4)$$

Where, E_{ij} is an element located in row i and column j of the judgement matrix.

Consistency checks are also performed to verify if the pairwise comparison judgements are consistent or in agreement with each other. Saaty (1977) proposed a term called the consistency ratio (CR) for this purpose which can be calculated from Equation 3.5. CR indicates the level of logical agreements between the judgements used to populate the pairwise comparison matrix. In general, the judgements are accepted as being consistent if the calculated CR does not exceed 0.10. Otherwise, improvements are made to the judgement matrix before it can be used with confidence.

$$CR = \frac{CI}{RI_n} \qquad (3.5)$$

Where CI is the consistency index calculated using Equation 3.6

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (3.6)$$

Where λmax and n respectively represent the maximum eigenvalue and size of the pairwise comparison matrix being investigated. And RIn or random index is an estimate of the average consistency index obtained from a large enough set of randomly generated n-sized matrices. The random indexes for different values of n are shown in Table 3.7.

Table 3.7: Random Index values for different matrix sizes (Brunelli 2015)

Matrix Size (n)	3	4	5	6	7	8	9	10
Random Index	0.525	0.882	1.109	1.248	1.342	1.406	1.45	1.485

4. Aggregation: Combine the products of each criterion weight with the score of an alternative when evaluated with reference to the criterion to obtain the weighted score for that alternative as shown in Equation 3.7 (Na et al. 2017; Nnaji and Banigo 2018). The procedure is repeated for all considered alternatives and their obtained weighted scores are used for comparatively ranking the alternatives.

$$W_i = \sum_{j=1}^{n} w_j * s_{ij} \qquad (3.7)$$

Where W_i is the weighted score for alternative i, w_j is the weight of importance of criterion j and s_{ij} is the score of alternative i with respect to criterion j.

Note that steps 1-3 alone generate priorities or relative weights for the criteria and sub-criteria which show how important they are to achieving the desired objective and step 4 is purely for the purpose of ranking the alternatives. The AHP technique was used in this research to develop the decommissioning decision model (i.e., objective 1) in Chapter four.

Despite its extensive application, the AHP technique suffers from several weaknesses which include ambiguous questions, rigid measurement scales, and variations in results depending on the hierarchy structure (Song and Kang 2016; Çalişkan et al. 2019; Çetinyokuş et al. 2020). Overcoming these issues requires proper structuring of the decision problem into AHP hierarchy and soliciting for expert opinion in a manner that effectively captures their judgements and minimises inconsistencies (Hossain, Adnan and Hasin 2014). The latter measure is achieved in this research with the Likert-AHP technique.

3.4.2. Integration of Likert Scale with AHP (Likert-AHP)

The number of judgements required for populating a decision matrix increases with the number of elements involved (see equation(3.2)). This leads to challenges with inconsistencies when using AHP to solve decision-making problems that require plenty of comparisons due to having a high number of criteria and alternatives (Çetinyokuş et al., 2020). Moreso, real-life problems are often complex and multi-faceted, and Saaty (1977) defined the allowable bound of consistency ratio to be 0.01 which is quite a small margin. This has led to a recent increase in research efforts to simplify the AHP process while ensuring that the accuracy of its results meet acceptable standards (Song and Kang 2016).

Hossain, Adnan and Hasin (2014) asserted that the weightings provided by AHP are only useful for prioritising or ranking the alternatives and should not be interpreted as the actual proportion of relative importance of alternatives. Franek and Kresta (2014) also concluded that judgment scales have a profound impact on criteria priorities but not on ranking of criteria. This assertion is supported by the analysis performed by Shapira and Goldenberg (2005). Furthermore, some authors have taken a broader view and posited that MCDA methods tend to yield same ranking results despite variations in the scores (Ertuğrul and Karakaşoğlu 2008; Dehe and Bamford 2015). Thus, suggesting that the primary target of AHP is ranking alternatives according to their preferences.

Hossain, Adnan and Hasin (2014) further proposed a combination of Likert scale and AHP to improve the weight assignment process. In their proposed approach Likert scale is used for eliciting responses from the survey participants which are then used to perform AHP calculations with some modifications. The benefits from using this approach are threefold.

i. Likert scale enables its user to clearly capture the opinions of individuals hence its widespread applications in the areas of psychometry, prioritisation, and resource allocation (Joshi et al. 2015). This scale reduces the likelihood of survey participants misunderstanding the posed questions, a potential challenge when using the traditional AHP technique (Shapira and Goldenberg 2005).
ii. The Likert-AHP approach ensures that there are no inconsistencies in the judgements (i.e., consistency ratio = 0) while yielding results that are sufficient for ranking the evaluated alternatives.
iii. It results in a more user-friendly input and time savings from requiring a lower number of judgements than the traditional AHP technique as shown in Figure 3.2. The number of judgements required when using Likert-AHP approach is n whereas using the traditional AHP approach requires $(n^2 - n)/2$ judgements, where n is the number of elements being compared with each other at the same hierarchy level.

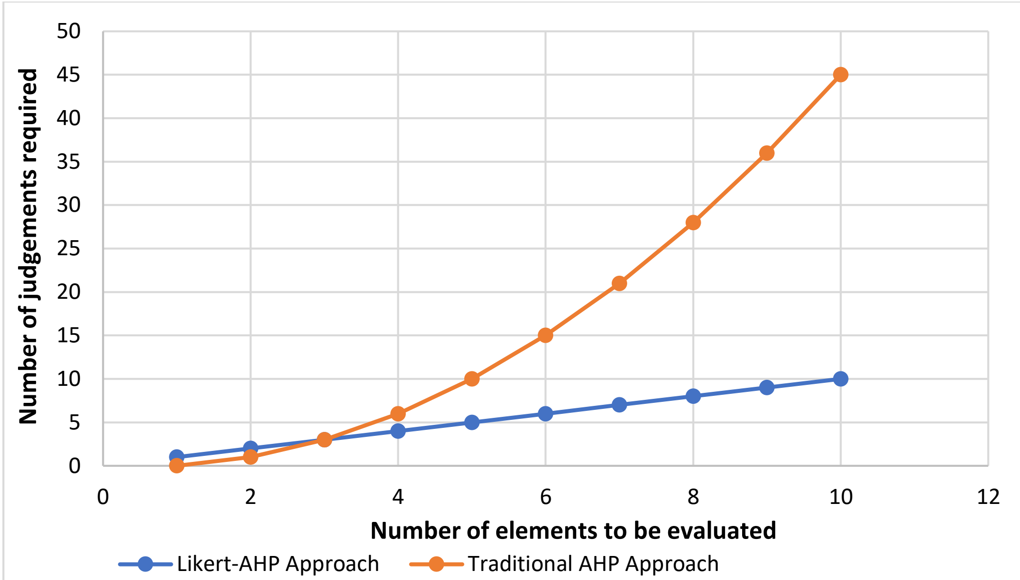


Figure 3.2: Comparison of the number of required judgements for the traditional AHP approach and the Likert-AHP approach.

Due to these benefits, the Likert-AHP technique was applied in this research for designing the survey questionnaire and analysing the responses from participants i.e., objective 2.

The procedure for using the Likert-AHP technique is depicted in Figure 3.3. It differs from the traditional AHP process in that the prioritisation stage is replaced with suggestion matrix formulation.

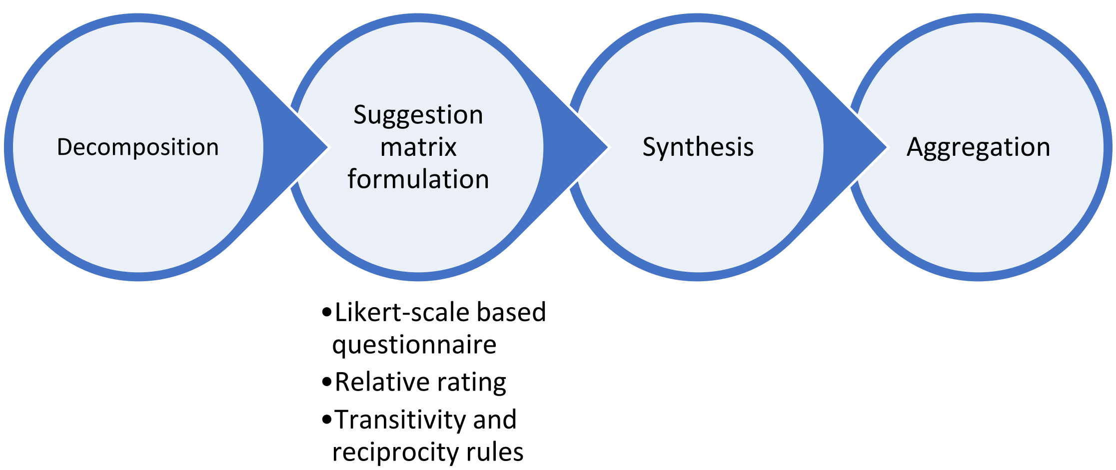


Figure 3.3: Likert-AHP procedure

The Likert-AHP calculations in this research are detailed in appendix 3. For further details about using the procedure, the reader is referred to Hossain, Adnan and Hasin (2014).

3.4.3. Sensitivity Analysis

Sensitivity analysis is a mathematical procedure for investigating how results or decisions might change with different input data (Goepel 2017). The analysis is a viable means of validating the input data of a model and the results obtained from its use (Smith et al. 2008). It is considered risky to rely on the current inputs of a decision model if sensitivity analysis of the model results suggest that a change of 5% or less to any of the model's input parameters causes a change in the most-preferred alternative (Abu-Shabeen 2008). Such findings warrant further review and validation of the initial weights of the input parameters. This analysis was applied in Chapter six of this research to check validity of the input data i.e., objective 3 and constituted part of the model implementation for the case study (objective 2).

Numerical incremental analysis (NIA), which is adopted in this research, is the most popular sensitivity analysis method in the literature for cases where AHP is used to solve MCDA problems and for software tools which implement AHP (IJzerman, Groothuis-Oudshoorn and Hummel 2011; Chen and Kocaoglu 2008; Siraj et al. 2013). This method, also known as One-at-a-time analysis, entails incrementally changing the numerical values of specific parameters and observing the corresponding changes in the model result. Only one parameter of interest is investigated for each sensitivity analysis run, hence the name one-at-a-time analysis. The procedure used to implement NIA for the developed decision model after obtaining its results for the case study was adopted from the literature (Barker and Zabinsky 2011; SHELL 2017; Rahman and Szabó 2021; Enyinda et al. 2022; Haag, Aubert and Lienert 2022). The weights of each of the five decision criteria were varied from 0% to 100% while distributing the remaining weight proportion to the other four criteria in proportion to their original weights, with the corresponding changes in the ranking of the decommissioning options recorded. The sensitivity for each decision criterion was then visualised with a graphical plot.

3.4.4. Machine Learning

Machine learning refers to the use of statistical and mathematical models to obtain a general understanding of data and to make predictions. It is the application and science of algorithms that make sense of data. This field of learning evolved in the latter part of the 20th century as an aspect of artificial intelligence involving self-learning algorithms that derive knowledge from data to make predictions (Raschka and Mirjalili 2019). Furthermore, use of machine learning for mathematical modelling is increasingly becoming popular due to abundance of data and advances in computing technology (Arasu, Seelan and Thamaraiselvan 2020; Chaudhary et al. 2021). A significant rise in the frequency of applying machine learning modelling within the petroleum industry has been observed over the past few years, driven by increasing data availability, computational power, and development of more advanced computational algorithms (Khan et al. 2022).

Machine learning is sub-divided into supervised and unsupervised learning. Unsupervised learning deals with unlabelled data or data of unknown structure and comprises techniques for exploring the structure of data to extract meaningful information without the guidance of a known outcome variable. Supervised learning, on the other hand, entails creating a model from labelled training data to understand underlying relationships between its parameters and making predictions about unseen or future data as shown in Figure 3.4. This is achieved through analysing a set of training examples (or data inputs) where the desired output signals (or labels) are already known.

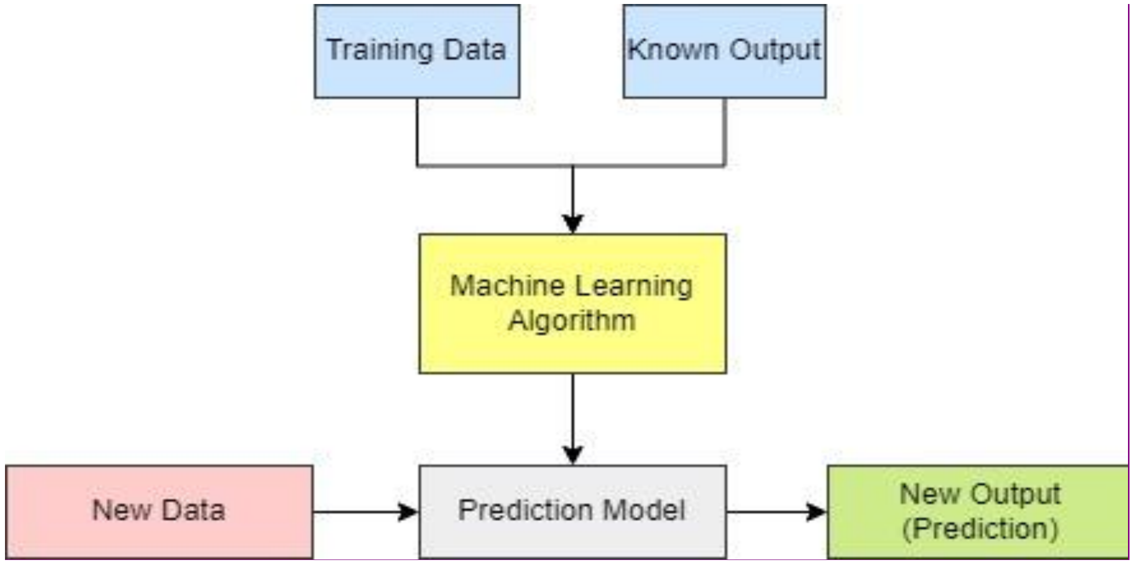


Figure 3.4: Workflow of supervised learning

Supervised learning tasks are further divided into tasks involving discrete class labels or classification, and tasks involving continuous values or regression. Nonetheless, there is some overlap between classification and regression tasks, and algorithms such as decision trees and artificial neural networks can be used for performing both task with little modifications. Regression analysis is the primary concern of this research because the nature of most historical data pertaining to decommissioning is continuous with real numerical values.

This technique was used in Chapter eight to create a mathematical model for predicting the costs of utilising different options for a decommissioning project based on historical data (objective 4).

3.4.5. Data Scaling

Data scaling is a technique used to mathematically transform quantitative values into magnitudes that are easily comparable. Through data scaling, quantitative historical data can be expressed in a relative format and made comparable to expert opinion, thus enabling the integration of both data sources as model input (ALHababi 2015). Therefore, this technique was applied to improve the quality of input data to the decision model developed in this research.

McCann et al. (2017) applied interpolation in scaling decommissioning data with the formula shown in Equation 3.8 for any given numerical parameter, X.

$$X_s = \frac{X_i - X_{worst}}{X_{best} - X_{worst}} \qquad (3.8)$$

Where, X_s is the scaled value, X_i is the original value of the parameter, X_{worst} is the value corresponding to the most undesirable state of the parameter, and X_{worst} is the value corresponding to the most desirable state of the parameter.

It can be inferred from Equation 3.8 that actual quantitative values of a parameter such as decommissioning cost are scalable to relative ratios, provided there is knowledge of the desired target scale and range of values for the target parameter. However, the equation suffers a limitation of only being able to scale values between the range of 0 to 1, therefore it cannot be used to reduce values into a range with a non-zero minimum value such as the input data for Likert scale which has a custom range of 1-9. Nevertheless, this drawback was overcome in this research by adopting the range transformation scaling method proposed in the literature (Akanbi, Amiri and Fazeldehkordi 2015; Liu et al. 2022) for performing linear transformation of numerical data.

Suppose that $OMIN_i$ and $OMAX_i$ are the minimum and the maximum values for a parameter, i. Range transformation scaling can be used to map a value V of i to V' in the range ($NMIN_i$, $NMAX_i$) by computing as shown in Equation 3.9.

$$V' = \frac{V - OMIN_i}{OMAX_i - OMIN_i}\ x\ (NMAX_i - NMIN_i) + NMIN_i \qquad (3.9)$$

To scale decommissioning cost values into their equivalent values in the Likert scale using Equation 3.9, $OMIN_i$ is replaced by the cost value of the most expensive decommissioning option and $OMAX_i$ becomes the cost value of the cheapest decommissioning option. Similarly, the new range ($NMIN_i$, $NMAX_i$) becomes (1,9) and V is replaced by the decommissioning cost value of interest.

Equation 3.9 is applied in this research for transforming the decommissioning costs for the case study platform into the Likert scale after their estimation in Chapter eight i.e., objective 4(c).

3.5. Summary

This chapter outlined the key elements of the research methodology in detail and explained the data analysis techniques applied throughout the research to achieve the aim and objectives stated in Chapter one. Firstly, the deductive approach was identified to be the most adequate for this research. This was followed by a presentation of the design adopted for this research. The research design comprises a synthesis of quantitative and qualitative research methods and utilises several data analysis techniques. Descriptions of the case study and survey research methods were also presented with the justification for their adoption in this research. Finally, the main data analysis techniques used in this research (i.e., AHP, Likert-AHP, sensitivity analysis, machine learning and data scaling) were discussed with regards to how they are applied and the justification for their adoption. The next chapter describes the logical development of a decision support model for decommissioning decision-making in line with the discussed methodology.

Chapter 4 : DEVELOPMENT OF DECOMMISSIONING DECISION MODEL

As highlighted in Chapter one, the complexity of decommissioning decision-making necessitates the requirement for a decision model to aid the process.

Following the review of existing approaches to decommissioning options evaluation in Chapter two, a decision model which harnesses the strengths and mitigates the weaknesses of these approaches was developed. This chapter discusses the development of the decommissioning decision model (DDM). It also highlights benefits that are envisaged to accrue to decommissioning decision-makers from a widespread adoption of the model.

4.1. General Framework

An overview of the decision model's underlying framework is illustrated in Figure 4.1. From start to finish, it comprises of four primary phases namely pre-assessment (process A-B), data gathering (process B-C), alternatives evaluation (process C-D) and results interpretation (process D-E). These phases have been carefully identified such that usage of the model will streamline the efforts and resources that a decision-maker expends in determining the optimal option for decommissioning an offshore platform.

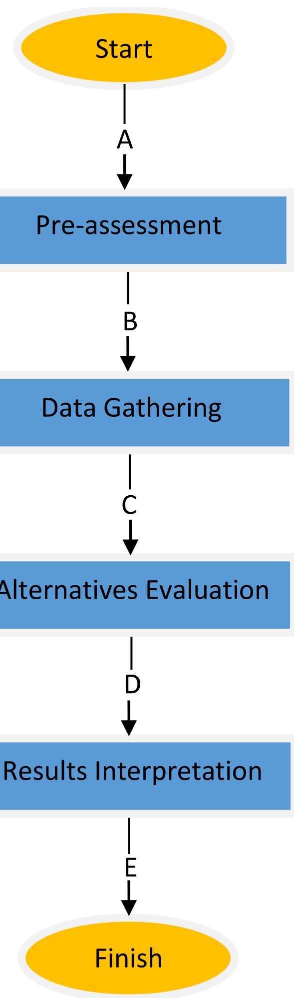


Figure 4.1: Framework of Decommissioning Decision Model

Further details of the activities which constitute each of the phases are subsequently provided.

4.2. Detailed Design

4.2.1. Phase I: Pre-Assessment

The first phase in using the decision model entails gaining an initial understanding of the offshore platform to be decommissioned, the options being considered for executing the project and the applicable legislative context. The activities that comprise this phase are shown in Figure 4.2.

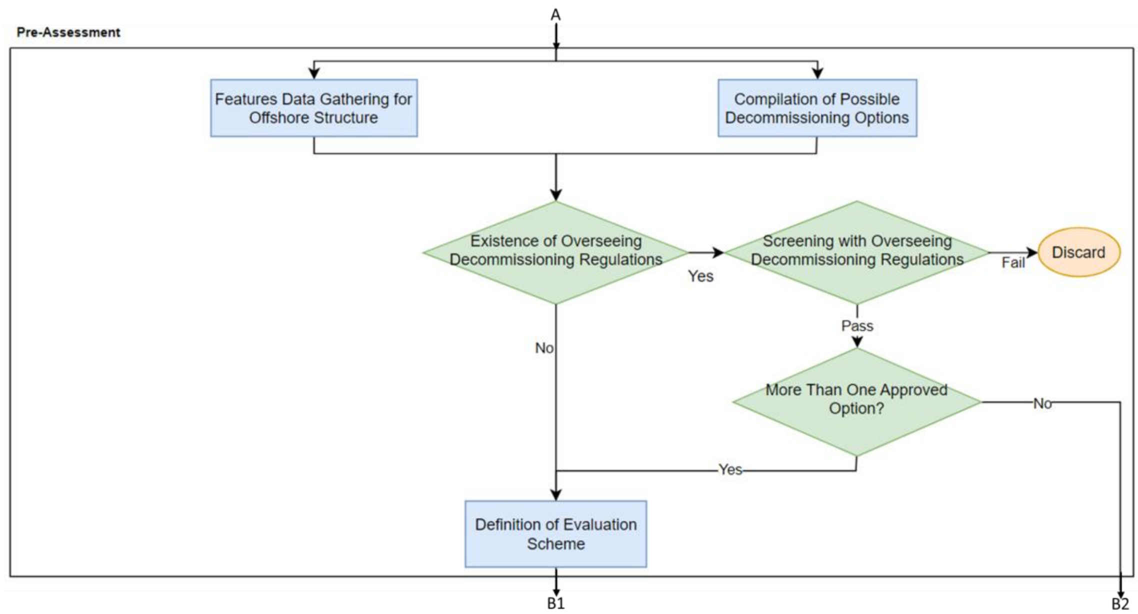


Figure 4.2: Pre-Assessment Phase of the DDM

Some key physical features of an offshore platform to be identified at this phase include the size and configuration of its components, water depth, structural integrity, and proximity to land. Also, the decision-maker is required to compile a list of all the possible decommissioning options for the project. This compilation is necessary because a wide range of decommissioning options are in existence (Chen 2017) and some of these might not be applicable to the platform due to its physical features. Next, the considered decommissioning options are screened against the regulations which oversee decommissioning in the location where the platform is situated, provided that these regulations exist. Decommissioning options not permitted by the overseeing regulations are discarded and only permitted options are progressed for further analysis. According to Andrawus, Steel and Watson (2009), establishing a screening medium which defines the minimum standard requirements is the first step in selecting an optimal decommissioning option. Government regulations were adjudged in this study to be a valid medium for screening decommissioning options because it encapsulates several measures that align with industry best practice (McCann et al. 2017). Screening of decommissioning options leads to efficiency savings to the decision-maker from timely discarding of options not approved by the overseeing legislation.

In the UK, regulatory screening of decommissioning options depends on the platform type and substructure weight as shown in Table 4.1, thus necessitating initial knowledge of the platform's physical features.

Table 4.1: Possible decommissioning options for offshore structures located in the UKCS (Adapted from BEIS 2018)

Platform Type	**Weight of Substructure (tons)**	**Complete Removal**	**Partial Removal**	**Leave in Place**	**Reuse**	**Disposal at Sea**
Fixed Steel	<10,000	Yes	No	No	Yes	No
	>10,000	Yes	Yes	No	Yes	No
Concrete-gravity	Any	Yes	Yes	Yes	Yes	No
Floating	Any	Yes	No	No	Yes	No
Subsea	Any	Yes	No	No	Yes	No

If only one decommissioning option passes the screening exercise, the option becomes selected as being optimal for the project. However, it is more likely that several options are approved, and these are then carried forward for further analysis.

Lastly, an evaluation scheme specifying the decision criteria to be used for evaluating the decommissioning options and the desired level of detail is defined in agreement with the project stakeholders. The evaluation scheme is also influenced by the decommissioning approach of the regulator which can either be a prescriptive or goal-setting approach.

4.2.2. Phase II: Data Gathering

The decision criteria that are relevant to decommissioning options evaluation for offshore platforms have been identified in Chapter two of this thesis. Figure 4.3 shows the main activities involved in the data gathering phase. These activities are directed towards ensuring that there is adequate information for the decision maker to evaluate the considered decommissioning options for the platform in terms of these decision criteria.

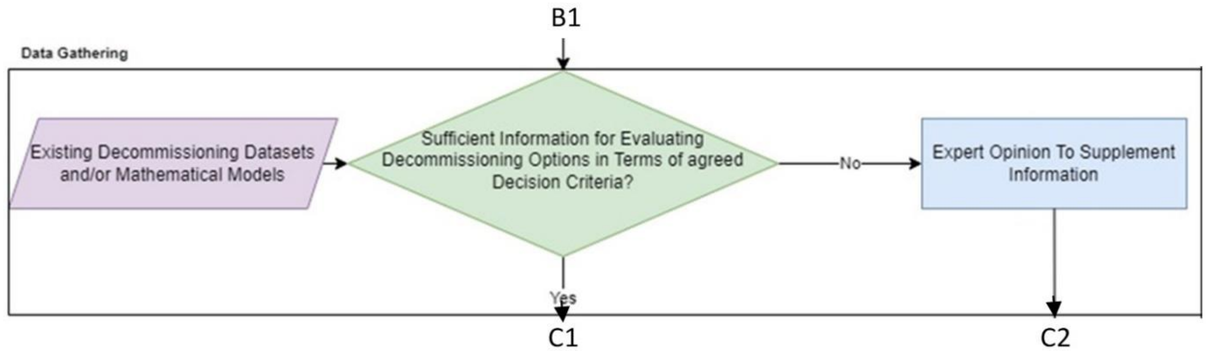


Figure 4.3: Data Gathering Phase of the DDM

Supporting studies such as Environmental Impact Assessment and Technical Feasibility studies are conventional sources of decommissioning information. Historical data from previous decommissioning projects is also a valuable source of quantitative data to support the decision-making, especially when collated into datasets or formulated into mathematical models (Eke et al 2021; Kaiser and Liu 2014, TSB 2016). In the absence of sufficient information, and for furnishing qualitative aspects of the decision criteria, inputs from decommissioning experts supplement the available information. This enables a thorough assessment of all aspects of the decommissioning options being considered for the platform vis a vis the decision criteria in the next phase.

4.2.3. Phase III: Alternatives Evaluation

Figure 4.4 illustrates the Alternatives Evaluation phase. This phase involves the logical evaluation of all considered decommissioning options for the platform with reference to the decision criteria i.e., safety, technical feasibility, environmental impact, cost, and public perception. This is achieved using an MCDA technique and information from the data gathering stage as input.

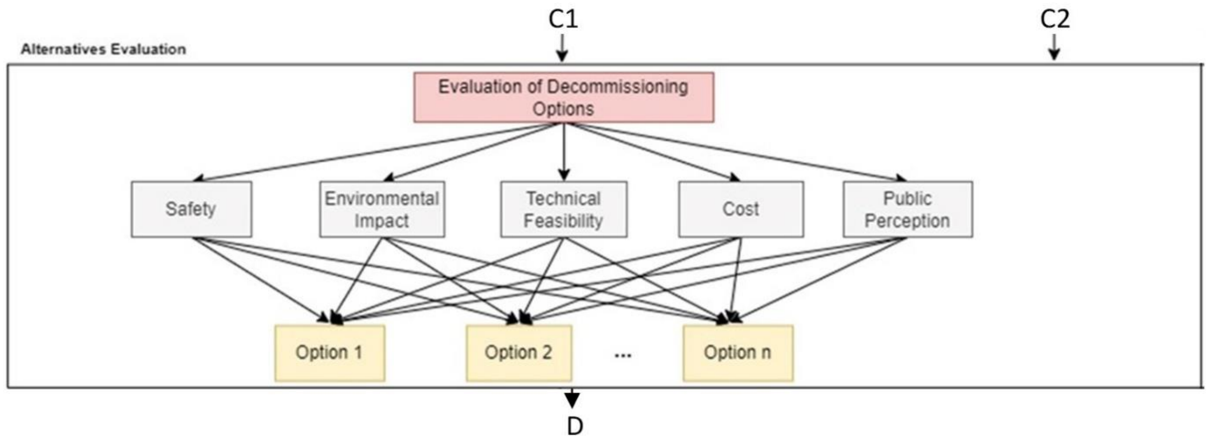


Figure 4.4: Alternatives Evaluation Phase of the DDM

The Analytic Hierarchy Process was determined in Chapter two of this thesis as the most suitable MCDA technique for this purpose due to its flexibility in handling different data types and well-documented record of use. Evaluating the decommissioning options with this technique minimises bias in expert opinion by enforcing logic in their judgement. Through AHP, weighted scores which comparatively quantify the expected performance of the decommissioning options are calculated for each option. These weighted scores are the key result from options evaluation phase and are progressed into the next phase.

4.2.4. Phase IV: Results Interpretation

In this phase of the model, the results obtained from evaluating the decommissioning options are further probed for insights and then put to final use by guiding the decision maker to identify the optimal option for the decommissioning project. The activities that constitute Results Interpretation are shown in Figure 4.5.

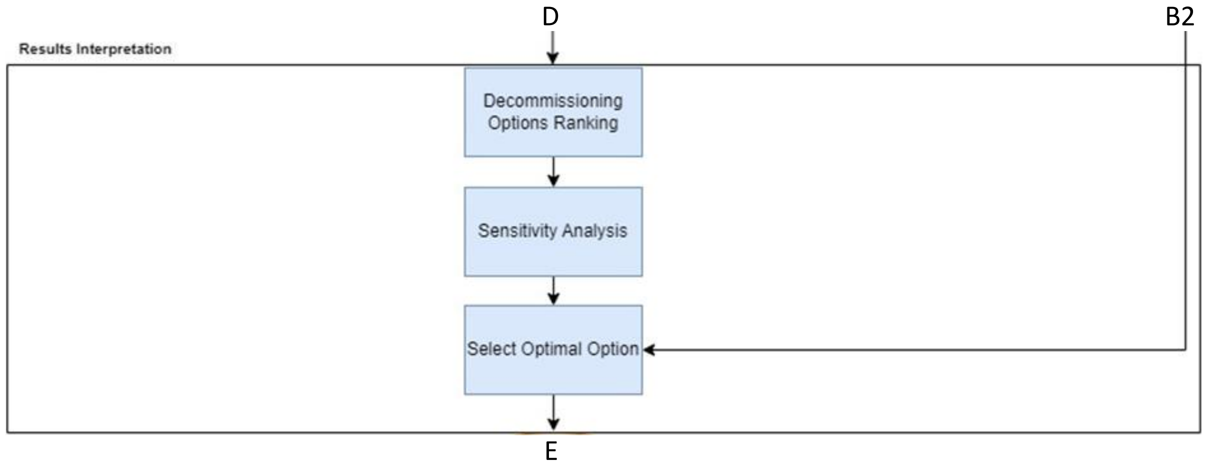


Figure 4.5: Results Interpretation Phase of the DDM

First, the options are ranked in ascending order of their weighted scores such that the option with the highest weighted score becomes the top-ranked option. For example, given three evaluated decommissioning options, the best option would be assigned a rank value of 1 and the worst option assigned a rank of value 3. Following this ranking, a sensitivity analysis is conducted to validate the input data used for the options evaluation and robustness of the obtained results. Ranking of the evaluated options and sensitivity analysis of results unlocks further insights into other scenarios. Thus, effectively capturing concerns of the decommissioning stakeholders to ensure an optimal course of action for the decommissioning project is identified. Finally, the decision-maker chooses the top-ranked decommissioning option as the optimal course of action, thus completing the decision-making process.

4.3. Decommissioning Decision Model

A comprehensive view of all phases of the model's framework along with the constituent activities and their interdependencies is shown in Figure 4.6 (Andrawus, Steel and Watson 2009). This integration of all the components into a logical structure represents the model developed in this research for optimising decommissioning decision-making, also called the decommissioning decision model.

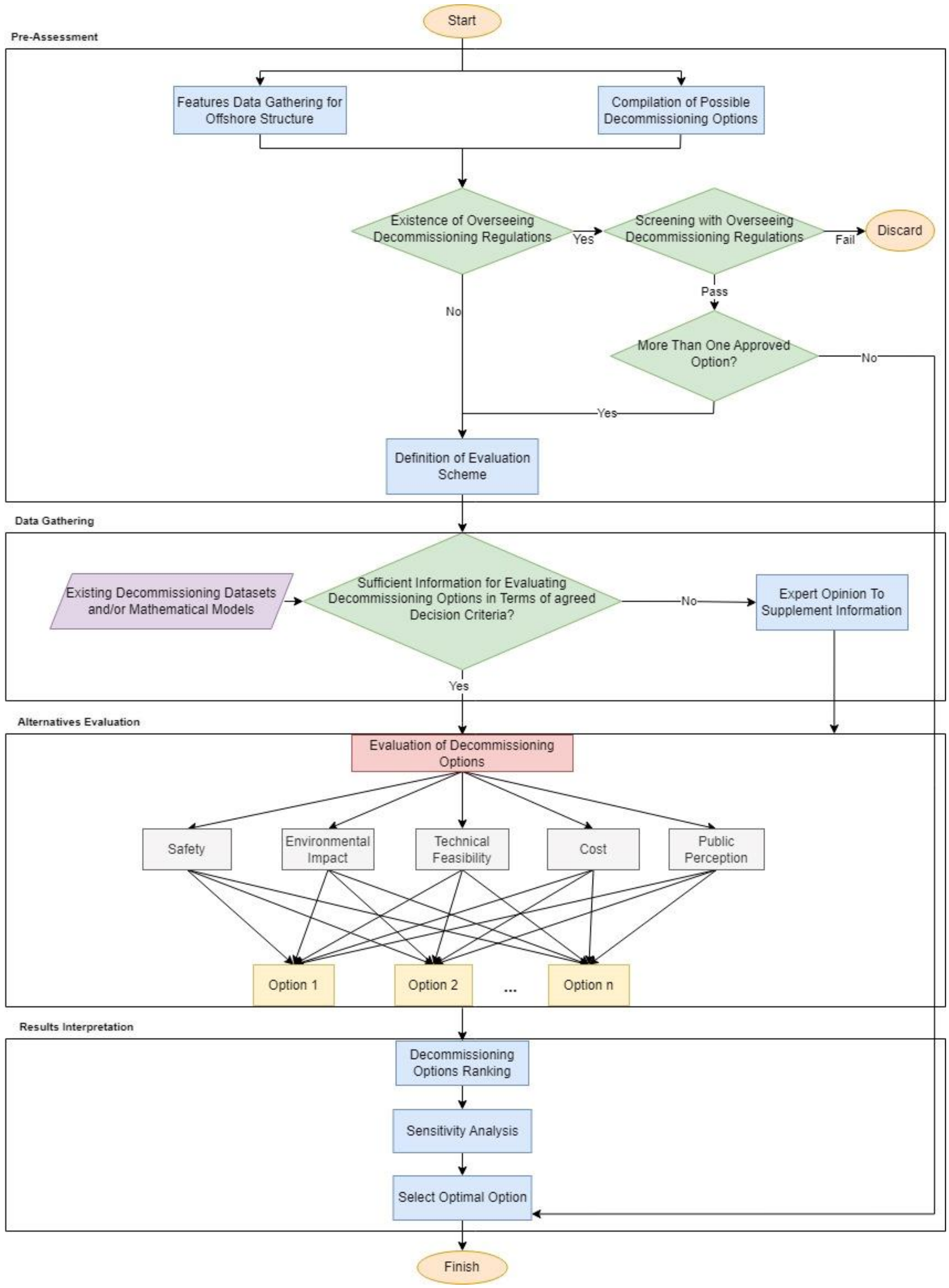


Figure 4.6: Decommissioning Decision Model

4.4. Benefits of the Decision Model

By leveraging on the strengths of previous works on decommissioning decision-making as identified in Chapter two, the DDM enables the decision-maker to unlock higher levels of efficiency and effectiveness in the decision-making process of option selection. Note that the model is a decision-support system and specifically serves the purpose of facilitating the decision-making process but does not assume the decision-taking role of its user (Minguella and Buj 2019).

The developed model is unique, and specific benefits are envisaged to accrue from its widespread adoption by the offshore decommissioning industry. Some of these benefits are subsequently outlined.

i. The model represents a systematic and auditable decision-making process. It minimizes human subjectivity in the decision-making process through the provision of structured guidance on steps for the decision-maker to follow. Traceability of the final decision to the information inputs will ensure accountability of the platform owner and clarity in communicating the justification for choosing a decommissioning option. Thus, reducing the likelihood of conflicts between stakeholders of the decommissioning project.

ii. The model provides a transparent, logical framework for structuring the decommissioning option selection process; it holistically synthesizes all the available information that is relevant to solving the decision-making problem. Its use will streamline efforts towards decommissioning data collection by enabling the platform owners to decipher what information is required for determining the optimal option for decommissioning their asset.

iii. It is highly flexible and makes use of data from diverse sources to facilitate an efficient decision-making process, irrespective of the desired level of detail. In addition to information from platform-specific studies, existing decommissioning datasets/models from historical data and expert opinion are harnessed by the model to ensure a proper evaluation of all the considered decommissioning options. Therefore, it can yield results even in circumstances when available data is minimal.

iv. The model is reusable and easily adaptable to different contexts and offshore areas. Consequently, its widespread adoption by the global decommissioning industry will enable direct comparison of the decommissioning decision-making approach of different countries to identify lapses and areas of improvement in current practices.

4.5. Summary

This chapter described the development of a structured decision model for determining the optimal option for decommissioning offshore platforms. The model harnesses the strengths of existing works in the domain and comprises of four phases, i.e., pre-assessment, data gathering, alternatives evaluation and results interpretation phase. Each of the model phases and their associated activities were discussed independently and then logically arranged to form the model. Finally, the envisaged benefits from adoption of the developed model by the oil and gas offshore decommissioning industry were discussed. These include minimisation of human subjectivity, streamlining of efforts, data flexibility, reusability, and adaptability. The next chapter introduces a case study platform for demonstrating the applicability of the developed decision model and discusses the results for evaluating decommissioning options for the case study.

Chapter 5 : MODEL APPLICATION TO A CASE STUDY PLATFORM AND PRESENTATION OF SURVEY RESULTS

As stated in section 3.2, demonstrating the decommissioning decision model's applicability with the case study research strategy involves using the model to determine the optimal option for decommissioning an offshore platform. Detailed description of the case study adopted for this purpose is presented in this chapter. An overview of the application of the decommissioning decision model to the case study is also outlined alongside key results from the survey of decommissioning experts conducted as part of this research.

5.1. Regional Context of Case Study

The case study is a theoretical fixed steel jacket-type platform situated in the California Pacific Outer Continental Shelf, USA. It is pertinent that a physical location be used as reference location for the case study platform. This is because the evaluation of decommissioning options is heavily influenced by this factor. The applicable regulation, weather and climate conditions, and public perception are all variable elements that are location-dependent (Fam et al. 2018; Tung 2020).

5.1.1. Decommissioning in California, USA

The USA offshore industry was birthed in the early years of the 20th century and since then has contributed immensely to the economic development of the state (Mount and Voskanian 2005). The country's major oil producing states are Louisiana, Texas, Alaska, and California (IOGP 2017). Currently there are twenty-three platforms in federal waters on the Pacific Outer Continental Shelf (POCS) of California in water depths ranging from 150 feet to nearly 1,200 feet. These are shown in Figure 5.1.

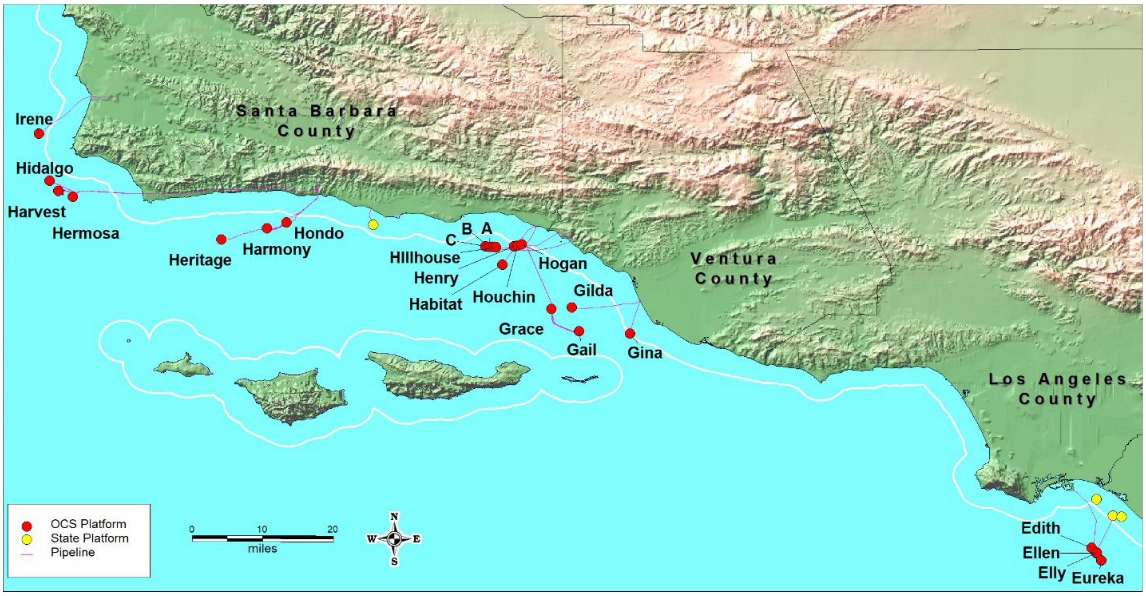


Figure 5.1: Geographical location of the offshore oil and gas facilities in california (MRS Environmental Inc 2019 p. 11)

As stipulated by federal regulations, decommissioning of these offshore assets is a compulsory requirement for operators when the structures are no longer useful for operations or when the leases expire (Bull and Love 2019). This process is overseen by the Bureau of Safety and Environmental Enforcement (BSEE) and Bureau of Ocean Energy Management (BOEM) to ensure that it is completed in a timely fashion without significant adverse environmental impact (Bressler and Bernstein 2015).

BOEM is responsible for managing the development of California's offshore energy and mineral resources such as oil and gas; wind, wave, and current energy; sand, gravel, and other minerals in an environmentally and economically responsible way. BSEE, on the other hand, is tasked with promoting safety, protecting the environment, and conserving offshore resources through vigorous regulatory oversight and enforcement. Although it is the prerogative of the asset operator to propose their decommissioning project and timeline to the government, the BSEE, BOEM, and other federal and state agencies with regulatory authorities are responsible for reviewing and approving the proposed decommissioning process and approach.

The regulations require removal of platforms to at least 15 feet below the mud line during their decommissioning. However, BSEE may grant a departure from this requirement and permit other decommissioning options such as partial removal, rigs-to-reef, and reuse or alternative use if certain conditions are met. In such situations, the platform operator must support their decommissioning application with the most up-to-date information regarding ecology, engineering, and socioeconomics of the planned project. Peradventure there are information gaps, the regulatory agencies may request that studies be conducted, or additional information be provided. Therefore, decommissioning project plans require careful and detailed preparation with scientific backing to gain regulatory approval (McCann, Henrion and Bernstein 2016).

Moreso, decommissioning is particularly important to California's populace. Decisions made during the decommissioning process, such as the choice of a decommissioning option, can have long-term effects on the surrounding marine resources and coastal areas and adversely impact the future use of the area (Meyer-Gutbrod et al. 2020). Execution of such projects can affect the water quality and result to disruptions for marine vessels, fishers, and other sea users (Mount and Voskanian 2005; Birchenough and Degraer 2020). There is also the potential for these to result to air pollution which will be harmful to people living in the location. Hence, the public closely observes decommissioning-related activities especially as many of the offshore facilities are close to land and highly visible. Focus groups that represent public interest are included in the decision-making process as stakeholders to ensure their opinions are considered and to consequently reduce the likelihood of a backlash from them (Bernstein et al. 2010; Wilkinson et al. 2016; Bull and Love 2019; IDWG 2019).

Owing to its precarious nature, offshore decommissioning in California has always been and will continue to be a fiercely debated topic (Mount and Voskanian 2005). Since the early 2000s, numerous studies and public workshops have been conducted in partnership with various academic institutions and agencies around decommissioning in the POCS, most of which are government funded. The topics covered by these studies include policies, economics, ecology, and recent experiences of decommissioning in other offshore locations. As a result, the literature is replete with platform ecology studies on fish, other biota, and cultural resources including shell mounds and studies regarding decommissioning technology and cost studies that are focused on the platforms in this location. Further information about these studies is outside the remit of this report but their compendium (BOEM and BSEE 2022) is publicly available for interested readers.

At present, all the major decommissioning projects offshore California have been in state waters where relatively smaller platforms are located while none of the platforms in the federal waters have been decommissioned (Byrd, Smith and Spease 2018). Thus, despite the offshore decommissioning experience, a challenge is envisaged with the future decommissioning of larger platforms and these projects are expected to be accompanied by unique removal problems because of the large weights and greater water depths involved (Twachtman Snyder & Byrd Incorporated 2000; Wilkinson et al. 2016). The largest of these platforms, Platform Harmony, sits in a water depth of 1,198 feet and weighs about 70,000 tons. To put this size in context, Figure 5.2 compares the platform to other megastructures including the empire state building which extends to 1,250 feet and the world record for a large platform decommissioning as at 2005 (Mount and Voskanian 2005).

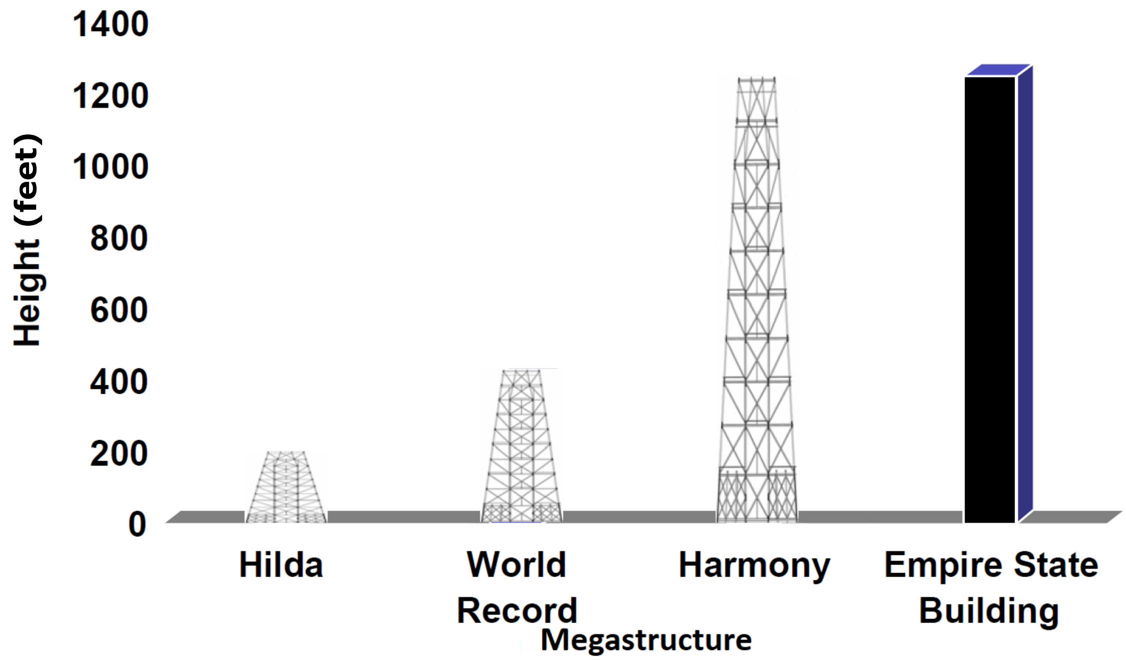


Figure 5.2: Size comparison of platform harmony with some of the world's megastructures (Adapted from Mount and Voskanian 2005)

There has already been a considerable amount of discourse surrounding the future of these sizeable platforms in federal waters, especially with the issue of determining the best option for their decommissioning (McGinnis 2001; Mount and Voskanian 2005; Gourvenec 2018). This is because there are a plethora of merits and demerits associated with using any option for decommissioning a platform and these issues are more significant for larger platforms (Schroeder and Love 2004; Fowler et al. 2014; Bernstein 2015). Also, the situation is becoming increasingly alarming as the timeline for decommissioning these platforms draws near (Bull and Love 2019; Kulovic 2021). Consequently, there is currently a pressing need in the POCS California for research endeavors which are focused on optimising offshore decommissioning such as this research. Moreso, the insights unlocked from these endeavors will, by extension, be beneficial to other offshore locations in the world with upcoming decommissioning projects such as the North Sea and Offshore Australia, Asia, and Africa (Sea and Enterprise 2014; Chandler et al. 2017; Fam et al. 2018; Bull and Love 2019; Martins et al. 2020).

5.2. Case Study Platform Description

A theoretical case study is used in this research instead of an actual platform. This is to avoid conflicts with platform operators who typically regard their platform information as confidential and safeguard it to avoid reputational damage and loss of competitive advantage to other operators (Lakhal, Khan and Islam 2009; Murray et al. 2018).

The decision to select a platform in the California region for the decommissioning study was informed by four primary reasons.

i. The US Offshore region has the highest number of decommissioning projects in the world and, along with the North Sea region, is most advanced in terms of the maturity of decommissioning technology and legislation (Offshore Engineer 2016; IOGP 2017). This rich experience of decommissioning makes the region ideal for this research.
ii. The decommissioning regulations in POCS California permit a wide range of decommissioning options including Toppling, and the few decommissioning projects that have been completed in this location witnessed strong opposition from stakeholder groups (Fowler et al. 2014).
iii. Secondary data about platforms in the location is easy to gather because California is the subject of several decommissioning-related studies reported in the literature (TSB 2000; Schroeder and Love 2004; Bernstein et al. 2010; Claisse et al. 2014; Kaiser and Liu 2014; Bressler and Bernstein 2015; Cantle and Bernstein 2015; McCann, Henrion and Bernstein 2016; TSB 2016a, 2016b; McCann et al. 2017).
iv. Decommissioning activity in the region is expected to increase and hence there is a real need for studies to support the successful planning and execution of these projects.

Since the case study platform is theoretical, its features were determined as the average of the features of the platforms in the POCS. Thus, ensuring that the platform is an adequate representation of the platforms in this location. Given this representative nature, it can be argued that the results from evaluating decommissioning options for the case study can be extended (to various degrees) to all the platforms in California POCS.

Details of the case study platform features are presented in Table 5.1 below. This was provided to the survey respondents as background information to ensure clarity and serve as a common reference for their judgments. Further details about generation of the data in Table 5.1 can be found in the appendix 1 of this thesis.

Table 5.1: Features of Case Study Platform

Platform Feature	**Description**
Location	Pacific Outer Continental Shelf, California
Platform type	Fixed steel jacket structure
End of economic life?	Yes
Water depth	406 feet (124 metres)
Topsides weight	4,715 tons
Substructure weight	11,137 tons
Jacket weight	8,774 tons
Piles weight	2,363 tons
Number of piles	16 (8-main and 8-skirt piles)
Conductors weight	3,926 tons
Distance from land	7 miles (11 kilometres)
Date of installation	1979 (43 years)

5.3. Decommissioning Options Considered for Case Study

Asides the substantial number of decommissioning options currently in existence, there is potential for new options to emerge as technology advances. Therefore, a limited number of decommissioning options for the case study platform have been selected for detailed analysis to streamline the efforts. Nevertheless, the findings from this analysis can be extended to other options.

The decommissioning options considered for the case study include leave in place (with topsides removed, wells plugged and abandoned, and the entire underwater portion of the platform is preserved as an artificial reef), complete removal (to 3 meters below the mudline) and three partial removal variants as shown in Figure 5.3. In all cases, the removed part of the platform is assumed to be disposed on land.

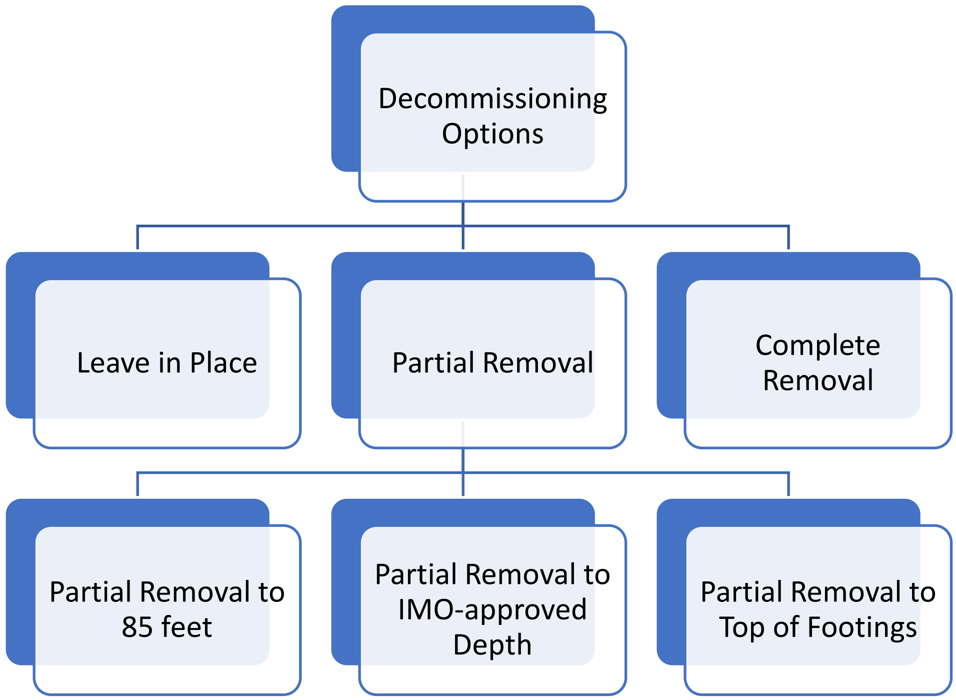


Figure 5.3: Decommissioning options considered for the case study

Leave in place decommissioning option has been included in this work due to its mention in several publications (Schroeder and Love 2004; SEPA 2018; Sommer et al. 2019; Meyer-Gutbrod et al. 2020). Also, with the wells plugged while the entire underwater portion of the platform is preserved, this option can potentially support alternative uses of platforms such as energy generation, aquaculture, prisons, meteorological stations, navigational landmark, hotels, gambling casinos, and water desalination plants (Schroeder and Love 2004; Bernstein 2015).

Further information about the decommissioning options is detailed in Eke et al. (2021) and OGUK (2017). However, a key differentiator between them is their depth of removal as shown in Figure 5.4 below.

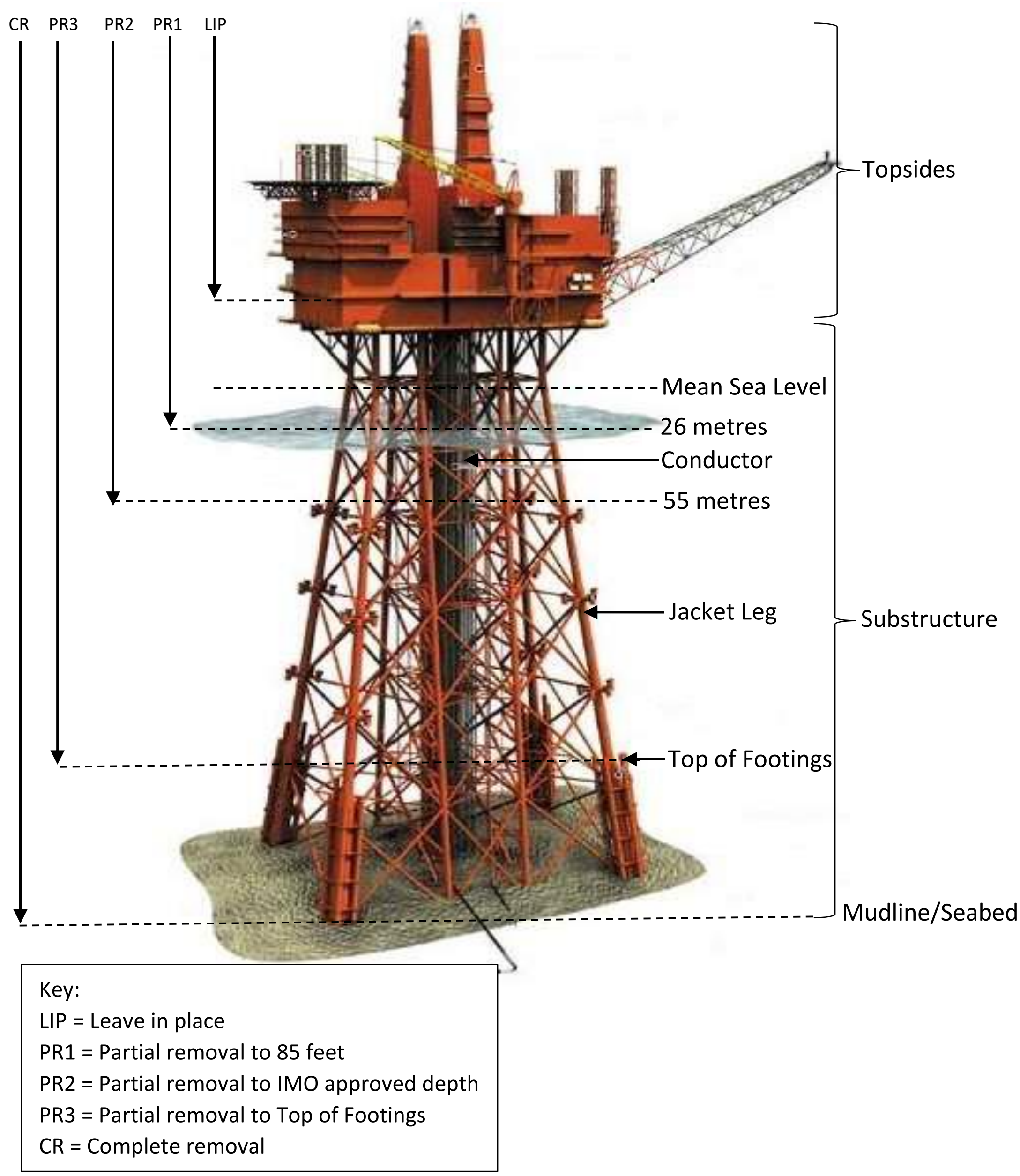


Figure 5.4: Illustration of decommissioning options considered for the case study

5.4. Application of Decommissioning Decision Model to Case Study

Using the developed decommissioning decision model to solve the problem of determining the optimal option for decommissioning the case study involves going through the phases of the model as described in Chapter four.

i. Pre-Assessment: The physical features of the case study platform are as shown in Table 5.1. The platform is a fixed-steel jacket structure situated in a water depth of 406 feet (124 metres) and located in the California POCS, USA. Its topsides and substructure weigh 4,715 tons and 11,137 tons, respectively. Also, after 43 years since its installation, the platform has come to the end of its economic life and set to be decommissioned. Regarding options screening, it is possible to use any of the five considered options for decommissioning the platform under the California decommissioning regulations, therefore no option is discarded at this phase.

   In terms of the evaluation scheme, the decision criteria identified in Chapter two (i.e., safety, technical feasibility, environmental impact, financial cost, and public perception) are adopted for evaluating the options. To facilitate detailed analysis, these criteria have been further expatiated by highlighting their sub-criteria as identified from the literature (Ekins, Vanner and Firebrace 2006; Andrawus, Steel and Watson 2009; Fowler et al. 2014; Oil and Gas UK (OGUK) 2015; Truchon et al. 2015; Cheng et al. 2017; McCann et al. 2017; Na et al. 2017; GOV.UK 2022). The sub-criteria for each criterion are described in Table 5.2, Table 5.3, Table 5.4, and Table 5.5, respectively.

Table 5.2: Safety Sub-Criteria

Safety sub-criteria	**Description**
Risk to onshore personnel	What is the likelihood and extent of harm from using the decommissioning option to personnel who receive the removed structure and handle its demolition and disposal?
Risk to offshore personnel	What is the likelihood and extent of harm from using the decommissioning option to personnel who execute the removals offshore?
Risk to other sea users	How much risks arise from using the decommissioning option to fishers, ships, and other sea users during and after the project completion?

Table 5.3: Environmental Impact Sub-Criteria

Environmental Impact sub-criteria	**Description**
Energy use	How much energy will be required to execute the decommissioning project with the option?
Emissions	What is the anticipated level of gas emissions to the atmosphere associated with the decommissioning project when using the option?
Waste generation	How much waste material will be required to be sent to landfill when the decommissioning option is used?
Impacts on fish stocks	What is the anticipated net effect of using the decommissioning option on fishes?
Loss of the developed community	To what extent will using the decommissioning option result to mortality of organisms and ecosystem supported by the platform, and its potential to act as an artificial reef?
Water pollution	What is the tendency of accidental spills or harmful discharges to the marine environment from vessels and other machinery on site when using the decommissioning option?
Physical disturbance	What is the expected level of vibrations, noise and disruptions from vessels and divers' activities in the platform vicinity when using the decommissioning option?
Legacy impacts	What is the likely extent of long-term detrimental impacts on the environment due to using the decommissioning option?

Table 5.4: Technical Feasibility Sub-Criteria

Technical Feasibility sub-criteria	Description
Probability of a major technical failure	What is the likelihood of occurrence of significant setbacks that make the project infeasible to complete as planned when using the decommissioning option?
Use of proven technology and equipment	Are technology and equipment for decommissioning a structure having the platform's features, such as water depth, location, and weight, with the option currently within the State of the Art?
Ease of recovery from excursion	How readily can the project get back on track in the event of unforeseen setbacks while using the option? Are the contingency measures well understood?
Logistic requirement	What is the proximity of the disposal site that will be required for the decommissioning project if it is executed with the option? Are the required vessels readily available?
Structural integrity	How much fatigue life does the platform have left, and is the structure strong enough to allow using the decommissioning option?

Table 5.5: Costs Sub-Criteria

Costs sub-criteria	Description
Financial expenditures	How much money is required to execute the decommissioning project using the option?
Revenue generation	Are there any financial incentives that will accrue to the platform owners from using the decommissioning option?
Post Decommissioning liability	How much monitoring costs and other future liabilities will remain for the platform owners after completing the project with the decommissioning option?

ii. Data Gathering: There is insufficient information for evaluating the decommissioning options in terms of the agreed decision criteria. Therefore, the evaluation will be heavily reliant on expert opinion from a survey of decommissioning practitioners. A decommissioning mathematical model will also feed into the options evaluation after its development in Chapter eight of this thesis.

iii. Alternatives Evaluation: Decommissioning options for the case study are evaluated using the AHP MCDA technique. The results are presented in the next section since decommissioning options evaluation comprises a major part of the survey analysis.

iv. Results Interpretation: Ranking of decommissioning options, sensitivity analysis of the results and selection of the optimal decommissioning option for the case study are also reported in the next section.

5.5. Presentation of Survey Results

The conducted survey was used to evaluate decommissioning options for the case study platform and investigate the relative relevance of platform features to decommissioning options selection. The exercise took a duration of four months in the period between January 2022-April 2022. A total of seventy-eight responses were received from decommissioning practitioners, all of which were complete and valid for inclusion into the analysis. The average time for completing the survey was fifteen minutes.

Summary data of the survey responses was generated from the JISC Online Survey tool and further data analysis was performed on these using Excel spreadsheets. Key findings from the analysis are subsequently presented.

5.5.1. Demographics

As previously mentioned, information about the defining characteristics of a population sample is important for creating the survey interpretation context and the first section of the survey focused on this. Graphical representation of the survey participants’ demographics is shown in Figure 5.5.

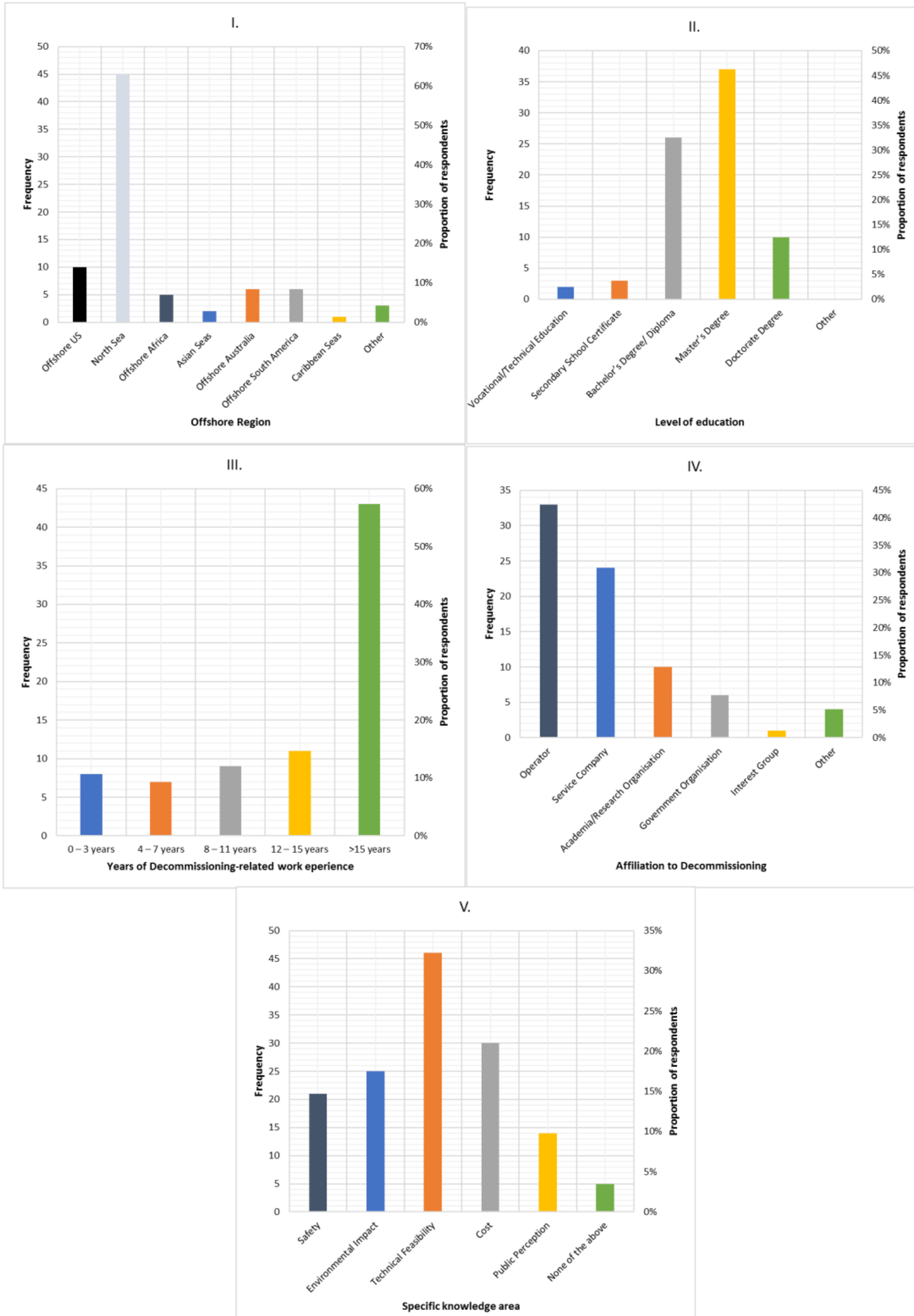


Figure 5.5: Demographics of survey participants showing the distribution of Offshore region, Level of Education, Work Experience, Affiliation to Decommissioning, and Specific Knowledge area.

Figure 5.5(I) shows that about 60% of the respondents are based in the North Sea. The predominance of North Sea-based respondents is expected as this is one of the leading regions of the world in terms of documented decommissioning activities. In second position is the 13% of respondents from Offshore USA (Louisiana, Texas, California, and Alaska), another region with a mature decommissioning industry. The least represented regions are the Caribbean Seas, and the Asian Seas, a region with a decommissioning industry still in the early stages (Tung and Otto 2019). Note that the "Other" group comprises respondents who operate in more than one region.

It can be observed from Figure 5.5(II) that the respondents are well educated as almost 94% of them are educated up to university level. Also, Figure 5.5(III) indicates that approximately 70% of the respondents have worked in the decommissioning industry for over 12 years. This indicates that the survey, to a reasonable extent, adequately reflects the opinion of subject matter experts. With respect to their affiliation to the decommissioning industry, Figure 5.5(IV) shows that about 40% of the respondents are affiliated to operating companies with an additional 31% from service companies. Respondents from these two groups are likely to have rich practical knowledge of offshore decommissioning from their experience of carrying out these projects. However, only one respondent was from an interest group. This is a concern because interest groups are strongly influential stakeholders in decommissioning projects (Fowler et al. 2014, 2020). The respondents in the "Other" group are respectively a Retired Decom Project Leader, a Trade Association member, and an individual whose job role involved working as a Contractor, Operator and Consultancy.

Lastly, Figure 5.5(V) indicates that about half of the respondents are most knowledgeable in the aspect of technical feasibility. Additionally, most respondents considered themselves to be knowledgeable in multiple aspects of offshore decommissioning. This outcome is an accurate reflection of the interdisciplinary and multifaceted nature of the decommissioning industry (Ahiaga-Dagbui et al. 2017; Invernizzi et al. 2020).

5.5.2. Decommissioning Options Evaluation for Case Study

The AHP-Likert technique was applied using the survey data to evaluate decommissioning options for the theoretical case study platform based on the five decision criteria. All calculations required for this analysis were performed on Excel Spreadsheets with the aid of AHP equations as described in section 3.4.1 of this thesis. Only the key results are presented here. Further information about the calculations is included in appendix 3.

5.5.2.1. Hierarchy Structure for the Case Study

The problem hierarchy structure for selecting the best decommissioning option to be used for decommissioning the case study combines all the key elements of the decision-making problem into a single structure (Figure 5.6).

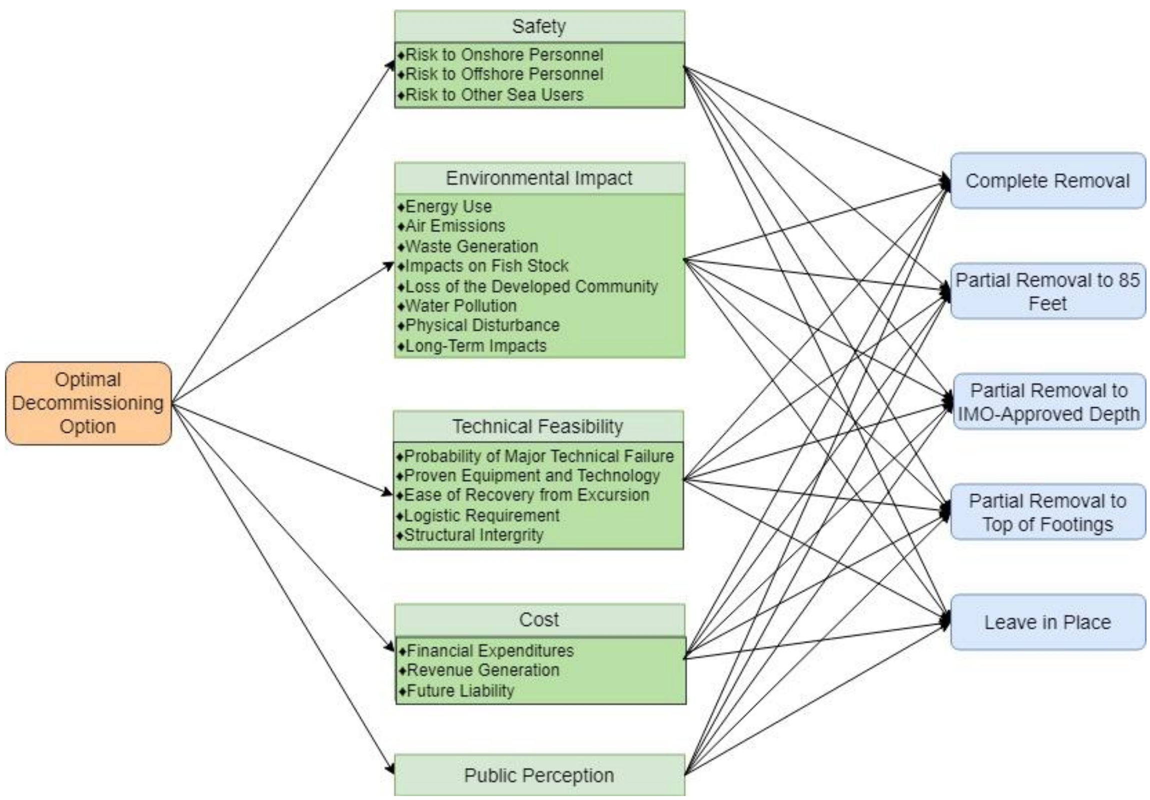


Figure 5.6: Hierarchy structure of decommissioning option selection for the case study

The goal of the analysis is to determine the optimal decommissioning option for the case study. To achieve this, the five considered options are individually evaluated with reference to safety, environmental impact, technical feasibility, cost, and public perception.

As stated in Chapter three, the number of required judgements when using the Likert-AHP approach is n but using the traditional AHP approach requires $(n^2 - n)/2$ judgements, where n is the number of elements being compared with each other at the same hierarchy level. Therefore, it can be inferred from Figure 5.6 that the number of elements to be compared is 5 for both the criteria weighting level and the decommissioning options scoring level. This implies that a total of 60 judgments would have been required for evaluating the decommissioning options using the traditional AHP (i.e., 10 judgements for criteria weighting and 50 judgments for decommissioning options scoring across the five criteria). However, using the Likert-AHP approach only required 30 judgements (i.e., 5 judgments for criteria weighting and 25 judgments for decommissioning options scoring across the five criteria), implying a 60% efficiency savings in time taken to complete the analysis.

5.5.2.2. Criteria Weighting

The consensus of the values that the survey respondents assigned to the relative importance of safety, environmental impact, technical feasibility, cost, and public perception respectively are shown in Table 5.6. This is calculated as the geometric mean of individual responses with respect to the decision criterion of interest.

Table 5.6: Aggregation of survey responses for criteria weighting

How would you rank the importance of the following criteria in determining the optimal decommissioning option for the Case Study Platform?	**Safety**	**Environmental Impact**	**Technical Feasibility**	**Cost**	**Public Perception**
Geometric Mean of responses ($GM = \sqrt[n]{\prod_{i=1}^{n} x_i}$)	8.267	6.802	6.464	4.986	4.225

The pairwise comparison matrix generated from the aggregated data above is shown in Table 5.7. Consistency checks verified that this matrix was perfectly consistent, hence there was no need for any remedial calculations to correct inconsistencies in the judgements (Benítez et al. 2011; Na et al. 2017).

Table 5.7: Judgement Matrix for Criteria Weighting

Decision Criteria	Safety	Environmental Impact	Technical Feasibility	Cost	Public Perception	Priority (%)
Safety	1.0000	1.2155	1.2789	1.6580	1.9567	27%
Environmental Impact	0.8227	1.0000	1.0522	1.3641	1.6098	22%
Technical Feasibility	0.7819	0.9504	1.0000	1.2964	1.5300	21%
Cost	0.6031	0.7331	0.7714	1.0000	1.1801	16%
Public Perception	0.5111	0.6212	0.6536	0.8474	1.0000	14%

The priority column in Table 5.7 shows the criteria weights of importance, calculated from equations 3.3 and 3.4 as shown in appendix 3.

From these priorities, it is deduced that the respondents judged safety to have the highest importance when assessing decommissioning options for the case study. This is followed by environmental impact while public perception has the least importance to the assessment. A graphical depiction of the criteria priorities is shown in Figure 5.7.

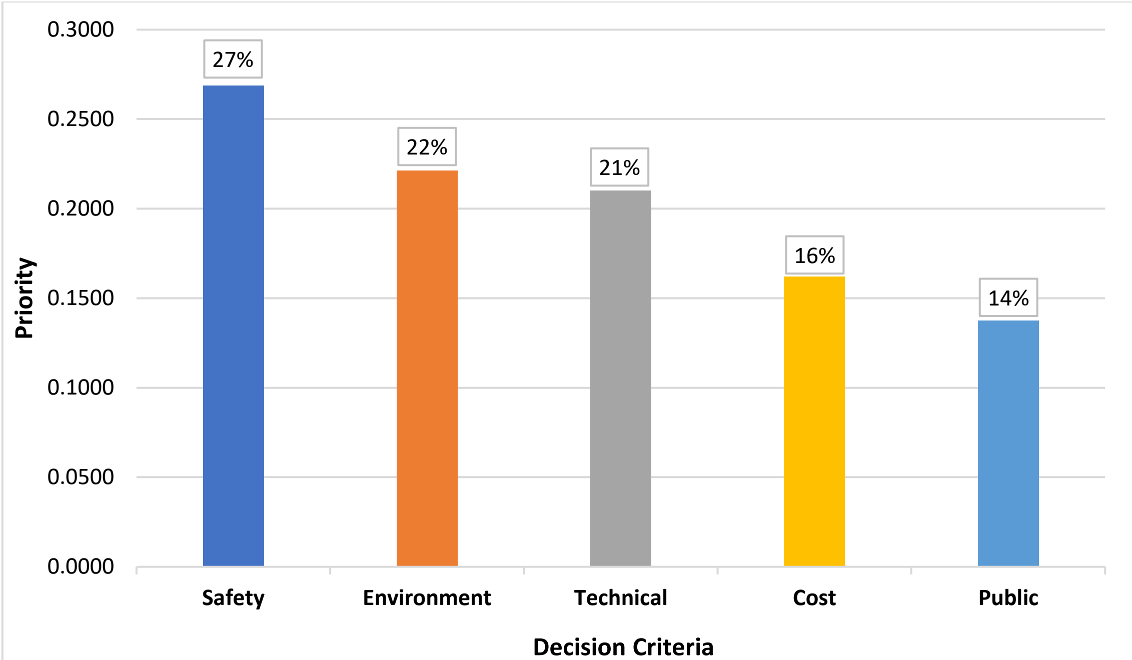


Figure 5.7: Calculated weights of importance for the decision criteria

It is important to note that the above result only captures the preferences of the respondents about the criteria in a strictly comparative or relative sense. Also, the results obtained from using the AHP-Likert procedure to determine the relative weights of the sub-criteria are shown in appendix 4.

5.5.2.3. Decommissioning Options Scoring

After establishing the weights of all decision criteria and sub-criteria, the expected performance of decommissioning options for the case study platform with respect to each criterion was determined as priority values or scores as graphically presented in Figure 5.8. These values were calculated from synthesising the survey responses and the step-by-step procedure is shown in appendix 3.

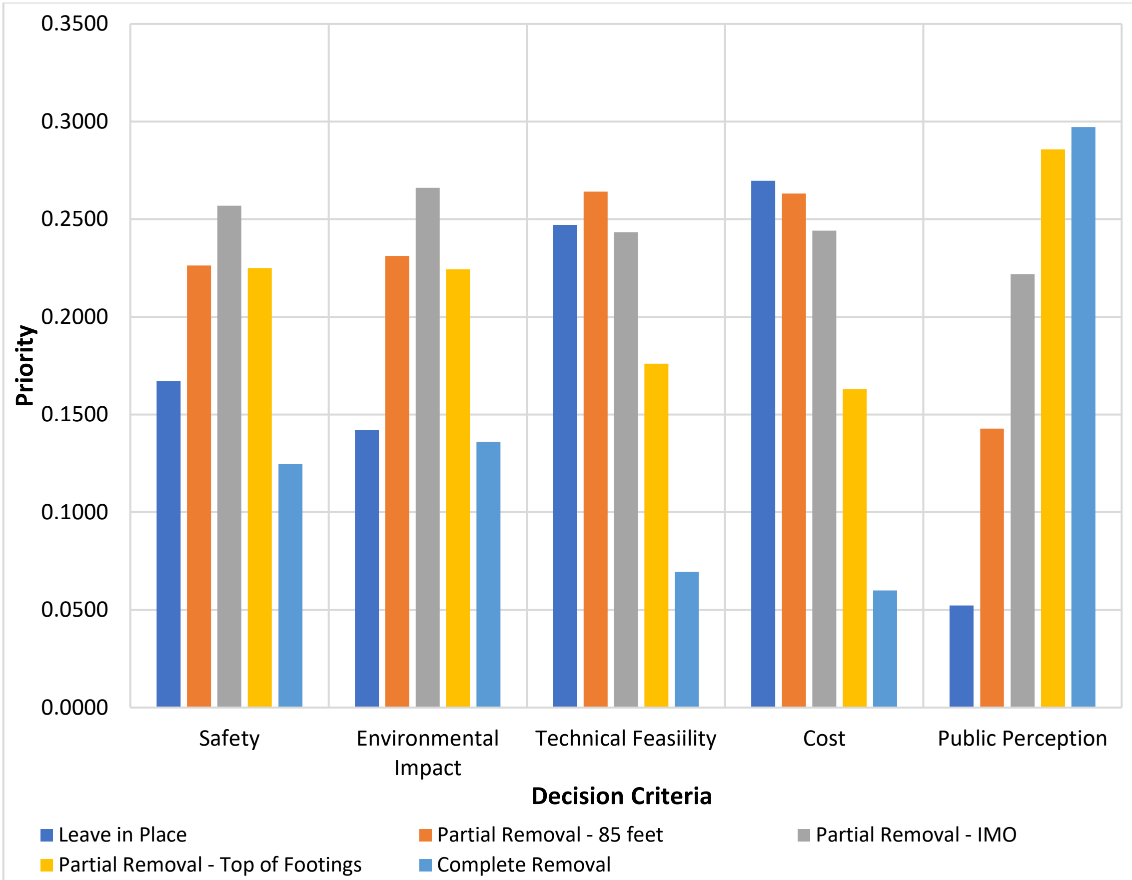


Figure 5.8: Decommissioning options performance scores for safety, environmental impact, technical feasibility, cost, and public perception criterion

The performance scores (or priorities) for Leave in Place, Partial Removal to 85 feet, IMO approved depth, and Top of Footings respectively, and Complete Removal decommissioning options with reference to the five decision criteria are shown in Figure 5.8.

With regards to the Safety criterion, Figure 5.8 shows that the partial removal options are more suitable for decommissioning the case study than Leave in Place and Complete Removal options when evaluated exclusively in terms of Safety. Partial removal to IMO-approved depth emerged as the most preferred (i.e., safest) decommissioning option for the project whereas Complete Removal was adjudged to be the least suitable option based on safety alone.

The performance scores for the decommissioning options with reference to the Environmental Impact criterion follow a similar ranking order to the results obtained from safety-based scoring of the options. Figure 5.8 indicates that the partial removal options were adjudged to be more suitable for decommissioning the case study when the options are evaluated exclusively in terms of Environmental Impact. Again, partial removal to IMO-approved depth emerged as the most preferred (i.e., environmentally friendly) decommissioning option for the project while Complete Removal is the least preferred option.

Considering only the Technical Feasibility criterion, it is observed from Figure 5.8 that decommissioning the case study by Partial Removal to 85 feet is the most preferred (i.e., technically feasible) option while Complete Removal was adjudged to be the least preferred option for the project. Additionally, the Leave in Place decommissioning option scored highly for this criterion, emerging as the second most preferred option.

With reference to the Cost criterion alone, it is observed from Figure 5.8 that the most preferred option (i.e., cheapest) for decommissioning the case study is the Leave in Place decommissioning option. Conversely, the least preferred option for the project with reference to Cost alone was determined to be the Complete Removal option. These results are identical to those obtained when evaluating the decommissioning options based on technical feasibility with the only difference being that the Partial Removal to 85 feet option emerged as the best option in that scenario.

Finally, with regards to only the Public Perception criterion, it is inferred from Figure 5.8 that the most preferred (i.e., publicly acceptable) decommissioning option for the case study platform is the Complete Removal option and leaving the platform in place is the least preferred course of action. Note that the ranking of decommissioning options based on the Public Perception criterion was based on the perspective of decommissioning practitioners and therefore might contain an element of bias as compared to the actual reality.

5.5.2.4. Aggregation of Results and Ranking of Decommissioning Options for the Case Study

The final stage of the AHP analysis entailed combining the obtained criteria weights and option scores to obtain weighted scores as shown in Table 5.8. The results suggest that Partial removal to IMO-approved depth is the best option for decommissioning the case study platform while Complete Removal is the worst option for the project. Furthermore, the partial removal options were preferred over other decommissioning options and leaving the platform in place was deemed to be a better alternative than its complete removal.

Table 5.8: Evaluation of Decommissioning Options for Case Study Platform

Decision Criteria	**Weight of Importance**
Safety	27%
Environmental Impact	22%
Technical Feasibility	21%
Cost	16%
Public Perception	14%
Total	**100.00%**

Decommissioning Option / **Decision Criteria**	**Leave in Place**		**Partial Removal to 85ft**		**Partial Removal to IMO Depth**		**Partial Removal to Top of Footings**		**Complete Removal**	
	Option score	Weighted score	Option score	Weighted score	Option score	Weighted score	Option score	Weighted score	Option score	Weighted score
Safety	0.167	**0.045**	0.226	**0.061**	0.257	**0.069**	0.225	**0.060**	0.125	**0.033**
Environmental Impact	0.142	**0.031**	0.231	**0.051**	0.266	**0.059**	0.224	**0.050**	0.136	**0.030**
Technical Feasibility	0.247	**0.052**	0.264	**0.056**	0.243	**0.051**	0.176	**0.037**	0.069	**0.015**
Cost	0.270	**0.044**	0.263	**0.043**	0.244	**0.040**	0.163	**0.026**	0.060	**0.010**
Public Perception	0.052	**0.007**	0.143	**0.020**	0.222	**0.030**	0.286	**0.039**	0.297	**0.041**
Weighted Score (Sum)	0.1793		0.2299		0.2492		0.2129		0.1287	
Rank	4		2		1		3		5	

5.5.2.5. Results Interpretation

Sensitivity analysis of the results obtained for the case study are detailed in Chapter six as one of the validation techniques used in this research.

Furthermore, deeper insights can be extracted from the information in Table 6.4 for communicating the options evaluation results to project stakeholders. A summary of the performance of decommissioning options with respect to each decision criteria as denoted by their weighted scores is graphically illustrated with the spider chart in Figure 5.9. This clearly highlights that the most preferred decommissioning option for the case study was also adjudged to be the most preferred option in terms of Safety and Environmental Impact respectively, and by a significant margin. Hence, its emergence as the best option is an expected outcome considering that these were the highest-weighted criteria. Moreover, the figure clearly depicts the complex interaction between the decision criteria for each decommissioning option.

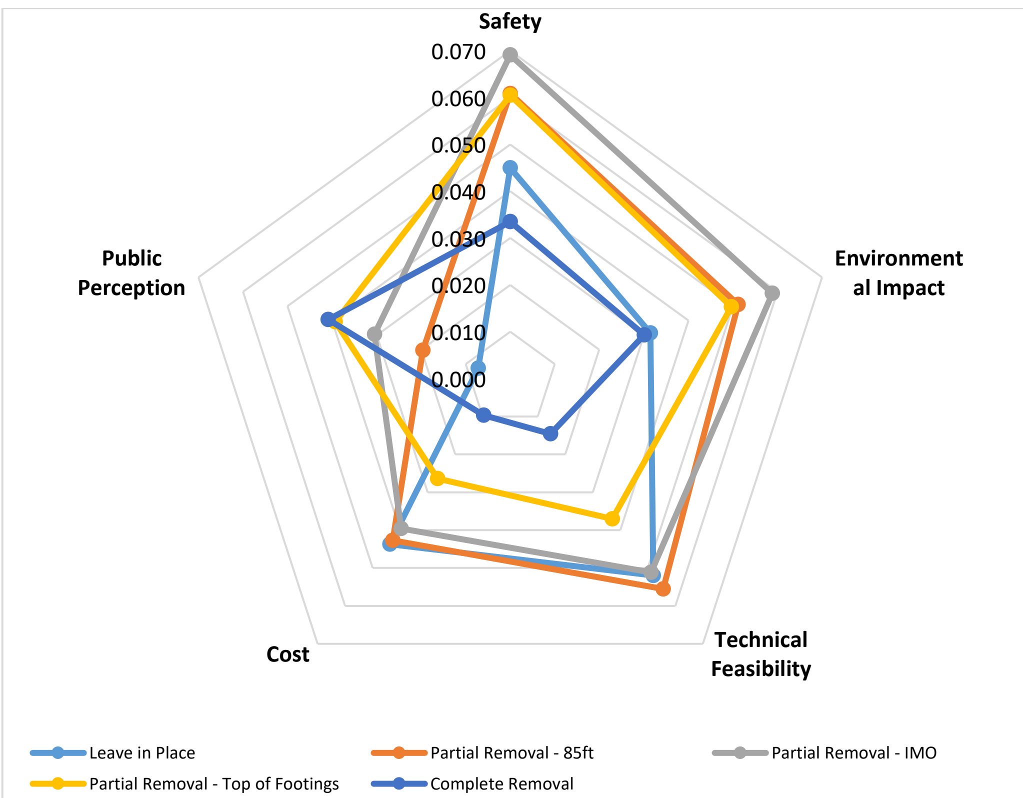


Figure 5.9: Performance of decommissioning options with respect to each decision criteria for the case study.

Lastly, recall that it had been established in Chapter three that the key result from AHP which feeds into decision-making is the final ranking of alternatives. This ranking for the options that have been evaluated for decommissioning the case study platform is shown in Figure 5.10. The figure indicates that Partial Removal to IMO-approved depth is the optimal option for decommissioning the case study. This proposition is deemed to be correct because the approach taken to arrive at it holistically considered the safety, environmental impact, technical feasibility, cost, and public perception implications of all considered options.

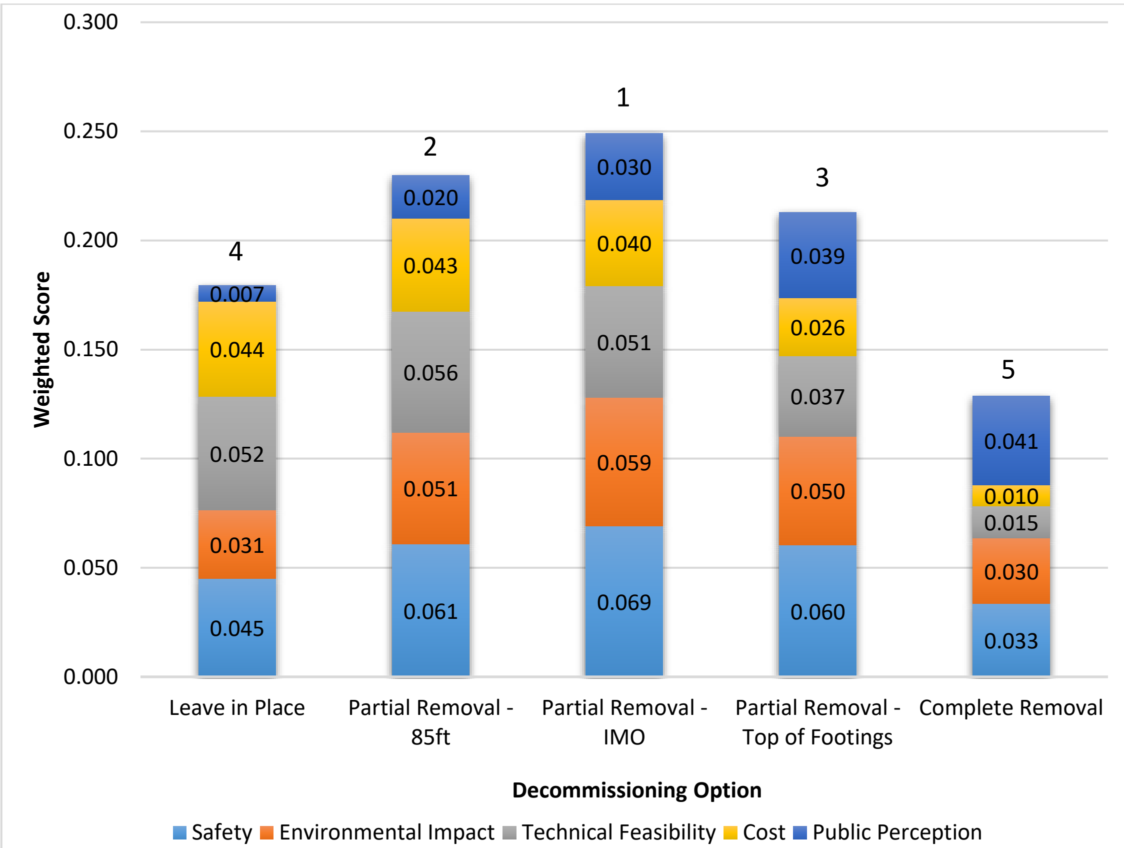


Figure 5.10: Ranking of decommissioning options for the case study

Despite the unavailability of quantitative data, the information obtained from analysing the expert opinion (survey input data) have been used to evaluate the five decommissioning options for the case study platform. Through this evaluation, the decommissioning decision model has been demonstrated to ensure a clear and auditable decision-making process. It has also facilitated structured analysis of expert opinion to arrive at a logical conclusion.

Moreso, the effectiveness of the Likert-AHP technique has been demonstrated by using it to determine the optimal option for decommissioning the case study with 60% less judgements than would have been required when using the traditional AHP process for the same analysis.

5.5.3. Additional Information

5.5.3.1. Suggested Additional Sub-Criteria

The survey participants generally agreed that the sub-criteria detailed in the survey covered the key aspects of all the decision criteria. However, several additional sub-criteria were suggested for inclusion, and these are shown in Table 5.9 for completeness. Note that the actual survey responses have been edited for conciseness and to avoid duplication.

Table 5.9: Additional Sub-Criteria Suggested by Survey Participants

Decision Criteria	**Suggested Additional Sub-Criteria**
Safety	Removal methodology - single-lift or multiple-lift (reverse of installation).
	Risk to onshore public
Environmental Impact	Impact on SACS, SPAs, MPAs, and Sensitive Areas (protected habitats, species, marine mammals)/ Loss of protected habitat for breeding nurseries.
	Risk of dissemination of invasive species
Technical Feasibility	Original design and installation method of structure
	Vulnerability to weather conditions
Cost	Cost certainty/Risk of cost overrun
Public Perception	Stakeholder concerns
	Corporate Reputation
	Cultural heritage preservation

5.5.3.2. Platform Features Prioritisation

Analysis of survey responses to the platform features prioritisation question yielded results which suggest that Substructure Weight, Water Depth, and

Platform Age are the platform features adjudged to have the highest relevance to options selection. These features should be prioritised when gathering information about the structure to be decommissioned as they have high relevance to the decision-making process of selecting the optimal decommissioning option for an offshore platform. The ranking of platform features based on their relevance to decommissioning decision-making as indicated by their weighted geometric mean (WGM) is shown in Table 5.10. Note that despite being the platform feature with the highest WGM, a decision was made to exclude Jacket Weight from the top-ranking features because it already constitutes a part of the substructure weight. The substructure of a fixed-steel jacket type platform comprises of the platform's jacket and piles.

Table 5.10: Ranking of Platform Features with respect to Relevance to Decommissioning Decision-making

Platform Feature	**WGM of Relevance**	**Ranking**	**Reason for Exclusion**
Topsides weight	5.22	5	-
Substructure weight*	6.04	2	-
Water depth*	5.95	3	-
Platform age*	5.80	4	-
Distance from land	3.58	8	-
Jacket weight	6.49	1	Main component of substructure
Piles weight	4.24	6	-
Number of piles	3.72	7	-

*Top-ranking platform feature

5.6. Summary

This chapter described the case study used in this research to demonstrate the applicability of the decommissioning decision model. The case study platform is a large fixed-steel jacket structure situated in California. With regards to applying the model to this platform, the chapter presented an overview and discussed the results from the pre-assessment and data gathering phases of the model process. Further details of the outcomes of the DDM's alternatives evaluation and results interpretation phases were subsequently presented. Key findings from the decommissioning survey used to facilitate implementation of the developed decision model on a case study, and the main results from analysing the survey response data were then discussed. It was observed from the demographics of the survey participants that these individuals were appreciably knowledgeable of offshore decommissioning. The chapter also investigated the relationship between a platform's physical features and its decommissioning options selection with substructure weight, water depth, and platform age emerging as the platform features that most influence the choice of a suitable decommissioning option.

The next chapter discusses validation of the decommissioning decision model and the results obtained from its application to the case study platform.

Chapter 6 : VALIDATION OF THE DEVELOPED DECOMMISSIONING DECISION MODEL

The applicability of the decommissioning decision model (DDM) was demonstrated in Chapter five by using the model to evaluate decommissioning options for a case study platform with survey input data. A decommissioning project is an expensive venture and using an ill-designed tool to support decision-making while executing such a project is risky. Therefore, the developed model, and the results of its application to the case study are validated in this chapter as a quality check on the tool and its applicability.

This chapter discusses the steps that have been taken in this research to investigate the validity of the DDM, namely sensitivity analysis, comparison of model results with existing information, and validation with expert opinion. The key outcomes from using these validation techniques are also presented.

6.1. Background to Model Validation

Validation is the systematic assessment of a model to determine the soundness of its underlying structure and accuracy of its predictions based on comparison with established knowledge. Model validation, within the decommissioning context, is primarily aimed at strengthening the confidence of stakeholders in using the model (Oberkampf and Trucano 2008). However, it also provides feedback to the model developers that can be used to further improve the decision model and optimise its use (Dowding and Rutherford 2003).

Kerr and Goethel (2014) classified model validation into two types namely, conceptual validation and operational validation. Conceptual validation involves examination of a model’s theory and underlying assumptions to determine whether these are justifiable. This contrasts with operational validation which focuses on examining the agreement between results outputted by the model and existing information. Operational validation may be challenging when the tool is dealing with a scenario that extends beyond the realm of observed conditions or addressing a problem by incorporating new, currently immeasurable, or previously unassessed variables. Nevertheless, conceptual validation is always feasible.

Furthermore, several techniques exist for validating a decision model either subjectively or objectively, and these techniques can be used either exclusively or in some form of combination. A validation technique is regarded as objective if it incorporates any form of mathematical or statistical procedure, otherwise, the technique is subjective. Nevertheless, Gass (1983) pointed out that all model validation techniques entail the gathering of evidence pertaining to the credibility and applicability of the model by an interested party.

Validation techniques, as identified from the literature (Kennedy et al. 2005; Akadiri 2011) include Comparison to Similar Studies, Events Validity, Face Validity (Expert opinion), Fixed Values validity, Historical Data validity, Sensitivity Analysis, Predictive Validation, Turing Tests, and Tracing. Others include Animation, Internal Validity, Degenerate Tests, and Extreme Condition Tests. However, the end product of using any of these techniques is to justify confidence in the model and its applicability.

6.2. Adopted Techniques for Validating the Decommissioning Decision Model

The technique for validating a model primarily depends on the nature of the problem being addressed, functionalities of the model and nature of its results or predicted outcomes. In this regard, the developed model is an MCDA-centric approach for supporting decommissioning decision-making and its aspects that require validation are the input data, logical structure, and generated results.

As stated in Chapter three of this thesis, sensitivity analysis is appropriate for validating the model's input data. Additionally, considering the validation techniques identified in the preceding section, expert opinion and comparison to similar studies were deemed to be adequate for validating the model's structure and results, respectively.

6.3. Validation of Model Input Data by Sensitivity Analysis

Sensitivity analysis of the results from applying the model to the case study provided insights into the validity of the input data. In addition to acting as a sense-check to the survey data, the analysis is required when using the DDM. The outcomes from the sensitivity analysis are subsequently presented.

In Figures 6.1-6.6, as the criterion weight increases from left to right along the horizontal axis of the figure, the preference for each decommissioning option (represented by its weighted score) follows linear paths which are referred to as the sensitivity lines. Also, a black solid vertical line indicates the current weight of the criterion being investigated, and the weighted scores of the decommissioning options at any point determines their relative rankings. Lastly, a dotted vertical red line indicates the weight of the criterion for which a change in the ranking order, or rank reversal, occurs.

6.3.1. Sensitivity to Safety Criterion

The relationship between decommissioning options ranking for the case study and the weight of the safety criterion is graphically illustrated in Figure 6.1.

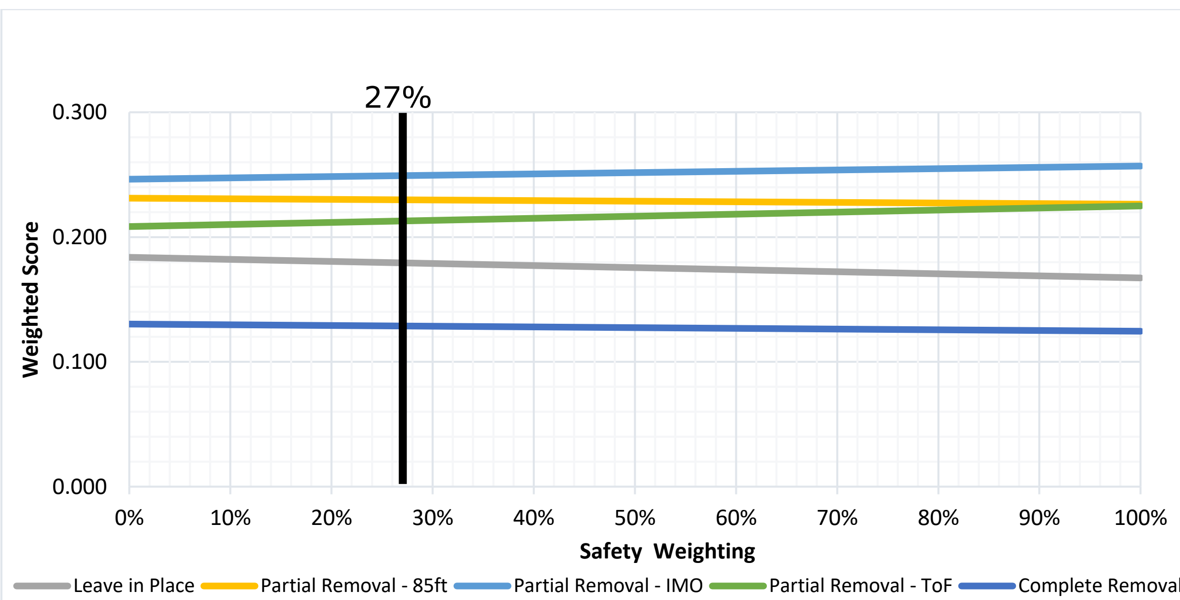


Figure 6.1: Sensitivity of decommissioning options ranking to the weight of safety criterion

Figure 6.1 shows that the current weight of the safety criterion is 27% and Partial Removal to IMO Depth is the most preferred decommissioning option. The plot further suggests that the decommissioning options ranking is insensitive to the variations in the weight of safety criterion. There is no crossover of the sensitivity lines for the full range of criterion weighting i.e., the preferred option does not change irrespective of the variations in safety criterion weighting.

6.3.2. Sensitivity to Environmental Impact Criterion

The relationship between decommissioning options ranking for the case study and the weight of the environmental impact criterion is graphically illustrated in Figure 6.2.

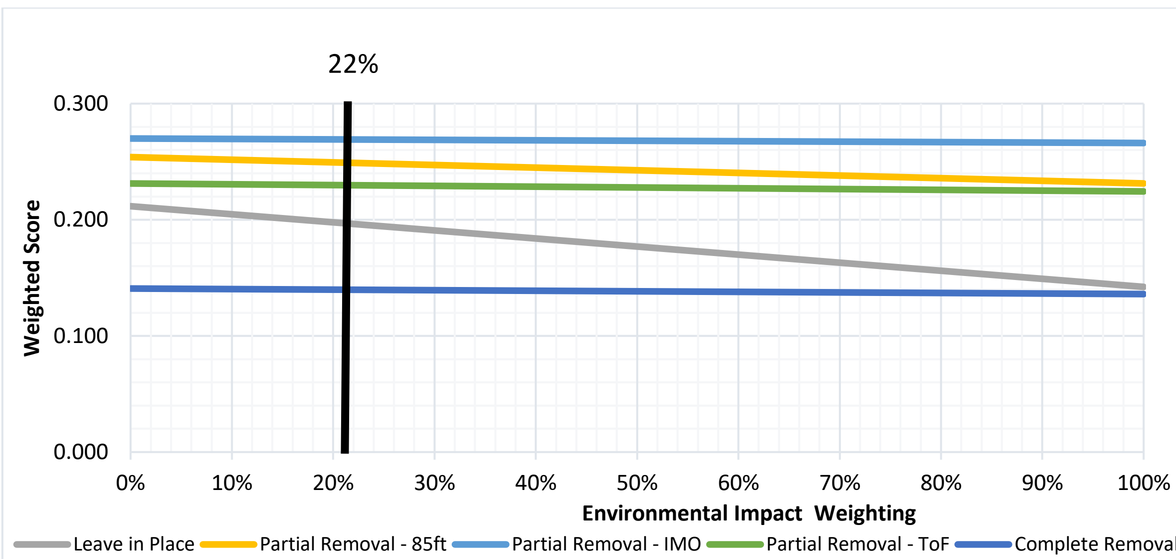


Figure 6.2: Sensitivity of decommissioning options ranking to the weight of environmental impact criterion

It can be inferred from Figure 6.2 that the current weight of the environmental impact criterion is 22%. Like the sensitivity results for safety criterion, the plot suggests that the decommissioning options ranking is insensitive to environmental impact criterion. There is no crossover of the sensitivity lines for the entire range of criterion weighting i.e., the preferred option does not change despite the weight variations.

6.3.3. Sensitivity to Technical Feasibility Criterion

Figure 6.3 shows a graphical illustration of the relationship between decommissioning options ranking for the case study and the weight of the technical feasibility criterion. It can be inferred from the figure that the current weight of the technical feasibility criterion is 21%.

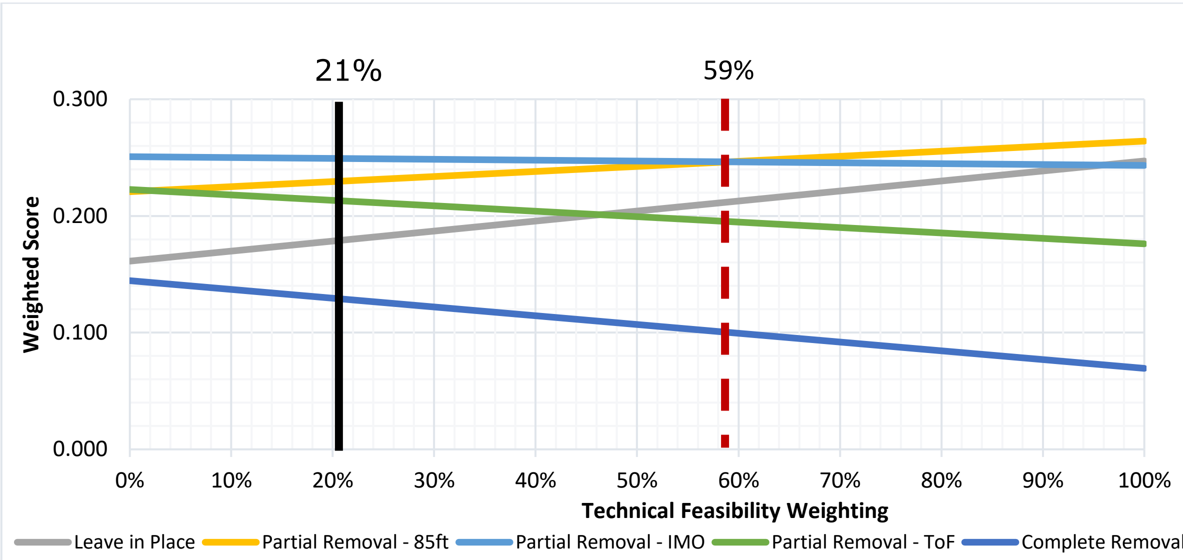


Figure 6.3: Sensitivity of decommissioning options ranking to the weight of technical feasibility criterion

Moreover, the crossover of the sensitivity lines when the weight of the technical feasibility criterion is 59% suggests that the decommissioning options ranking is affected by changes in the weight apportioned to the criterion. The rank reversal results to Partial Removal to 85 feet replacing Partial Removal to IMO depth as the most preferred option. Therefore, a 38% increase in the weight of the technical feasibility criterion results to rank reversal. The observed trend in Figure 6.3 can be interpreted to suggest that technical feasibility is related to the quantity of removed platform material. Options that require removal of a larger proportion of platform matter would be more technically challenging in terms of the associated cutting and lifting, and size of equipment. This also explains the upward trajectory of the weighted scores of options involving lower quantities of removed materials (i.e., Leave in Place and Partial Removal to 85 Feet) as the weight of Technical Feasibility criterion increases from zero to 100%.

6.3.4. Sensitivity to Cost Criterion

The relationship between decommissioning options ranking for the case study and the weight of the cost criterion is graphically illustrated in Figure 6.4. It can be inferred from the figure that the current weight of the cost criterion is 16%.

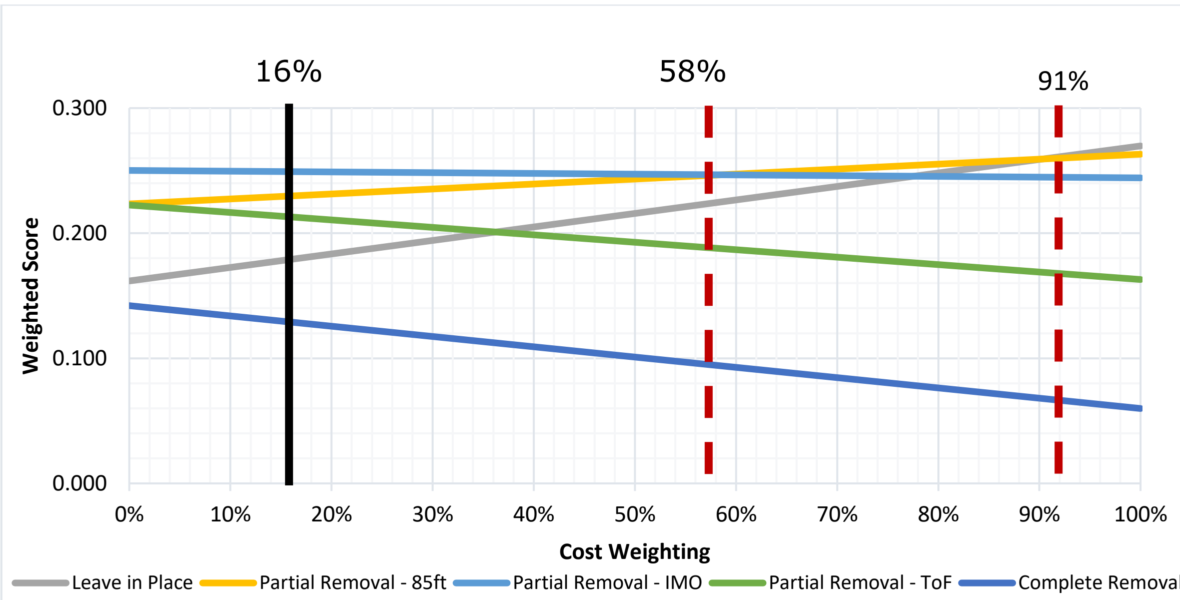


Figure 6.4: Sensitivity of decommissioning options ranking to the weight of cost criterion

Figure 6.4 suggests that the decommissioning options ranking is affected by changes in the weight apportioned to the cost criterion. Crossover of the sensitivity lines occurs when the weights of the cost criterion are 58% and 91% respectively. Partial Removal to 85 feet is observed to replace Partial Removal to IMO depth as the most preferred option at the first crossover while Leave in Place becomes the most preferred option at the second crossover. Therefore, increases of 42% and 75% in the original weight of the cost criterion results to rank reversal.

The observed trend indicates that cost, just like technical feasibility, is proportional to the quantity of removed material. Removal of more platform matter translates to higher costs owing to longer work duration, increased vessel costs, and increased complexity of removal operations. In addition, Leave in Place is the cheapest decommissioning option so preferring this option when cost is apportioned almost all the criteria weight (greater than 91%) is logical.

6.3.5. Sensitivity to Public Perception Criterion

The relationship between decommissioning options ranking for the case study and the weight of the public perception criterion is graphically depicted in Figure 6.5. From the figure, it can be observed that the current weight of the public perception criterion is 14%.

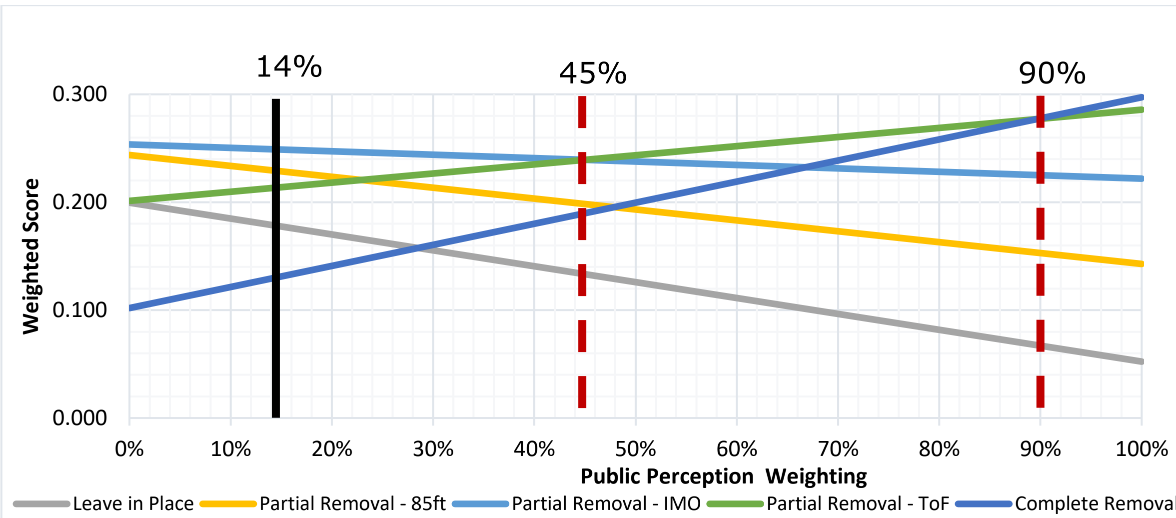


Figure 6.5: Sensitivity of options ranking to the weight of public perception criterion

Further, the plot suggests that the decommissioning options ranking is affected by changes in the weight apportioned to public perception criterion. Crossovers of the sensitivity lines occur when the weights of the public perception criterion are 45% and 90% respectively. Partial Removal to Top of Footings is observed to replace Partial Removal to IMO depth as the most preferred decommissioning option at the first crossover while Complete Removal becomes the most preferred option at the second crossover. Therefore, increases of 31% and 76% in the weight of the cost criterion results to rank reversal.

A plausible explanation for this outcome is that the public are likely to be averse to the leaving behind of any platform materials during decommissioning (Ekins, Vanner and Firebrace 2006; Fowler et al. 2014). Hence, their expected preference is for the entire platform to be removed. This is observable from the upward trajectory of the overall priorities of options involving higher quantities of removed materials (i.e., Complete Removal and Partial Removal to Top of Footings) as the public perception criterion weight increases towards 100%. Consequently, Complete Removal becomes the preferred decommissioning option for the case study when public perception is apportioned up to 90% of the criteria weight.

6.3.6. Summary of Sensitivity Analysis Results

The sensitivity analysis results for all the decision criteria are summarised in Table 6.1. The decommissioning options ranking is unaffected by changes in the weights of Safety and Environmental Impact criteria but can be altered by the changing the weights of Technical Feasibility, Cost and Public Perception.

Table 6.1: Sensitivity Analysis of Model Results to Decision Criteria

Decision Criteria	**Sensitivity of Model Results**	**Absolute Minimum Change in Current Weight before Rank Reversal**
Safety	Insensitive	-
Environmental Impact	Insensitive	-
Technical Feasibility	Low sensitivity*	38%
Cost	Low sensitivity	42%
Public Perception	Low sensitivity	31%

*Sensitivity is low if the minimum change in criterion weight for rank reversal exceeds 5% (see Section 3.4.3 for more information)

Nonetheless, Table 6.1 suggests that the model results are stable because for all five decision criteria, the minimum change required to cause a change in the decommissioning options ranking exceeds 5%. This implies that there is no need for further review and validation of the initial weights and options ranking results are deemed to be stable. Thus, the sensitivity analysis results indicate that the input data used for evaluating decommissioning options for the case study platform is valid, and the survey responses are sensible.

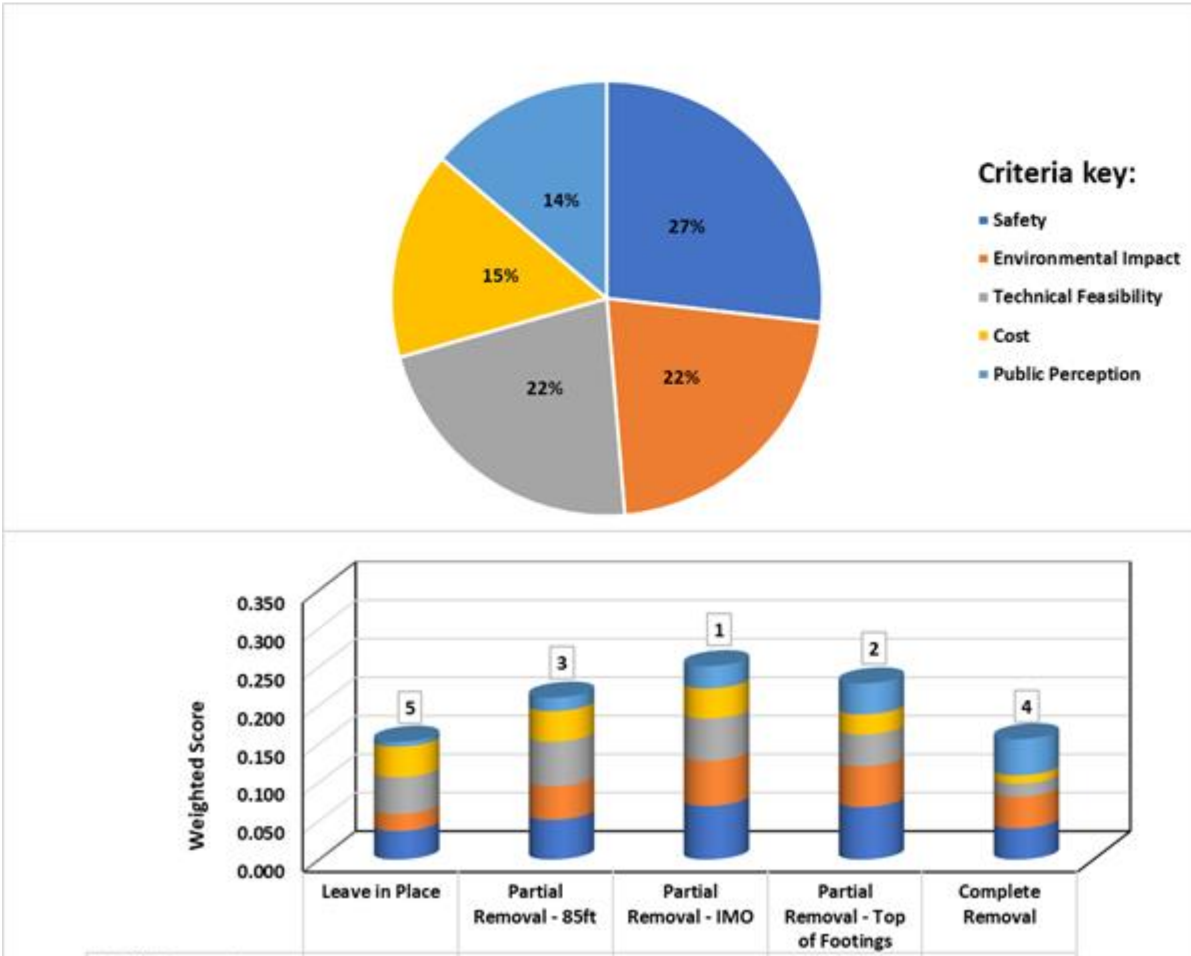
6.4. Validation of DDM Results by Comparison to Similar Studies in Literature

The decision criteria weighting and decommissioning options rankings that have been obtained from using the developed model to evaluate the case study platform are the two model results that require validation. These two aspects of the case study results are compared to the outcomes from similar studies in the literature to assess their accuracy and validity.

Additionally, differences exist across different offshore regions in stakeholders' perception of decommissioning, especially in attitude to leaving any part of the offshore structure in the sea (O'Connor et al. 2004; Palandro and Aziz 2018; Sommer et al. 2019; Tan et al. 2021; Trevisanut 2020). Stakeholders in the USA offshore region are more tolerant to leaving portions of offshore structures during decommissioning and this is understood to encourage biodiversity in the marine environment (Claisse et al. 2015; Bull and Love 2019; Meyer-Gutbrod et al. 2020). In contrast, stakeholders in the North Sea region often posit that offshore structures should be completely removed from the marine environment during decommissioning as encapsulated by the precautionary principle (BEIS 2018; Fowler et al. 2020). These differences in opinions have persisted despite the recent push for a shift in the North Sea stance on leaving some parts of offshore structures in-situ during decommissioning (Jørgensen 2012; Sommer et al. 2019; van Elden et al. 2019). Therefore, to facilitate comparison of results from the present study with information from literature, it is necessary to first identify differences in survey input data due to the location of the respondents and compartmentalise their contributions to the model results.

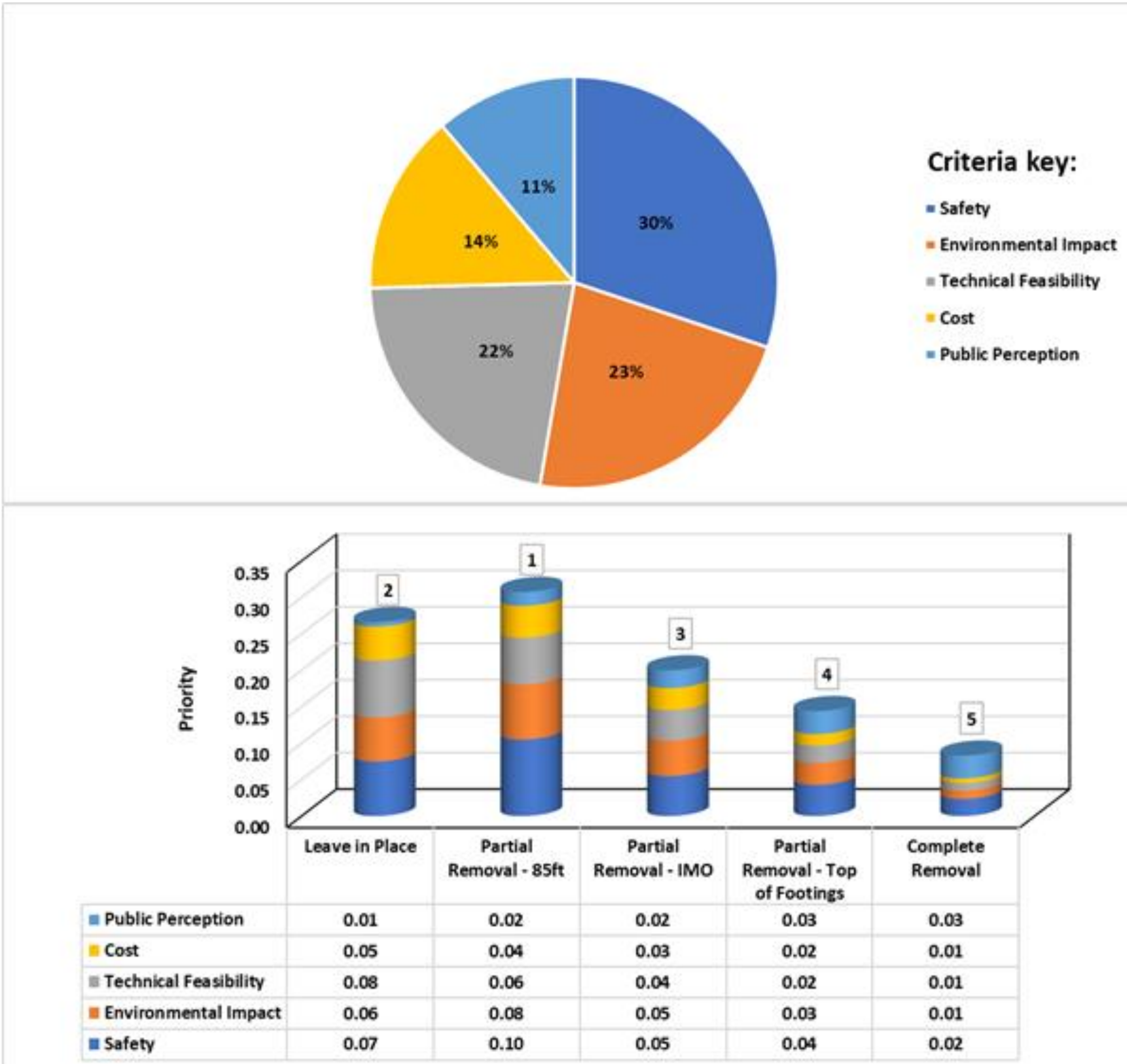
To achieve this, the survey participants were divided into three groups (North Sea, Offshore USA, and Others) based on their location to represent the major offshore regions in the world. The "Others" group comprises Offshore Africa, Asian Seas, Offshore Australia, Caribbean Seas, and Offshore South America.

Figure 6.6, Figure 6.7, and Figure 6.8 show the variations in the model results for the case study with reference to these offshore regions.



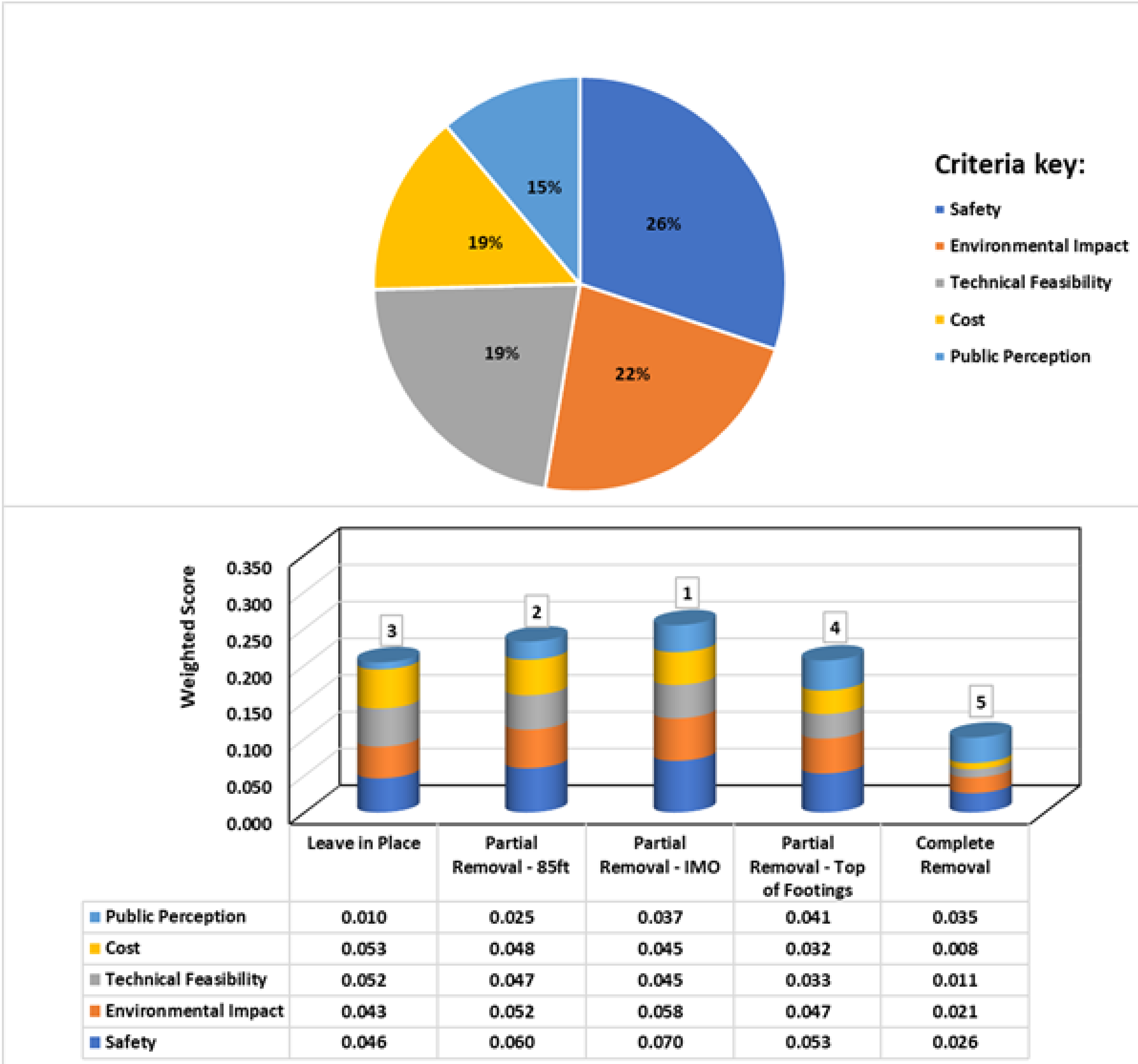
	Leave in Place	Partial Removal - 85ft	Partial Removal - IMO	Partial Removal - Top of Footings	Complete Removal
Public Perception	0.006	0.018	0.029	0.040	0.047
Cost	0.040	0.040	0.039	0.026	0.011
Technical Feasibility	0.048	0.058	0.055	0.041	0.017
Environmental Impact	0.022	0.044	0.059	0.053	0.041
Safety	0.037	0.052	0.070	0.068	0.041

Figure 6.6: Results from evaluating decommissioning options for the case study (North Sea, n=45)



	Leave in Place	Partial Removal - 85ft	Partial Removal - IMO	Partial Removal - Top of Footings	Complete Removal
Public Perception	0.01	0.02	0.02	0.03	0.03
Cost	0.05	0.04	0.03	0.02	0.01
Technical Feasibility	0.08	0.06	0.04	0.02	0.01
Environmental Impact	0.06	0.08	0.05	0.03	0.01
Safety	0.07	0.10	0.05	0.04	0.02

Figure 6.7: Results from evaluating decommissioning options for the case study (Offshore USA, n=10)



	Leave in Place	Partial Removal - 85ft	Partial Removal - IMO	Partial Removal - Top of Footings	Complete Removal
Public Perception	0.010	0.025	0.037	0.041	0.035
Cost	0.053	0.048	0.045	0.032	0.008
Technical Feasibility	0.052	0.047	0.045	0.033	0.011
Environmental Impact	0.043	0.052	0.058	0.047	0.021
Safety	0.046	0.060	0.070	0.053	0.026

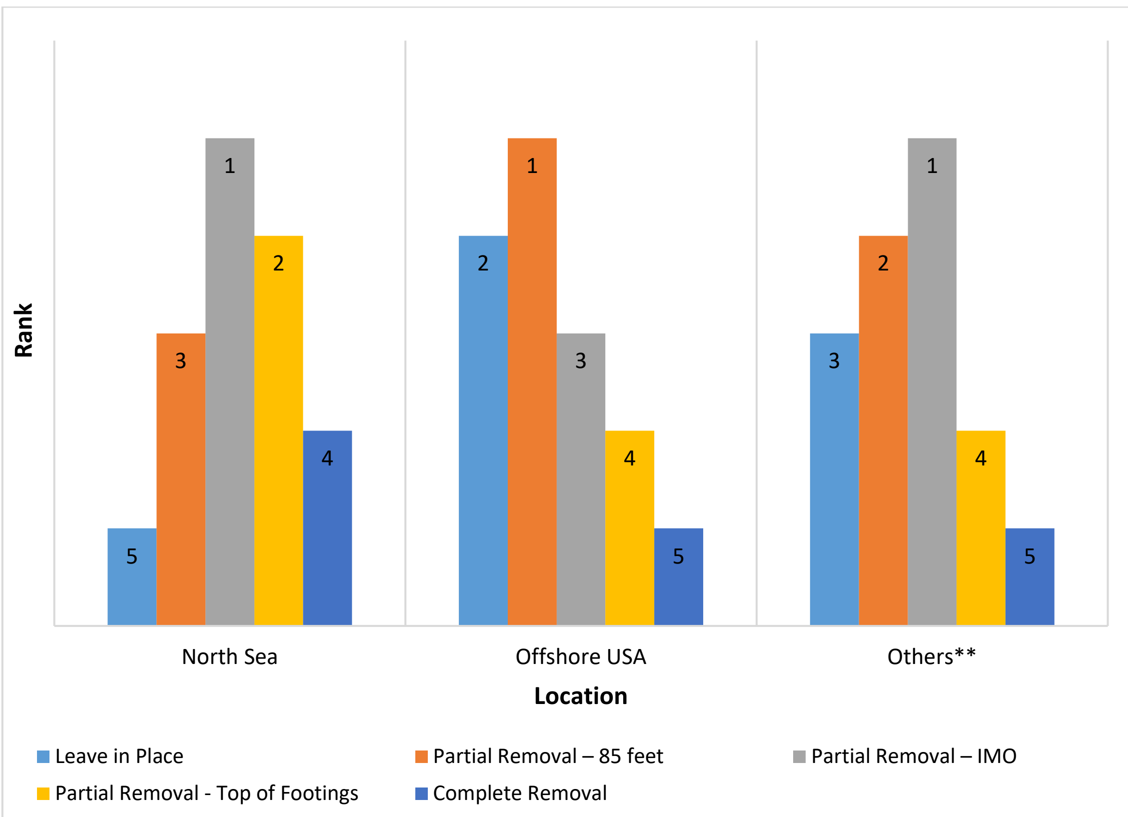
Figure 6.8: Results from evaluating decommissioning options for the case study (Others, n=23)

The weights of the decision criteria obtained from analysis of the case study platform for all three regions are observed to be of the same ranking order, despite differences in weight proportions. This ranking of decision criteria weights is shown in Table 6.2 and was used for comparison with information from literature.

Table 6.2: Decision Criteria Ranking for Case Study Platform Based on Weights of Importance

Decision Criteria	**Ranking**
Safety	1
Environmental Impact	2
Technical Feasibility	3
Cost	4
Public Perception	5

Also, the ranking of decommissioning options weighted scores for the case study when grouped according to the offshore location of the survey participants is shown in Figure 6.9.



**Others comprises Offshore Africa, Asian Seas, Offshore Australia, Caribbean Seas, and Offshore South America.

Figure 6.9: Decommissioning options ranking for case study based on location of survey participants

6.4.1. Comparison to TSB (2000)

The results from TSB (2000), an industry study in the USA which utilised expert opinion to quantitatively evaluate and compare three decommissioning options for platform removal, are presented in Table 6.3 and Table 6.4 below.

Table 6.3: Decision Criteria Weights Ranking (Adapted from TSB 2000)

Decision Criteria	Ranking
Safety	1
Environmental Impact	2
Technical Feasibility	2
Permitting Requirements	4
Disposal Option	4
Cost	6
Schedule	7

Table 6.4: Decommissioning Options Ranking (Adapted from TSB 2000)

Decommissioning Option	Ranking
Complete Removal	3
Partial Removal	1
Remote Reefing	2

Comparing the results from TSB (2000) with those obtained from applying the DDM to the case study, when filtered for responses from survey participants in the USA region, shows clear similarities. Firstly, the criteria weights rank order is similar for overlapping criteria in both analyses with the only difference being that Environmental Impact ranks higher than Technical Feasibility in this research whereas both criteria are equally ranked in TSB (2000).

With regards to the ranking of the decommissioning options based on their weighted scores, a strong agreement is observed between both results in that Partial Removal is the top-ranking option and Complete Removal is the least-ranking option. Remote Reefing option, as described in TSB (2000) is akin to the Leave in Place option in this research and this option ranks between Partial Removal and Complete Removal in both studies. These correlations suggest that, based on TSB (2000), the results obtained for the case study platform from using the DDM are accurate and reasonable.

6.4.2. Comparison to Bernstein et al. (2010)

Bernstein et al. (2010) conducted an investigative industry study on the implications of decommissioning platforms in the POCS by using either Complete Removal or Partial Removal option. The options were evaluated with reference to eight attributes (costs, air quality, water quality, marine mammals, birds, benthic impacts, fish production, ocean access and strict compliance to regulations). Their results suggested that partial removal of the platforms scores higher than complete removal across the attributes except for ocean access and strict compliance.

These findings from Bernstein et al. (2010) appear to support the outcomes of the analysis in this research. Partial Removal was identified by the developed DDM as the most-preferred decommissioning option and Complete Removal was also the least-preferred option when filtered to only represent responses from survey participants in USA. Therefore, the results from the DDM are accepted as valid and accurate based on comparison to Bernstein et al. (2010).

6.4.3. Comparison to Andrawus, Steel and Watson (2009)

Andrawus, Steel and Watson (2009) comparatively evaluated four decommissioning options for Hidalgo platform, an offshore platform in the USA with similar features to the case study platform in this research. Their results are summarised in Table 6.5 and Table 6.6.

Table 6.5: Decision Criteria Weights Ranking for Hidalgo (Adapted Andrawus, Steel and Watson 2009)

Decision Criteria	**Ranking**
Safety	4
Environmental Impact	5
Technical Feasibility	6
Regulatory Requirements	3
Future Liability	1

Revenue Generation	7
Public Requirements	1
Cost (Net Present Value)	-

Table 6.6: Decommissioning Options Ranking for Platform Hidalgo (Adapted from Andrawus, Steel and Watson 2009)

Decommissioning Option	**Ranking**
Complete Removal	4
Partial Removal	2
Re-use for Artificial Reefing	3
Re-use for Wind Power Generation	1

The results from the current research are observed to generally agree with the results from Andrawus, Steel and Watson (2009). In terms of criteria weighting, the overlapping decision criteria i.e., Safety, Environmental Impact and Technical Feasibility are observed to have an identical ranking or order of preference in both studies. However, if Public Perception in this research is deemed to have the same meaning as Public Requirements in Andrawus, Steel and Watson (2009), then a significant exception to the general agreement of both studies is observed in the ranking of this criterion. Public Perception criterion is the least-ranking in this research despite being a top-ranking criterion in Andrawus, Steel and Watson (2009). Reconciling the difference between both results is challenging due to the highly subjective nature of human opinion, and differences in the data gathering and analysis approach for the studies (Guevara 1998; Fowler et al. 2014).

Nonetheless, the ranking of decommissioning options is observed to be identical for both studies with Partial Removal emerging as the top-ranking option, Complete Removal is the least-ranking option, and Leave in Place (Re-use for Artificial Reefing) is mid-ranked in both cases. Note that Re-use for Wind Power Generation is a hypothetical decommissioning option which was adjudged to be the preferred decommissioning option for Hidalgo Platform by Andrawus, Steel and Watson (2009) primarily due to its potential to generate revenue unlike the other decommissioning options. Hence the cited study supports the validity of results for the case study obtained from using the DDM.

6.4.4. Comparison to UK Government Guidelines for Decommissioning

Government guidelines for any activity can suffice as an authoritative source of information pertaining to that activity because it leverages on best practice to address key concerns for that activity (McCann, Henrion and Bernstein 2016). According to the UK Government's guidelines for decommissioning, "…*the safety and environmental impacts of the options, including the impact on climate change, will clearly be important. Options where the safety risks are intolerable or involve major unacceptable environmental impacts may be ruled out without further consideration. Proportionality must also be considered but it is unlikely that cost will be accepted as the main driver*…" (BEIS 2018 p. 77). The statement appears to imply that Safety and Environmental Impact Criteria are expected rank high for decommissioning decision-making considerations based on their weights of importance while Cost criterion would rank low. This assertion is observable in the criteria ranking from the decision model as shown in Table 7.2. Thus, implying that the results from using the DDM are acceptable as valid and in agreement with the UK Government's guidelines for decommissioning.

6.5. Validation of DDM Logical Structure using Expert Opinion

The structure and underlying logic of the DDM was validated using the opinion of decommissioning subject matter experts since the model is conceptual and not akin to any physical real-world system. This technique was also adjudged to be adequate as a precursor to the industry-wide adoption of the model. Validation of the model logical structure entails assessing the feasibility of the model with regards to its fitness-for-purpose and fitness-for-use. Thus, enabling the accuracy of the model's representation of reality and its acceptability to users to be ascertained (Olewnik and Lewis 2005).

The semi-structured questionnaire used for this validation was carefully designed to capture the views of decommissioning experts about the model structure. In alignment with recommendations in the literature for validating decision-support models (Gass 1983b; Borenstein 1998; Moisil 2010), the questions focused on the accuracy, completeness, comprehensibility, and cost-effectiveness of the DDM. Respondents were also allowed to add any additional comments they had about the model.

A copy of the questionnaire is shown in appendix 6. The questionnaire was administered along with a presentation describing the model and its application to the case study to avoid any misunderstanding by the experts. Furthermore, the participants were chosen based on their expertise, experience, academic and professional qualifications to ensure that their views adequately represented those of the decommissioning industry.

6.5.1. Analysis of the DDM Logical Structure Validation Results

Ten decommissioning practitioners responded to the DDM validation questionnaire. Their profile, as shown in Table 6.7, indicates that they are appreciably knowledgeable about offshore decommissioning. Additionally, they are all highly educated and well experienced with a combined decommissioning-related work experience of over one hundred and fifty years.

Table 6.7: Profile of Validation Experts

Expert	Profession	Academic Qualification	Job Designation	Years of Work Experience
1	Engineering	MEng	Senior Consultant (Subsea & Decommissioning)	21
2	Decommissioning Manager	MSc	Decommissioning Strategist & Business Development	15+
3	Decommissioning (Oil and Gas)	MSc	HSE & Regulatory Lead	10

4	Energy Consultancy	MSc	Senior Decommissioning Engineer	3
5	Engineering	MSc	Energy Consultant/ Decommissioning Project Lead	1
6	Oil & Gas and Energy Transition	MSc	Decommissioning Study Manager	20
7	Energy Consultancy	PGDip BEng	Decommissioning and Integrated Project Lead	15+
8	Decommissioning Project Manager	MEng	Facilities Decommissioning & Optimisation Lead	15+
9	Decommissioning Consultancy	BSc Practitioner level, IEMA*	Decommissioning Manager	16
10	Structural Engineer, Marine Specialist in Offshore Facility Decommissioning	PhD	Retired Senior Consultant.	30

* Associate Member of the Institute of Environmental Management and Assessment

The experts provided their opinion of the model by individually responding to the validation questionnaire. This feedback was positive as inferred from the summary of their responses which is shown in Table 6.8.

Table 6.8: Summary of responses to DDM validation questions by Experts

Validation Criteria	**Expert Response**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Importance of addressed issue	QS	QS	QS	-	QS	QS	QS	NS	NS	QS
Accuracy	UCL	SCL	VCL	VCL	VCL	SCL	VCL	VCL	VCL	VCL
Completeness	SC	VC	VC	VC	SC	SC	VC	SC	SC	VC
Comprehensibility	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Cost-Effectiveness	JCB	JCB	JCB	JCB	JCB	DCB	JCB	-	JCB	JCB

Key

QS: Quite significant.

NS: Not significant.

VCL: Very close match between model's results and expected results.

SCL: Slightly close match between model's results and expected results.

UCL: Unsure of the match between model's results and expected results.

SC: Somewhat complete.

VC: Very complete.

JCB: Benefits of use justifies cost of implementation.

DCB: Benefits of use does not justify cost of implementation.

It is inferred from Table 6.8 that 70% of the experts agreed that the DDM addresses a significant issue in decommissioning. Similarly, the experts were strongly in agreement that the DDM accurately performs its intended function and 90% of them stated that the model results closely matched what they would expect from evaluating decommissioning options for the case study platform. This indicates that the model is fit for purpose.

Table 6.8 also shows that the experts generally agreed that the model's flow process is complete with respect to the problem it seeks to address. This response significantly buttresses the logic of the model, given the richness of the respondents' decommissioning knowledge. Regarding the comprehensibility of the DDM, 90% of the experts concurred that the model is understandable and easy to use with little or no practical difficulties. Thus, implying that industry adoption of the model would not be challenging. Lastly, 80% of the experts opined that the benefits of using the model in actual decommissioning projects would justify any attendant resource requirements.

Conclusively, the responses from the experts suggest that the DDM's logical structure is sound, and its adoption would be valuable for the decommissioning industry. Hence the DDM represents a positive contribution to the body of knowledge and practice of offshore decommissioning.

6.6. Summary

Complete validation of the DDM is impossible due to subjectivity of human opinion, conceptual nature of the model, and the fact that it was applied to a theoretical case study. However, the validation endeavors described in this chapter are deemed sufficient to indicate the accuracy and usefulness of the model. This included validation of model's input data by sensitivity analysis, validation of model's results by comparison to similar studies in literature, and validation of model's logical structure using expert opinion. The three validation techniques yielded positive results about the model's validity, ultimately making a case for its industry adoption. On this basis, the model is recommended to decommissioning practitioners, subject to future modifications that can improve its acceptability and performance. The next chapter builds on these findings by exploring the use of mathematical modelling to integrate historical data into the decision model in replacement of the survey-derived input data used for scoring decommissioning options for the cost criterion.

Chapter 7 : MATHEMATICAL MODELLING APPLICATION TO HISTORICAL DATA OF OFFSHORE DECOMMISSIONING

7.1. Historical Data of Offshore Decommissioning

Historical data refers to actual information that is gathered from previously completed projects. In the context of this research, this information relates to decommissioning projects that have been planned and executed in the past. A robust analysis of data from past projects is likely to reveal insights through which aspects of future projects such as causality, action, and consequence are logically predicted with reasonable accuracy (Guldi and Armitage 2014). This is because the patterns, structures and regularities uncovered by such analysis enable decision-makers to establish accurate generalisations which apply to current and future projects.

Information from completed decommissioning projects are increasingly becoming accessible to the public, especially in the offshore USA and North Sea regions where several projects have been successfully executed (Fam et al. 2018; Kaiser and Narra 2018; GOV.UK 2022). However, there are mitigating factors to this trend such as the risk perception by platform owners that sharing their project information can give a commercial advantage to their competitors or result to reputational damage (Murray et al. 2018). Hence, the commercially sensitive aspects of this historical data are protected as confidential information.

The paucity of decommissioning information makes it is pertinent that any available data is thoroughly analysed for helpful insights towards improvement of decision-making for future projects. This is likely to require that the historical data be preconditioned, structured, or contextualised into a form that is usable by the decision-maker (Sigsgaard et al. 2020). Therefore, the procedure for adapting historical data into a decision support model entails a three-staged data processing step as shown in Figure 7.1.

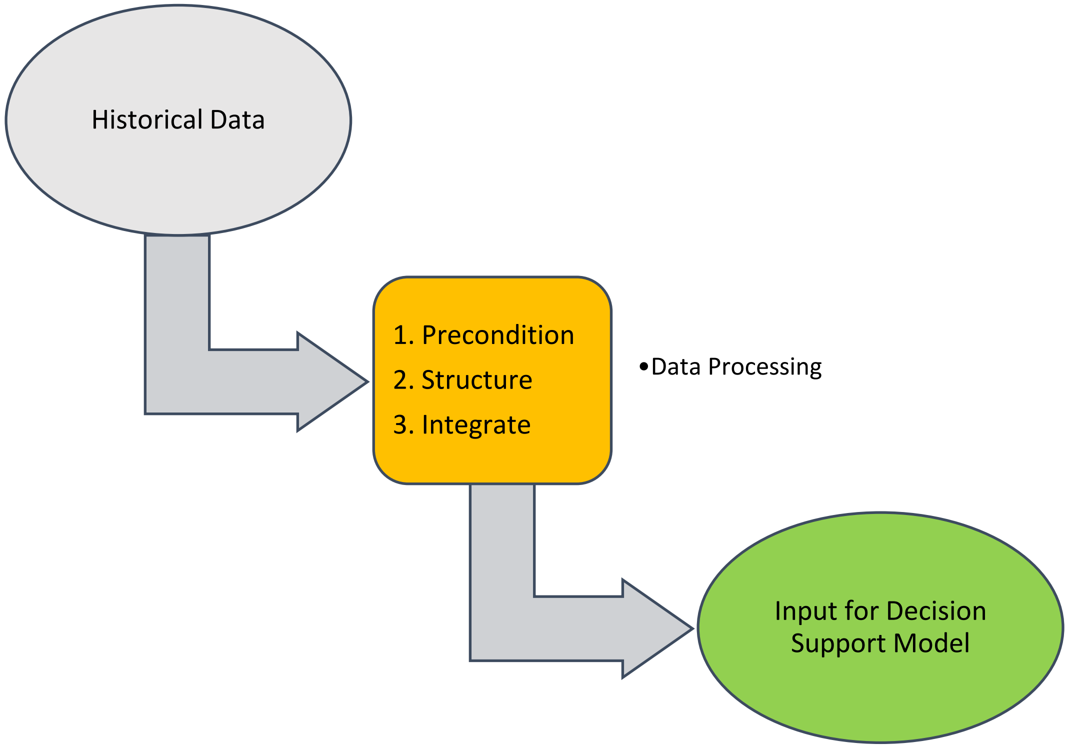


Figure 7.1: Adaptation of historical data into a decision support model

7.2. Mathematical Modelling

Mathematical modelling is the use of mathematical concepts and language to describe the behaviour of a system with the intent of developing understanding of the system, testing effects of changes within the system, and/or supporting decision-making (Daniel and Glenn 2008). It is particularly beneficial for exploring relationships between the entities within a system because the language is precise, has well-defined rules for manipulations, and can readily be analysed with computers in the form of numerical calculations (Towers, Edwards and Hamson 2020). Therefore, mathematical modelling approaches, such as Machine Learning and Generalised Reduced Gradient (GRG) method, are viable for data processing when adapting historical data into a decision-making tool (Eke et al. 2021).

The decision criteria for selection of decommissioning options for projects were investigated and partitioned into criteria and sub-criteria in Chapter two of this report. However, some sub-criteria such as financial expenditures and air emissions have previously been quantitatively assessed for past decommissioning projects and a few of these historical datasets are available in the public domain. The application of mathematical techniques on these datasets, especially when they are sufficiently large, makes it possible to predict the sub-criteria values for a platform based on its physical features when these are known as shown in Equation 7.1. These models can then be used for making forecasts when evaluating decommissioning options for platforms with similar characteristics and location as those platforms from which the datasets were obtained.

$$Score_{i,j} = f(Platform\, features) + \in_{i,j} \qquad (7.1)$$

Where $Score_{i,j}$ is the performance score of decommissioning option i with reference to criterion (or sub-criterion) j, $f(Platform\, features)$ is a mathematical function which requires as argument the prioritised features of the platform to be decommissioned and $\in_{i,j}$ represents the error term which accounts for noise and randomness in the data. Note that Equation 7.1 is parametric when the nature of $f(Platform\, features)$ is specified, and non-parametric when it is not specified a priori but instead is determined from the data set used to develop the model (Mahmoud 2019).

As there are numerous platform features, these must be carefully screened to shortlist the ones to be used in developing Equation 7.1 for effectiveness of analyses. The decommissioning survey described in the Chapter five was used to address this issue in the Platform Features Prioritisation section. The results suggested that substructure weight, water depth and platform age are the platform features most relevant to decommissioning option selection.

Notwithstanding, challenges with availability of decommissioning data from past projects is a prevalent roadblock to developing predictive models. Historical decommissioning data are often scarce and descriptive of platforms that are sparsely distributed across various locations (Fowler et al. 2014; Kaiser and Narra 2018; Vidal et al. 2022). Regarding the availability of decommissioning cost data in the public domain, Kaiser et al. (2003) observed that most of the reported values represent pre-job estimates as opposed to actual post-job cost data and particular care must be taken to ensure their accuracy before usage. Their assertion appears to suggest that estimates from credible experts are a viable alternative to historical data, and such decommissioning cost estimates exist in literature for offshore platforms in California's Pacific Outer Continental Shelf (Bernstein et al. 2010; TSB 2016b). The dataset includes financial costs for decommissioning the twenty-three fixed-steel jacket platforms in this location with the Complete Removal option along with descriptive information about the platforms' features. Therefore, mathematically linking these costs and platform features will enable estimation of decommissioning costs for the case study and other platforms with similar characteristics and location as the POCS platforms.

7.3. Modelling the Relationship Between Decommissioning Options Costs and Platform Features

Sufficient information will be available to mathematically model the relationship between the costs of different decommissioning options and platform features after these costs are determined. Equation 7.1 can then be re-written to Equation 7.2.

$$Cost_i = f(S\text{ubstructure weight, water depth, platform age}) + \epsilon_{i,j} \quad (7.2)$$

Where $Cost_i$ is the financial expenditure from using decommissioning option i for a project, $f(S\text{ubstructure weight, water depth, platform age})$ is a mathematical function which requires as argument the substructure weight, water depth and age of the platform to be decommissioned, and $\epsilon_{i,j}$ is the error term which accounts for randomness in data.

Recall that the nature of the model equation depends on the type of mathematical modelling technique used for its development. Machine Learning technique, which is used in this research, yields a non-parametric or "black box" model. Hence, despite such model's physical system behaviour not being directly visible from Equation 7.2, it would be flexible and defined by the available training data (Salvador 2017).

7.3.1. Machine Learning Regression Analysis for Decommissioning Options Cost Modelling

Regression analysis is the machine learning technique that constitutes the primary concern of this research because the nature of most historical data pertaining to decommissioning is continuous with real numerical values. For example, the cost of decommissioning North-West Hutton platform was £245m and total weight of topsides and jacket materials removed to shore was 28,427 tonnes (Jee 2014). In regression analysis, the goal is to try to find a relationship between several predictor (explanatory) variables and a continuous response variable (outcome) to enable prediction of an outcome for other values of the predictor variables. Within the field of machine learning, the predictor variables are commonly called independent variables while the response variables are referred to as the dependent variables. Therefore, regression analysis entails using data to determine empirical relationships between independent and dependent variables and using those relationships to predict the value of a dependent variable that corresponds to an independent variable.

Within the context of this research, this interprets to establishing an empirical relationship between the known decommissioning options costs and features of platforms (Equation 7.2) and using this relationship to forecast the decommissioning options costs of other platforms which have known features. Note that the empirical relationship or forecasting model will exist as a "black box" because machine learning yields a non-parametric model.

Regression is data-oriented in that it focuses on the data used for its development with no consideration for the underlying process of the system being analysed. Nevertheless, this technique introduced by Legendre (1805) is well-developed, and details of its scientific application abound in the literature (Ray 2019; Tai 2021). Additionally, several machine learning algorithms exist for implementing regression analysis such as Linear

Regression, Random Forest, and Support Vector Regression algorithms (Doan and Kalita 2015) and these are either classed as single output or multioutput depending on the number of predicted variables. However, the current research focuses on multioutput regression due to the nature of the use case which is such that the predictor variables are the substructure weight, water depth and age of the platform under consideration while the predicted variables are the individual decommissioning options costs for the project (see Figure 7.2).

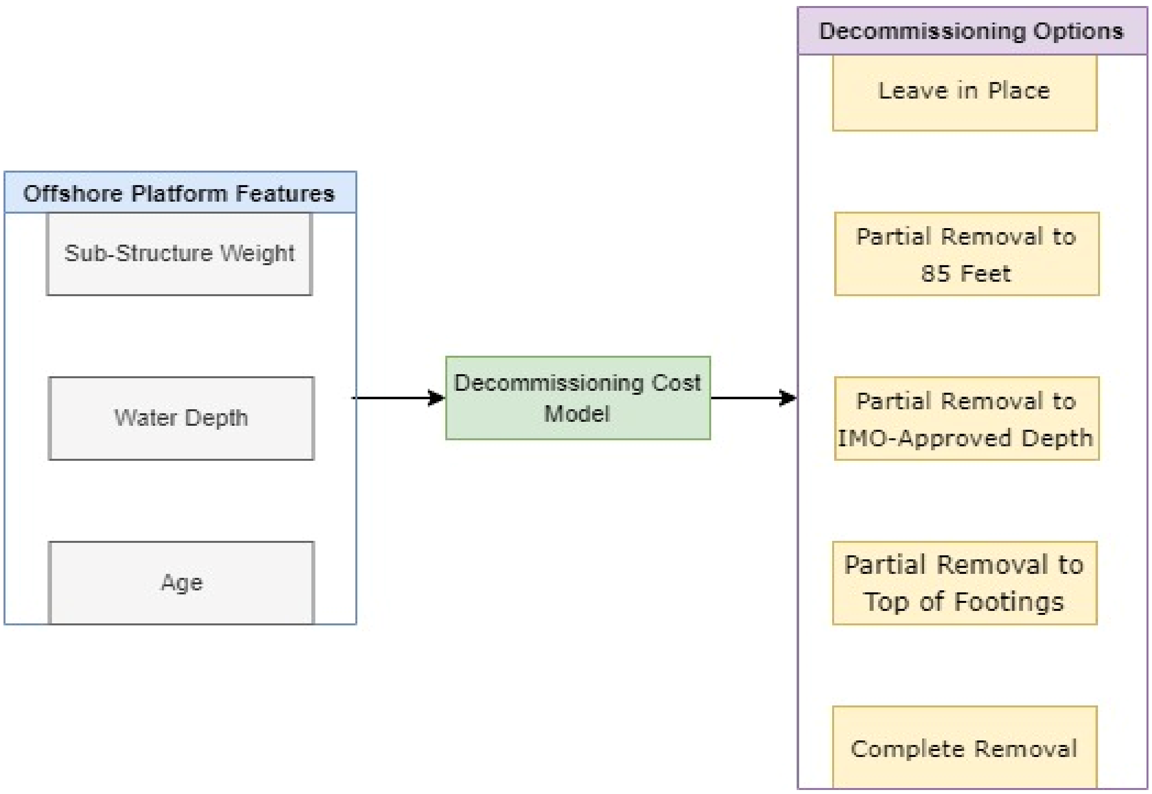


Figure 7.2: Input/Output variables relationship for decommissioning costing model

The requirement in a multi-output problem is to predict n number of outputs synchronically. In situations where no correlation exists between the outputs, this type of regression problem is solved by building n independent models, i.e., one for each output, and then using those models to independently predict each one of the n outputs. However, in situations like the current research where the parameters being considered (i.e., the substructure weight, water depth and age of a platform and the decommissioning options costs for the platform) are known to be correlated, a better approach is to build a single model capable of simultaneously predicting all n outputs. The benefits of using multi-output regression include lower training time since only a single estimator is built, and likelihood of increased generalization accuracy of the resulting estimator (Pedregosa et al. 2011).

Further information about multioutput regression is available in the literature (Borchani et al. 2015; Xu et al. 2019; Schmid et al. 2022) but this is outside the remits of this research.

Determining the most-suitable machine learning regression algorithm for developing the cost model is an iterative process which entails applying different machine learning methods, comparing their results, and selecting the most appropriate method based on the observed prediction performance (Ray 2019). Owing to this iterative process, machine learning traditionally requires large volume of data with number of required samples typically at a ratio of 15:1 to the number of predictor variables for multioutput regression (Harrell 2015). Additionally, limited amount of data results in a more severe bias/variance trade-off, hence making the model development more challenging. Therefore, the low volume of available data for this research (twenty-three samples) adversely impacts the applicability of machine learning to the model development. Thus, necessitating the inclusion of a resampling method called cross-validation for mitigating this challenge.

7.3.2. Cross Validation

Cross-validation is a method used by data scientists to measure and improve model accuracy while ensuring that minimal assumptions are made on the statistics of the data. Berrar (2018) defines cross-validation as a data resampling method for assessing the generalization ability of predictive models and preventing overfitting. The method was first formally proposed by Mosteller and Tukey (1968). Further information about its working procedure and reviews are available in the literature (Stone 1978; Camstra and Boomsma 1992; Browne 2000; Little et al. 2017).

Ensuring accuracy of the developed model is a predominant concern when using supervised machine learning. In this regard, problems with accuracy encountered during machine learning modelling are classified into underfitting and overfitting (Berrar 2018; Isakova 2019). Underfitting occurs when the developed model fails to adequately capture the relationship between the system parameters and is likely to occur when using simpler models such as Ordinary Least Squares, even though such models are less prone to noise in the data. This contrasts with overfitting in which the model is perfectly adapted to the data used for its development while also being unable to generalize well to new data (Burnham and Anderson 2002). Overfitting occurs when the model correlates too closely to the training dataset such that it not only reflects the relationship between the system parameters but also captures the inherent noise in the data as though this noise is part of the underlying structure of the model. Nonetheless, it is pertinent to seek the right balance between underfitting and overfitting due to the polar nature of these two accuracy problems.

For this reason, the standard approach for modelling with supervised machine learning is to split the available data into two sets such that one set (training data) is used to build the model while the other set (testing or validation data) is used to evaluate the model accuracy (Berrar 2018). However, this becomes a challenge when there is a limited quantity of data such as in this research where the available dataset contains only twenty-three records. Moreso, it is important to use as much of the data as possible for training the model, but this would result in the detrimental situation of only being able to obtain a noisy estimate of the model's predictive performance (Isakova 2019). Hence there was a critical need in this research to maximise usage of the small volume of available data by including cross-validation in the model development process.

Fundamentally, cross-validation involves splitting the available data into x number of equal parts, withholding the first part as test data, and training a model with all data samples comprising the remaining x-1 parts before testing this model's accuracy with the withheld data and recording the performance score. This procedure is repeated for x number of times and the average of all the obtained performance scores is calculated at the end, implying that all the data samples both serve as training and testing data at separate times. There are several types of cross-validation methods including hold-out method, leave-one-out cross-validation (LOOCV), K-fold cross-validation and stratified k-fold cross-validation.

Nevertheless, this research restricts itself to LOOCV method, a type of cross-validation best suited for cases where there is limited data, and in which x=N, where N is the total number of data samples (Berrar 2018). The use of LOOCV implies that hyper-parameter tuning during model development will require high computational cost because the computing machine will iterate through the entire code for N times to assess just one value of a hyper-parameter, and this process will be repeated severally before finding the optimal value of that hyper-parameter. Therefore, it was decided that the machine learning models will be developed with default values of the hyper-parameters, especially as various models were being investigated to find the optimal model and these models consist of several hyper-parameters.

7.4. Decommissioning Cost Estimation and Analysis

As highlighted in Chapter two, cost estimation for an offshore decommissioning project is a challenging task which often requires information about platform features that might not be readily available. To aid generation of decommissioning cost estimates, operators are constrained to perform several studies, some of which become more expensive as the project execution time draws nearer especially if there is some time constraint. Cost-savings can be realized if operators know what platform information influences decommissioning costs and start collecting these data much earlier. Furthermore, early knowledge of decommissioning cost is important to the operator for reasons such as budgeting, asset profitability evaluation and setting of lease transfer terms. Hence the industry will benefit from innovative techniques for easily generating initial estimates of decommissioning costs before detailed engineering analysis (Andrawus et al. 2011).

A fit-for-purpose decommissioning cost estimating model for performing cost analysis and generating early cost estimates would be useful to operators, regulatory bodies, and other project stakeholders in reducing the complexity of planning decommissioning projects. Moreso, it would enable companies that set aside some part of their revenue towards amortization of their decommissioning liabilities to keep track of the progress being made in this regard.

7.5. Cost Analysis for Decommissioning Case Study Platform

Detailed cost estimates by the USA0 Department of the Interior's Bureau of Safety and Environmental Enforcement (BSEE) for decommissioning offshore oil and gas platforms in the Pacific Outer Continental Shelf (POCS) of California with the Complete Removal option are detailed in TSB (2016b). The dataset consists of only the costs of completely removing the platforms and this is subdivided into thirteen decommissioning phases. The costs of the well plugging and abandonment phase are not included in this analysis to reduce complexity. These platforms share similarities with the case study platform in that they are all fixed steel jacket-type platforms and situated in same location. Hence, it is feasible to forecast the cost for decommissioning the case study from this costing information. The methodology developed in this research for this purpose is shown in Figure 7.3.

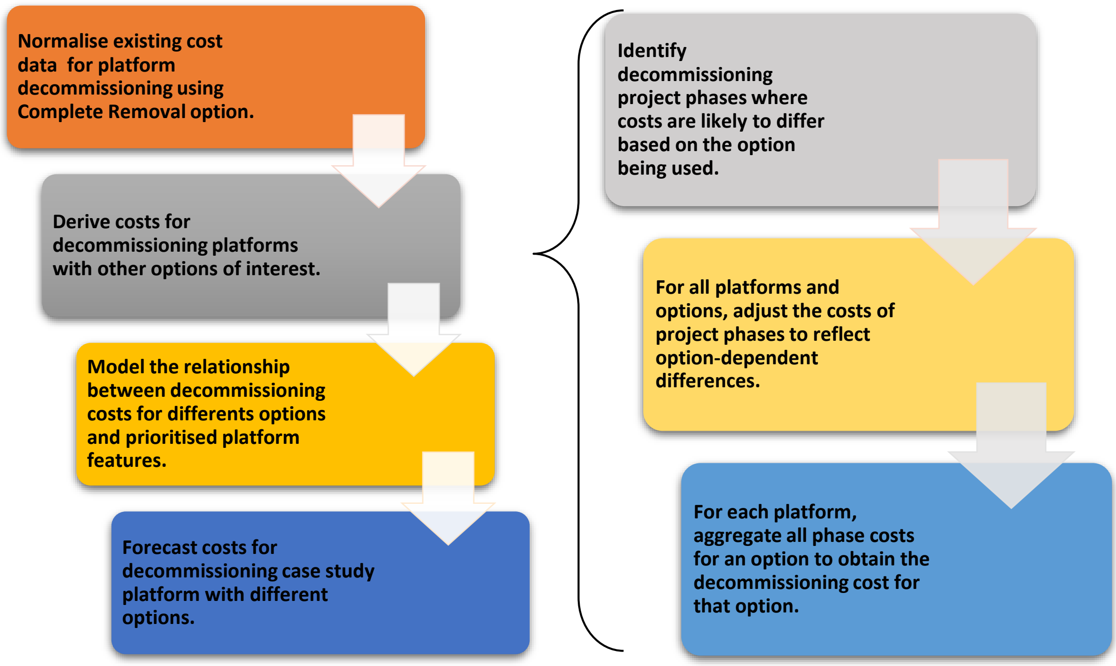


Figure 7.3: Methodology for forecasting decommissioning costs for case study platform from historical cost data

The first step is to precondition or normalise the dataset into a useable form. This is followed by the application of engineering judgement and assumptions based on decommissioning knowledge to estimate the costs of executing the projects with different options. Next, cost model which generates the costs for decommissioning a platform with different options based on the structure's features is developed from the now-enlarged cost dataset. Finally, the costs for using different options for decommissioning the case study platform are forecasted with the aid of the cost model since the platform's features are already known.

This methodology will be logically followed in Chapter eight of this thesis to forecast decommissioning options costs for the case study platform before integrating these into the decommissioning decision model.

7.6. Summary

This chapter described the procedure for integrating historical data into the decision model developed in this research. Firstly, the application of machine learning mathematical modelling to historical data of decommissioning was identified to be beneficial for predictive purposes. Next, the integration of cross-validation into machine learning regression analysis for the purpose of developing a model for costing decommissioning options is discussed. The chapter concludes by outlining a scheme for developing the costing model and using it to predict decommissioning costs for the case study platform introduced in Chapter five. This methodology is systematically implemented in the next chapter.

Chapter 8 : INTEGRATION OF DECOMMISSIONING COST DATA INTO DEVELOPED DECISION MODEL

As highlighted in Chapter two of this thesis, a robust decision model should have the capability for improving the quality of its results as more accurate information becomes available. This capability was incorporated as a key requirement of the decommissioning decision model (DDM).

To demonstrate this capability, this chapter describes the integration of decommissioning costs into the DDM after predicting these using a costing model developed from the methodology described in Chapter seven.

8.1. Normalizing Existing Decommissioning Cost Data

The California POCS Platforms were separated by TSB (2016b) into project groupings based on operator obligation, geographic location and working season before obtaining the decommissioning cost estimates. Altogether there are six groups. Platforms within the same group equally share the costs of two decommissioning phases: Permitting and Regulatory Compliance, and Mobilization and Demobilization of Derrick Barges. Whereas cost sharing within groups is a cost optimisation strategy, the costs of these two phases cannot be used in their raw state for the analysis in this research and hence require to be normalised. This entails apportioning the full cost of Mobilization and Demobilization of Derrick Barges, for example, to a single platform instead of what this would be in a Campaign approach scenario.

The BSEE cost estimates were developed with the assumption that topsides are removed by reverse installation while the substructures are removed with either single lift or piece-large method depending on structural weights involved.

In addition, it is assumed that only two heavy lift vessels (HLVs) are available for the projects. These vessels can be mobilized from Southeast Asia and their normalised mobilization and demobilization costs are shown in Table 8.1.

Table 8.1: Derrick Mobilization and Demobilization Costs for HLVs

Vessel ID	Lift Capability (tons)	Mobilization and Demobilization Cost ($)
DB500	500	14,850,000
DB2000	2000	18,810,000

8.2. Derivation of Other Decommissioning Options Costs from Complete Removal Cost

Deriving the partial removal and leave in place decommissioning options costs from the complete removal cost was achieved in this research by considering each decommissioning phase i.e., bottoms-up approach. This method, though more data intensive than a top-down approach, is known to produce more accurate results (Kaiser and Liu 2014). Moreso, the decommissioning phases were considered individually before aggregation because the unit costs of some of the phases for a project remain unchanged irrespective of the adopted removal option.

The three-stage process for deriving the costs of other decommissioning options from Complete Removal cost follows the methodology described in Section 7.5. For ease of analysis, future liability such as maintenance and inspection costs have not been considered.

- Stage 1: The differences between Complete Removal and the other options for each decommissioning phase are identified from engineering knowledge as shown in Table 8.2. The costs of the decommissioning phases were modified with the aid of simplifying assumptions to reflect these differences for each option. The newly derived costs were then aggregated for each platform with respect to each of the decommissioning options to obtain the cost estimate for decommissioning platforms with the options.

Table 8.2: Derivation of Partial Removal Cost from Complete Removal Cost for Decommissioning Phases (adapted from Bressler and Bernstein (2015)).

Decommissioning Cost Element	**Differences Between Complete Removal Option and Partial Removal Options**	**Differences Between Complete Removal Option and Leave in Place Option**
Permitting and Regulatory Compliance, Platform Preparation, Pipeline Decommissioning, Power Cable Removal, Site Clearance	None. Same in both options	None. Same in both options
Conductor Removal	Conductors removed in partial Removal options only to the depth of cut below mean sea level as specified by the Partial Removal option.	None. Same in both options
Mobilization & Demobilization of Derrick Barge	Smaller and less expensive lifting equipment for Partial Removal options depending on the heaviest single topside's module (or section) lift of platform	Smaller and less expensive lifting equipment for leave in place option depending on the heaviest single topside's module (or section) lift of platform
Platform Removal	Jacket and piles removed only to the depth of cut below mean sea level specified by the Partial Removal options	Only Topsides are removed.
Materials Disposal	Less mass to be transported and disposed for Partial Removal options.	Less mass to be transported and disposed (i.e., mass of the topsides) for Leave in Place option.
Weather Contingency, Miscellaneous Work Provision, Project Management Engineering and Planning	Lower costs for Partial Removal options. Calculated as percentages of other decommissioning phases.	Lower costs for Leave in Place option. Calculated as percentages of other decommissioning phases.

- Stage 2: The costs for the Conductor Removal, Platform Removal and Material Disposal phases for partial removal options were calculated for each platform based on the estimated quantity of residual material, that is, the amount of structural material that would be left in place after the removal process. For a platform, this is mathematically expressed as shown in Equation 8.1.

$$PR_X = CR_X - RM_X \tag{8.1}$$

Where for a project phase X, PR_X is the cost incurred when decommissioning the platform with a partial removal option. CR_X is the cost incurred when decommissioning the platform with the Complete Removal option (this is specified in the BSEE dataset). RM_X is the cost avoided due to leaving some residual materials.

Note that the Leave in Place option is a special case of the Partial Removal Option where only the topsides of the platform are removed during decommissioning. Therefore, Equation 8.1 will only apply to the Platform Removal and Material Disposal phases in that scenario.

The RM_X is calculated for conductors, jacket, and piles from Equation 8.2.

$$RM_X = CR_X \ x \ \%Weight \ x \ \frac{Height\ of\ component\ in\ Residual\ Material}{Height\ of\ component\ removed\ in\ Complete\ Removal\ option} \tag{8.2}$$

Where,

%Weight is a factor which represents the weight proportions of the platform components and described in Table 8.3.

Table 8.3: %Weight for Platform Components.

Component	**%Weight**
Conductor*	1
Topsides	$\frac{Topsides\ Weight}{Estimated\ Removal\ Weight\ **}$
Jacket	$\frac{Jacket\ Weight}{Estimated\ Removal\ Weight}$
Piles	$\frac{Weight\ of\ Piles}{Estimated\ Removal\ Weight}$

*All conductor-related costs are accounted for in the Conductor Removal phase.
**Estimated Removal Weight for a platform comprises the weights of Topsides, Jacket, and Piles down to 15 feet below the seabed.

The following assumptions apply when using equations 8.1 and 8.2 because only the topsides weight, jacket weight and height of each platform are known with confidence.

i. Complete Removal option entails removal of all topsides, jackets down to the seabed, and piles and conductors down to a depth of 15 feet below the seabed.

ii. Removal costs can be reduced to $/ton.

iii. There is a uniform weight distribution across the substructure height.

iv. Jacket extends to 5 meters or 16.404 feet above the mean sea level (Byrd, Miller and Wiese 2014).

v. All piles are considered as main piles which are installed through the jacket legs, as against skirt piles which are placed adjacent to the platform legs.

vi. On average, conductors extend to 65 feet above the mean sea level (TSB 2016b).

- Stage 3: The costs of individual project phases for each decommissioning option were aggregated across the platforms to obtain cumulative phase costs for all five options as shown in Figure 8.1. There are no cost savings in the Permitting and Regulatory Compliance, Platform Preparation, Pipeline Decommissioning, Power Cable Removal and Site Clearance phases irrespective of the option used. However, significant cost savings are realised from other project phases when partial removal decommissioning options are used. This is because of the option-dependent nature of these phases.

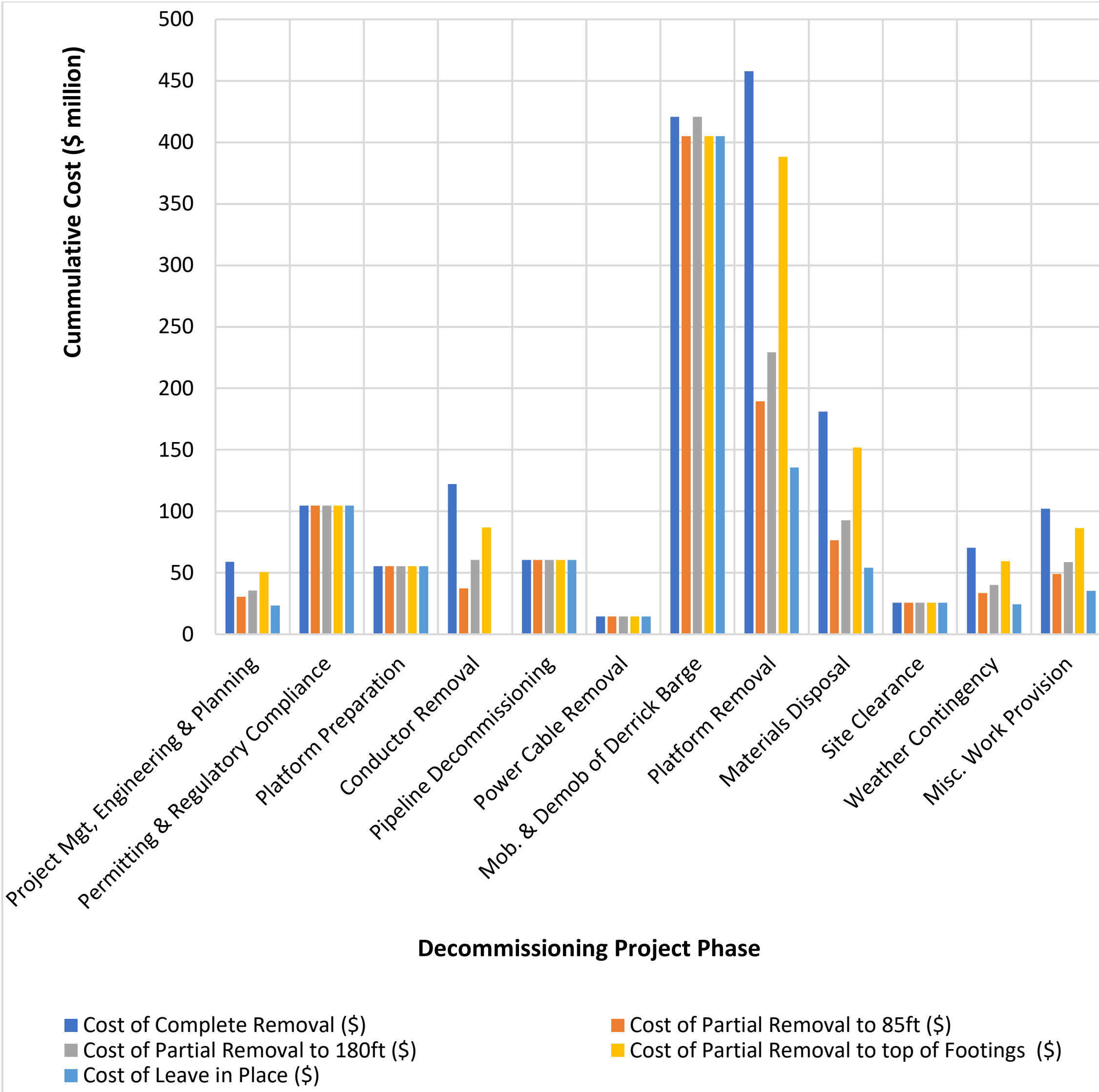


Figure 8.1: Variations in costs of project phases for different decommissioning options

Decommissioning options costs for individual platforms were then calculated by summing the costs of all project phases under an option for each platform. These costs are shown in Figure 8.2 in which platforms have been sorted in order of increasing jacket weight. Further details about the physical features and the decommissioning options costs of the platforms are respectively shown in appendix 1 and appendix 6 of this thesis.

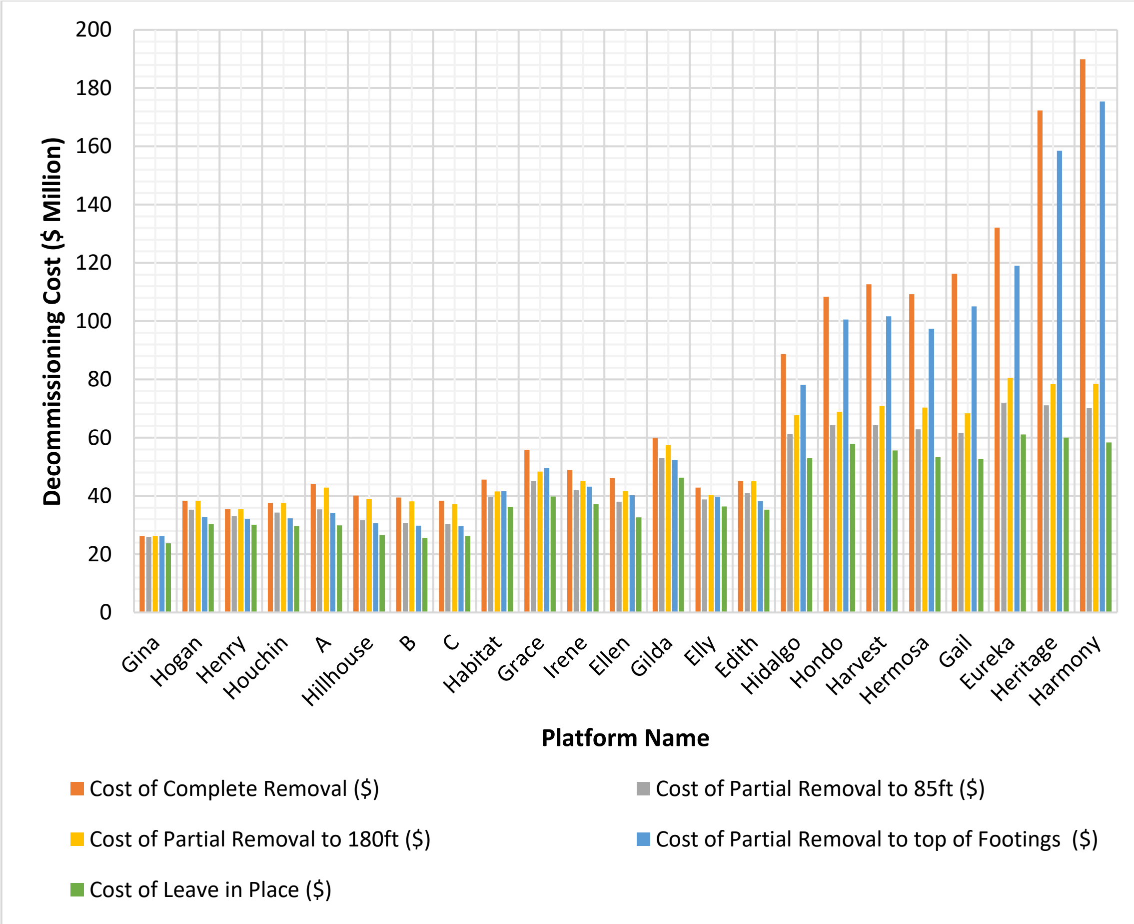


Figure 8.2: Costs of decommissioning POCS platforms using different options.

Project cost-savings due to options used varies across all platforms although the cost of Complete Removal is always more than that of any of the other options considered. The cumulative costs of using the decommissioning options across all the twenty-three platforms are compared in Figure 8.3.

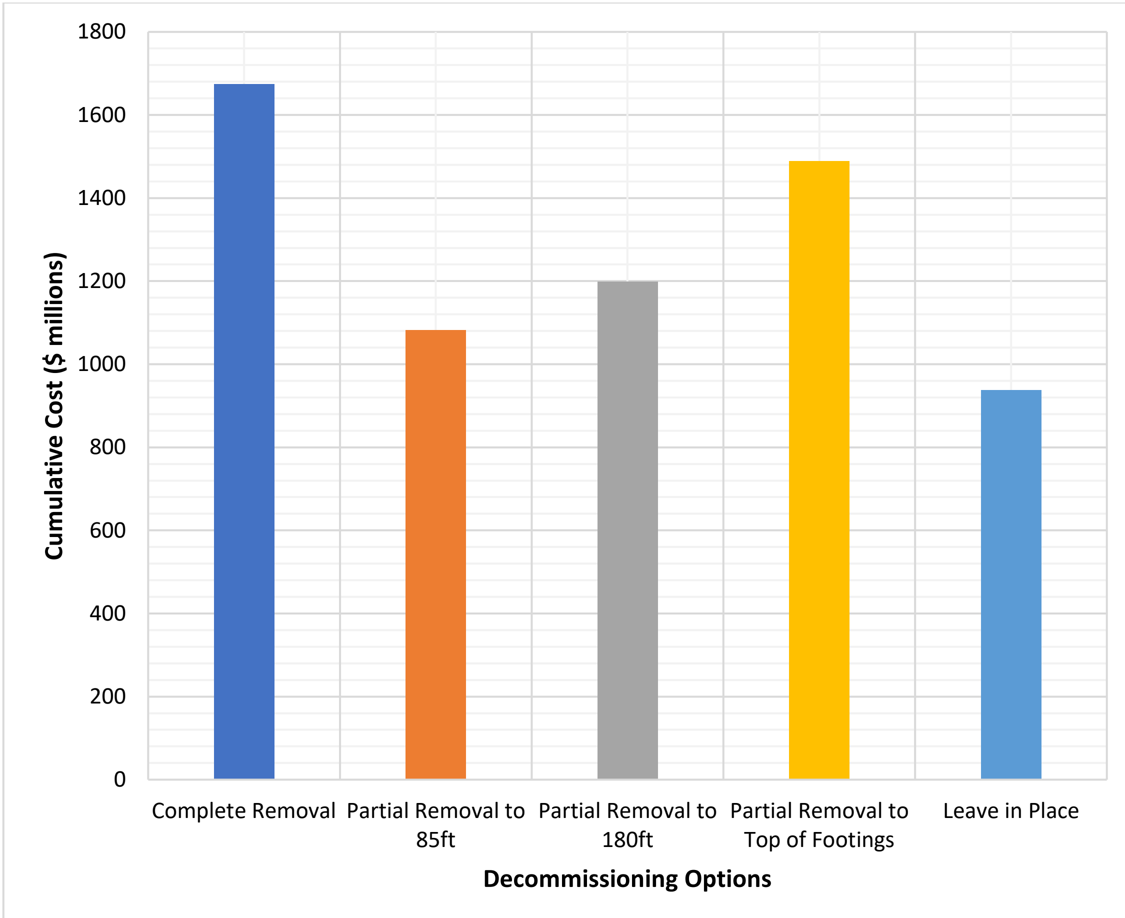


Figure 8.3: Costs of decommissioning all POCS platforms using different options.

It is observed from Figure 8.3 that Complete Removal of the platforms will cumulatively cost $1.67 billion. However, decommissioning all platforms with the Leave in Place option will cost just under $1 billion which is equivalent to a significant cost savings of 44%. Partial Removal of all platforms to 85 feet results to a cost of $1.08 billion, that is, a cost-savings of about 35% in comparison to Complete Removal. On the other hand, the option with the lowest potential cost-savings when compared to Complete Removal is Partial Removal to Top of the Footings. Using this option results to a cumulative cost of $1.49 billion which represents a cost-savings of about 11% on the cost of the Complete Removal decommissioning option.

8.3. Modelling the Relationship Between Decommissioning Options Costs and Platform Features

8.3.1. Developed Decommissioning Options Cost Models

Ten multioutput machine learning regression algorithms with capability for handling multi-output problems were investigated in this research for modelling decommissioning options costs. The investigated algorithms included Decision Tree, Elastic Net, Gradient Boosting, K Nearest Neighbour (KNN), Least Absolute Shrinkage and Selection Operator (LASSO), Multiple Linear, Multivariate Adaptive Regression Splines (MARS), Random Forest, Ridge, and Support Vector regression algorithms.

The algorithms were each used to regress the decommissioning options costs for the twenty-three platforms against their substructure weight, water depth and age. The dataset compiled for this purpose is shown in appendix 6. It comprises the physical features of the platforms from TSB (2016b) and their decommissioning options costs which were statistically derived in section 8.2.

8.3.2. Performance Evaluation of Developed Machine Learning Models

Following the development of these regression models, their prediction accuracies were evaluated graphically using cross-plots and quantitatively using accuracy metrics. The purpose of this performance evaluation was to investigate the accuracy of the developed models to identify the most suitable for forecasting the decommissioning options costs for the case study. Graphical evaluation of a prediction model provides a quick way of visually assessing its performance. Quantitative evaluation, on the other hand, is more tedious and requires some statistical analysis but generates more precise and objective numerical output as compared to those of graphical evaluation.

8.3.2.1. Graphical Evaluation of Machine Learning Regression Models' Performance using Cross-Plots

Graphical evaluation of the developed models entailed examining cross-plots of the actual versus predicted decommissioning options costs for the training and testing data. A cross-plot is a plot of predicted values from a model against the corresponding actual values of the modelled system, equated with a unit slope line or y=x line which is representative of the ideal model. In interpreting a model's cross-plot, the distance between the datapoints and the y=x line provides an indication of the accuracy of the model. Therefore, high predictive capability and accuracy of the model is inferred when substantial amounts of the datapoints are in proximity with this diagonal line (Balogun 2021). Conversely, deviations of the datapoints from the y=x line indicates predictions error in the model. Usually, a good model has datapoints scattered symmetrically around the y=x line.

The developed regression models and their graphically illustrated cross-plots are discussed below.

- Decision Tree Regression: This is a supervised learning method that works by creating a model which predicts the values of target variables by learning simple decision rules inferred from the data features (Pedregosa et al. 2011). The implementation of Decision Trees to regression problems is achieved by using the DecisionTreeRegressor class of the Python scikit-learn library. Figure 8.4 shows the cross-plot of the cost estimation model developed using this algorithm.

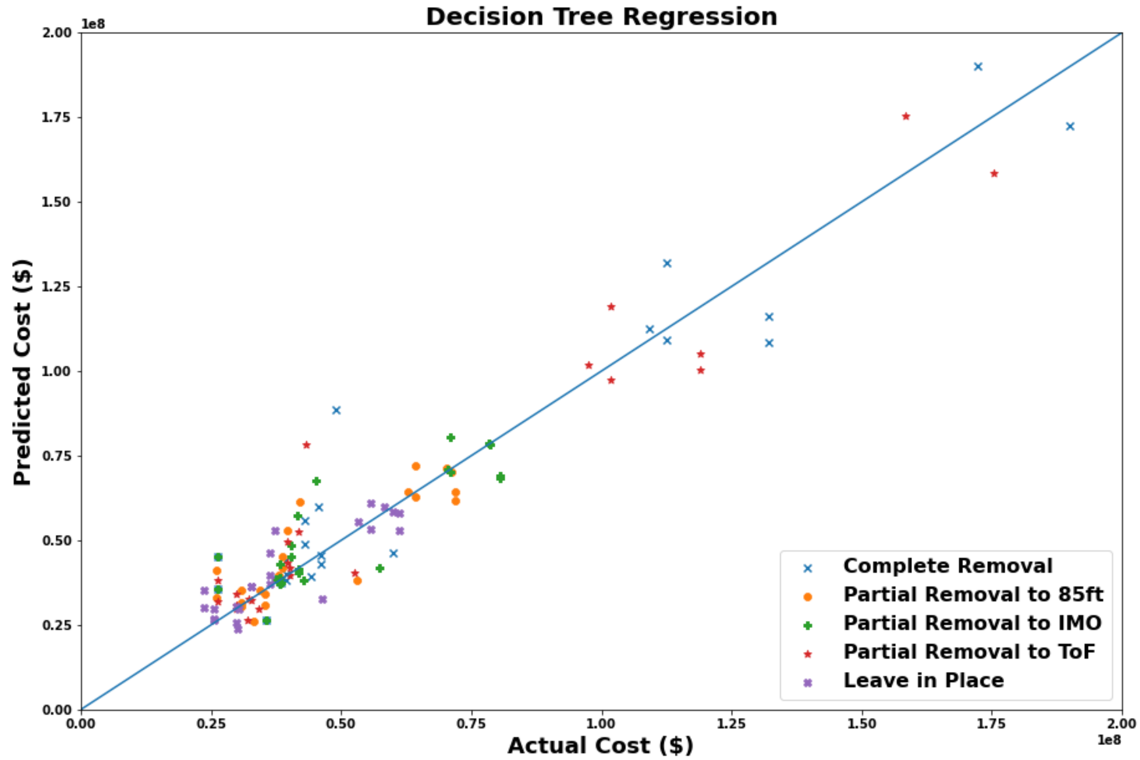


Figure 8.4: Cross-plot of decommissioning cost model predictions for POCS platforms (decision tree regression)

- Elastic Net Regression: This regression method assumes a linear relationship between the input and target variables and is trained by regularisation of the coefficients (Friedman, Hastie and Tibshirani 2010). For multi-output regression problems, this relationship can be conceptualised as a hyperplane which connects the input variables to the target variable. The method is particularly useful when there are multiple features that are correlated with one another. Figure 8.5 shows the cross-plot of the cost estimation model developed using this algorithm.

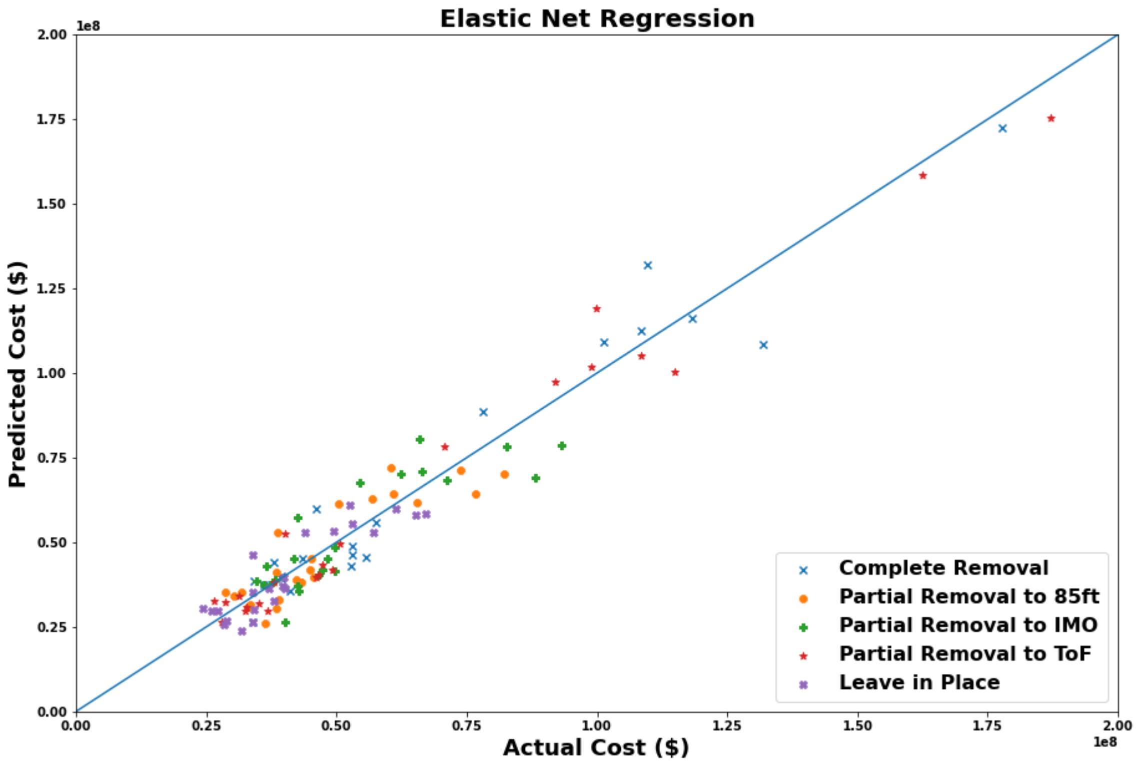


Figure 8.5: Cross-plot of decommissioning cost model predictions for POCS platforms (elastic net regression)

- Gradient Boosting Regression: This regression method is a generalization of boosting to arbitrary differentiable loss functions which can be applied to regression problems by using the GradientBoostingRegressor class of the Python scikit-learn library (Hastie et al. 2017). The Gradient Boosting estimator builds an additive model in a forward stage-wise fashion where a regression tree is fit on the negative gradient of the given loss function in each stage. Figure 8.6 shows the cross-plot of the cost estimation model developed using this algorithm.

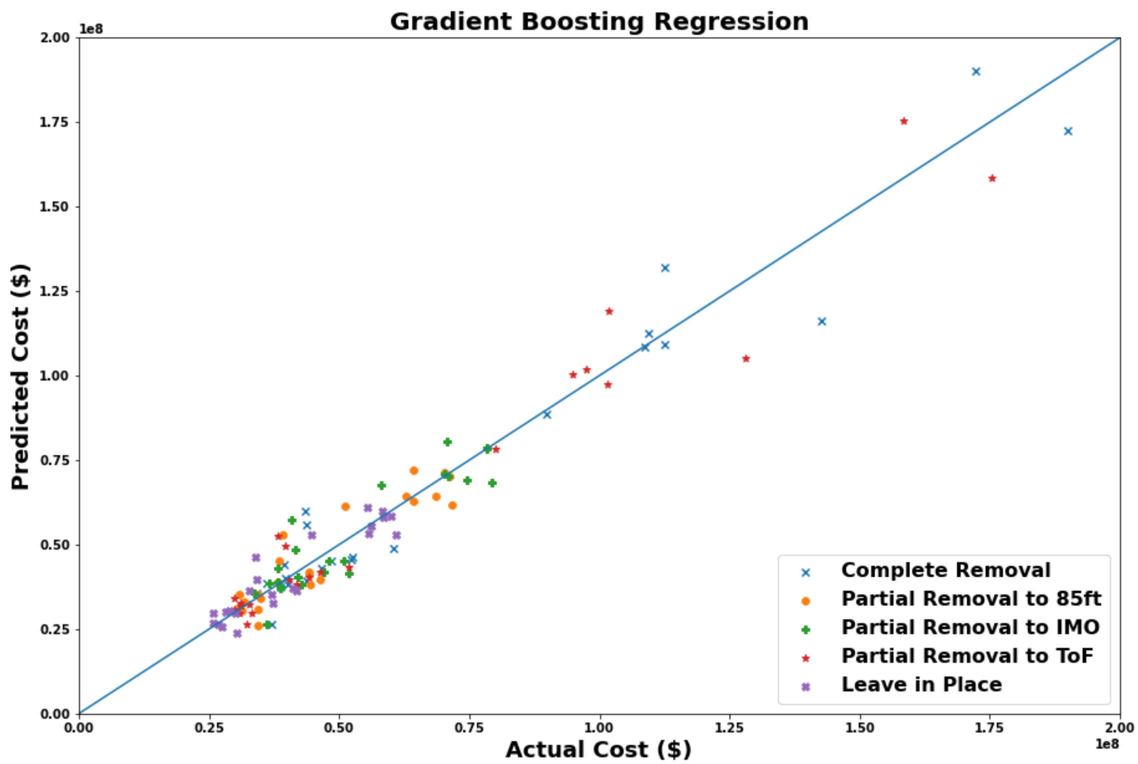


Figure 8.6: Cross-plot of decommissioning cost model predictions for POCS platforms (gradient boost regression)

- KNN Regression: This regression method works based on distance metrics by finding a predefined number of training samples closest in distance to the new point and predicting the label or target variables from these (Hastie et al. 2017). The KNeighborsRegressor class of the Python scikit-learn library implements this learning based on the nearest neighbours of each query point, where k is an integer value specified by the user or set to the value of 5 by default. Figure 8.7 shows the cross-plot of the cost estimation model developed using this algorithm.

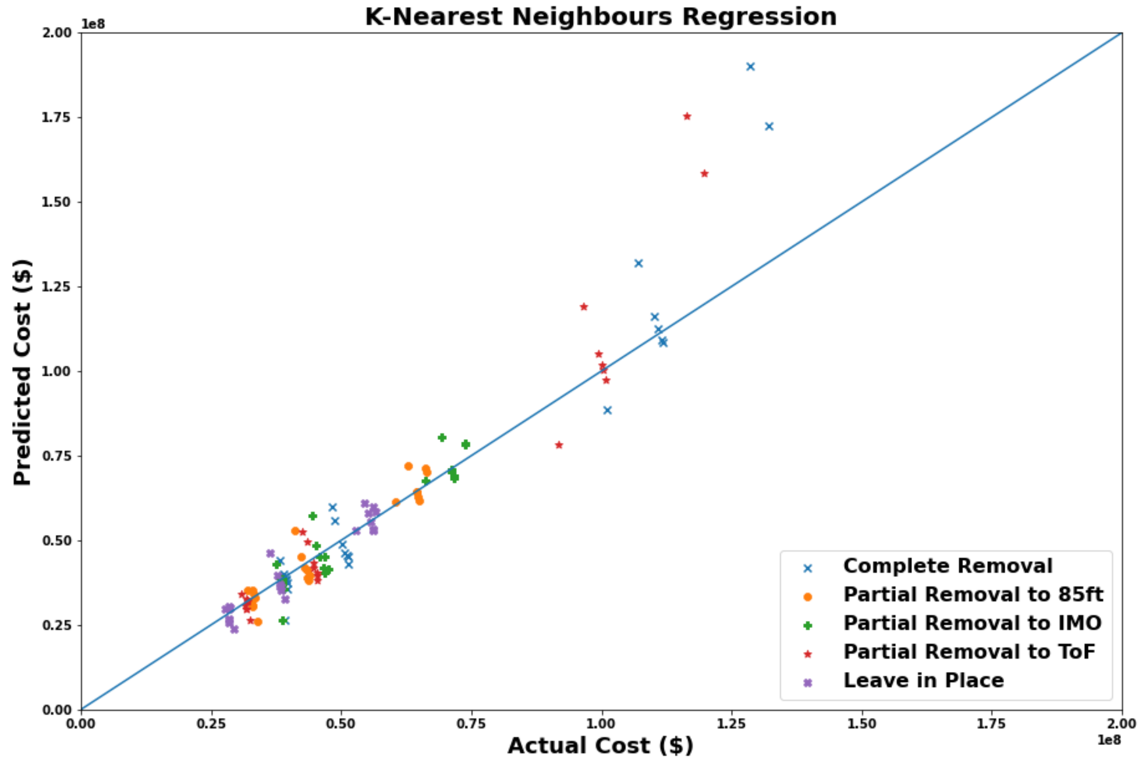


Figure 8.7: Cross-plot of decommissioning cost model predictions for POCS platforms (k-nearest neighbour regression)

- LASSO Regression: This regression method estimates sparse coefficients and mathematically consists of a linear model with an added regularization term (Hastie et al. 2017). The Lasso class of the Python scikit-learn library implements this method by using coordinate descent as the algorithm to fit the coefficients. Figure 8.8 shows the cross-plot of the cost estimation model developed using this algorithm.

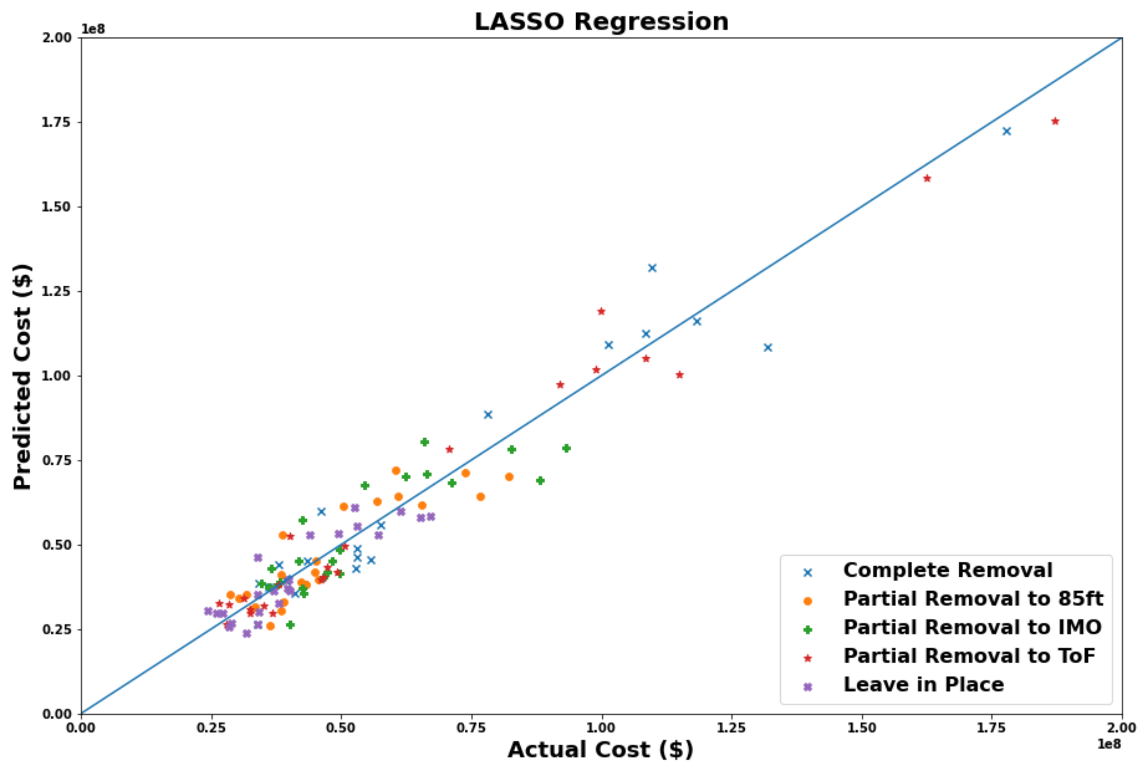


Figure 8.8: Cross-plot of decommissioning cost model predictions for POCS platforms (LASSO regression)

- Multiple Linear Regression: This regression method assumes a linear relationship between the input and target variables and works by minimising the residual sum of squares between the observed targets in the dataset, and the targets predicted by the linear approximation (Maxwell 1975). It is an extension of linear Ordinary Least Square regression with the only difference being that it attempts to simultaneously account for the variations of the explanatory variables in the target variables (Uyanık and Güler 2013). Figure 8.9 shows the cross-plot of the cost estimation model developed using this algorithm.

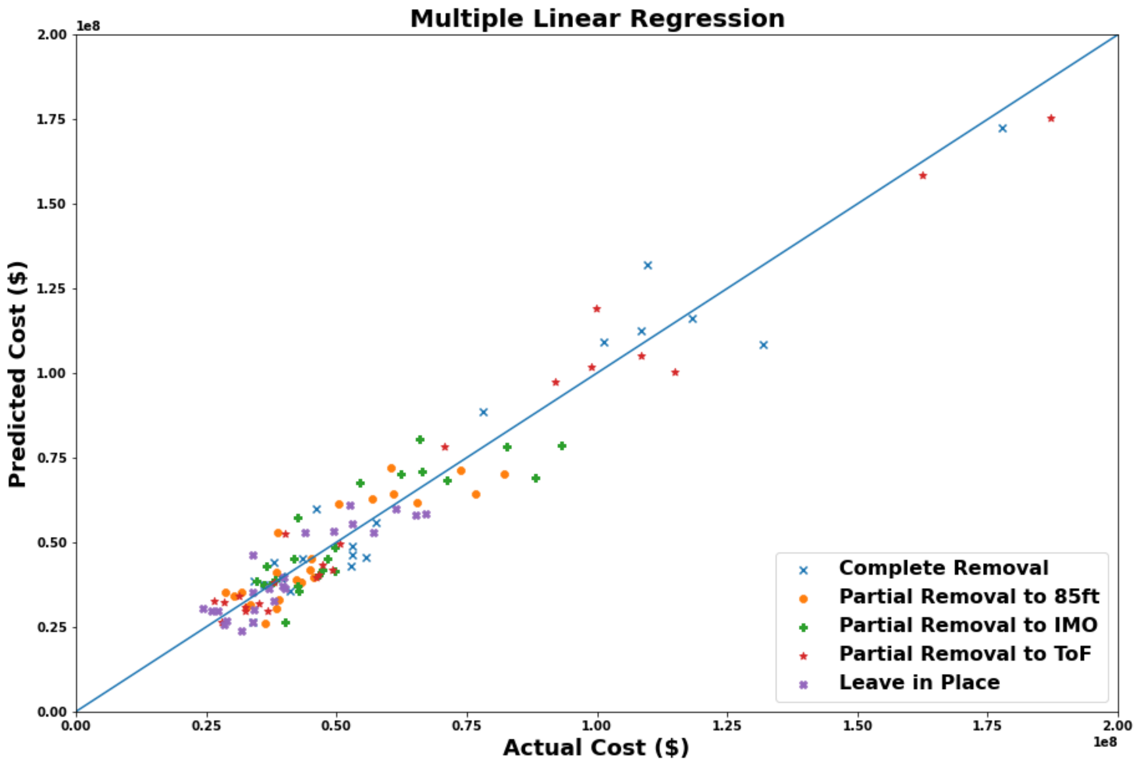


Figure 8.9: Cross-plot of decommissioning cost model predictions for POCS platforms (multiple linear regression)

- MARS Regression: This is a regression method for solving multivariate non-linear regression problems and works by finding a set of simple linear functions that results in the best prediction performance when aggregated (Hastie et al. 2017). It can be conceptualised as a generalization of stepwise linear regression where there is an ensemble of linear functions. Figure 8.10 shows the cross-plot of the cost estimation model developed using this algorithm.

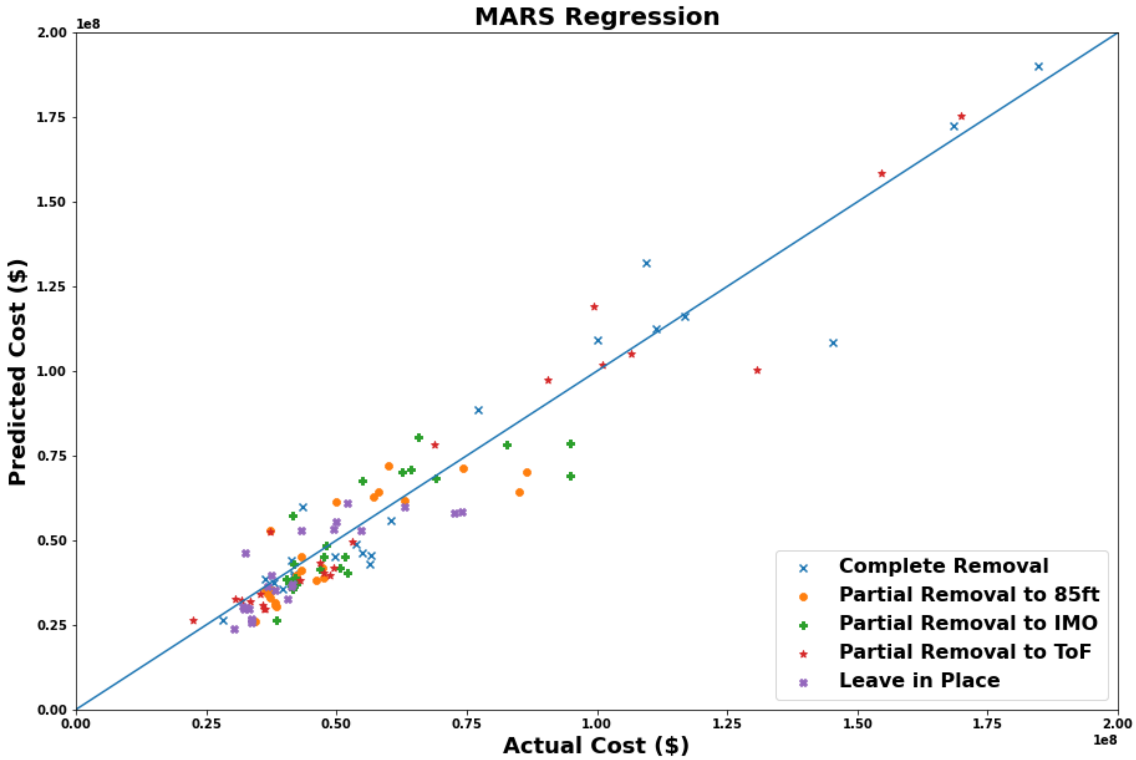


Figure 8.10: Cross-plot of decommissioning cost model predictions for POCS platforms (MARS regression)

- Random Forest Regression: Random Forest is an extension of the Decision Trees that works by using an ensemble of trees where each tree in the ensemble is built from a sample drawn with replacement from the training set (Biau and Scornet 2016). The combination of decision tress enables Random Forest to achieve reduced variance in the model predictions, though this can sometimes be accompanied by a slight increase in bias, and this variance reduction is often significant hence yielding an overall better model than that of the Decision Trees. Figure 8.11 shows the cross-plot of the cost estimation model developed using this algorithm.

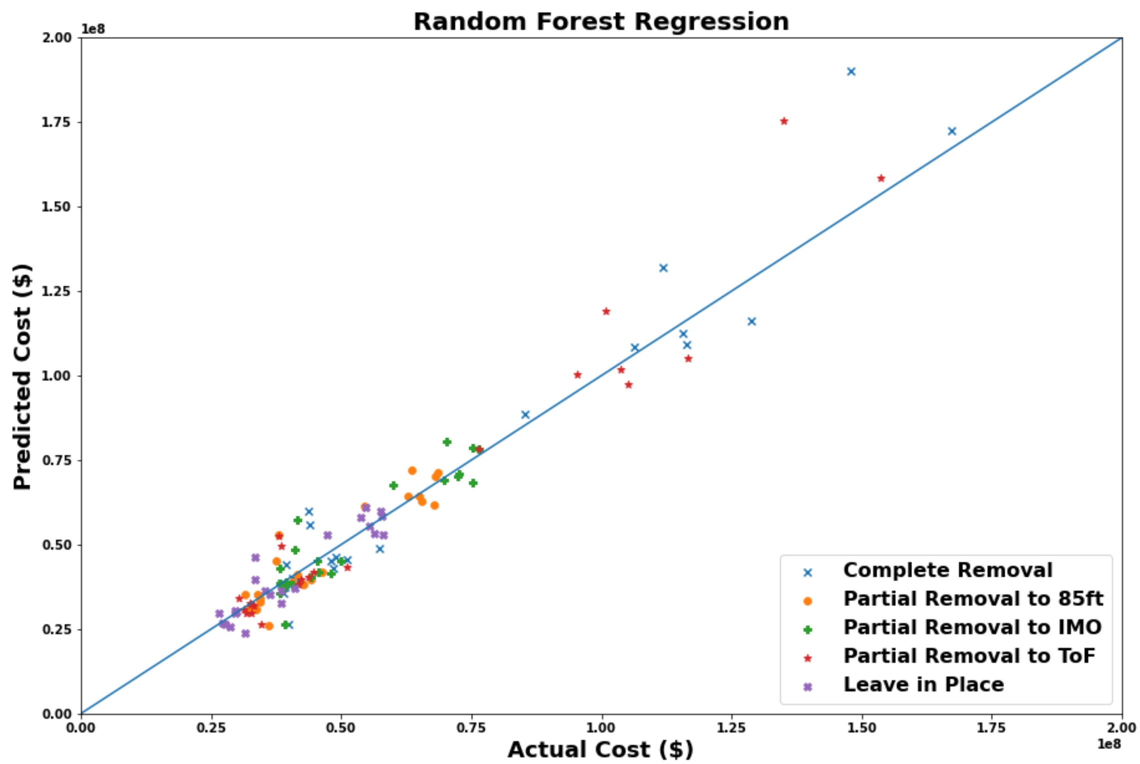


Figure 8.11: Cross-plot of decommissioning cost model for POCS platforms (random forest regression)

- Ridge Regression: This is a linear regression method that improves upon the Ordinary Least Squares regression by imposing a penalty on the size of the coefficients (Avila and Hauck 2017). By minimising a penalized residual sum of squares, Ridge regressions derives coefficients that are more robust to collinearity than the Ordinary Least Squares regression. Figure 8.12 shows the cross-plot of the cost estimation model developed using this algorithm.

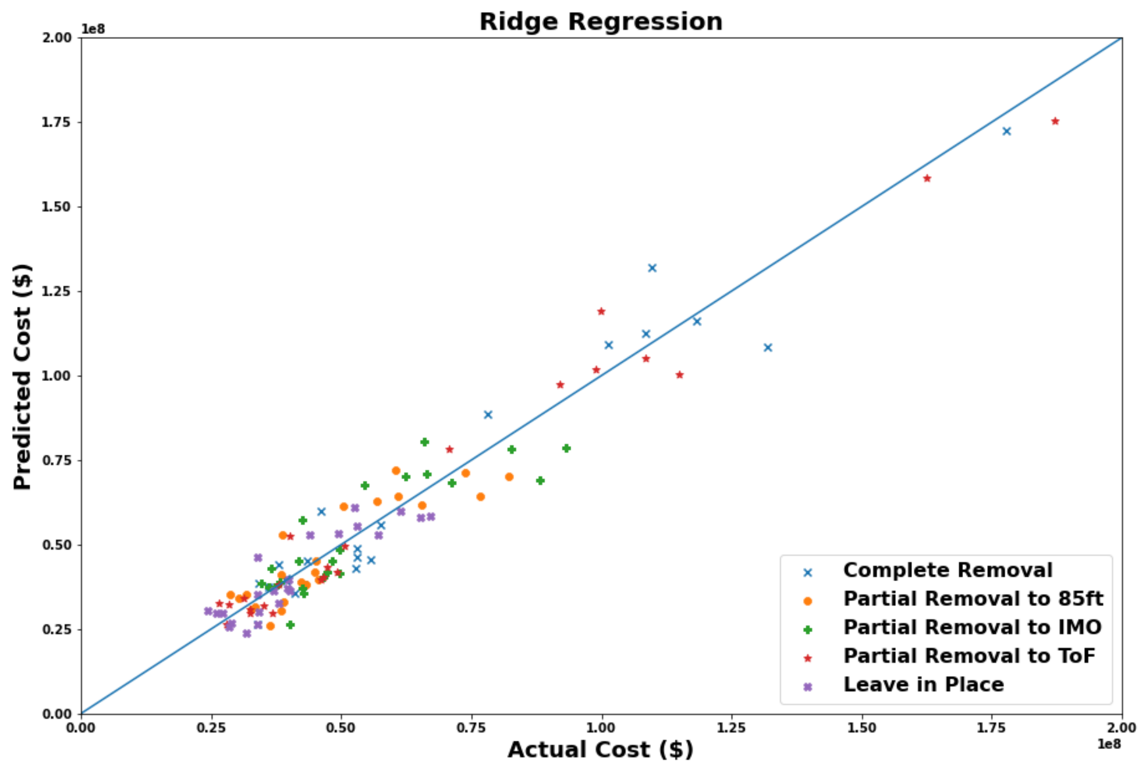


Figure 8.12: Decommissioning cost model predictions for POCS platforms (ridge regression)

- Support Vector Regression: This regression method works by using support vector machines to build a prediction model which depends only on a subset of the training data and has a cost function which ignores samples whose prediction is close to their target (Smola and Schölkopf 2004). It is implemented by the "svm" class of the Python scikit-learn library. Figure 8.13 shows the cross-plot of the cost estimation model developed using this algorithm.

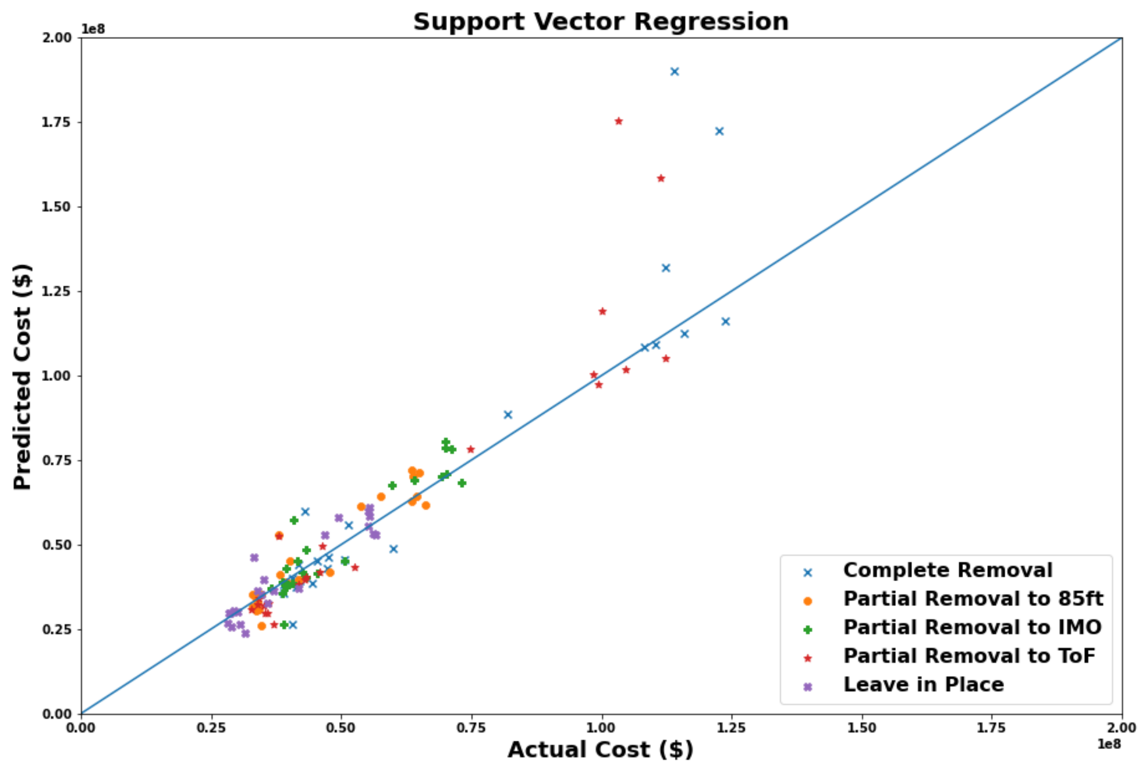


Figure 8.13: Decommissioning cost model predictions for POCS platforms (support vector regression)

The concentration of datapoints around the y=x line for all the investigated models indicate that they make predictions that are accurate to a reasonable degree. However, it is challenging to decipher the best performing model based on the cross-plots alone. Hence their quantitative evaluation was deemed necessary.

8.3.2.2. Quantitative Evaluation of Machine Learning Regression Models' Performance using Accuracy Metrics

Quantitative evaluation of a model entails comparing the model predictions with actual data and measuring the degree of deviation between both sets of values. Root mean square error, mean absolute error, mean absolute percentage error (MAPE), and R-Squared are some popular metrics used for evaluating machine learning models.

For metrics with values ranging between zero and infinity, a common drawback is that their value does not say much about the performance of the regression with respect to the distribution of the ground truth elements (Chicco, Warrens and Jurman 2021). In addition, since the order of magnitude of decommissioning costs is quite high (typically in millions of dollars), failure to assess the model's accuracy with performance metrics that are based on relative measurements is likely to lead to misinterpretations. Therefore, this research elected to evaluate the developed models with relative measurement metrics i.e., scale-free accuracy metrics whose values are bounded between 0 and 1 (or 0-100%). This includes Mean Absolute Percentage Error (MAPE), R-Squared, and Adjusted R-Squared.

- MAPE: MAPE has emerged as one of the most used accuracy metrics since the start of the 21st century (Gneiting 2011; Botchkarev 2018). MAPE is a unitless metric determined as shown in Equation 8.3 and expressed as a percentage (Velasco-Gallego and Lazakis 2020).

  $$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (8.3)$$

  Where *n* corresponds to the sample size, and y_i and $\hat{y}_i$ represents the *i*-th occurrence of the actual and the predicted values, respectively.

  One disadvantage of using MAPE is that its value is undefined when the observed value is zero. Nevertheless, it is beneficial for a problem domain like decommissioning costing which has a varying and sometimes unclear scale and context.

- R-Squared: The coefficient of determination, R^2, is a metric calculated as expressed in Equation 8.4 and defined as the proportion of variations in the data explained by the linear regression model (Montgomery, Peck and Vining 2021). It can be interpreted for a multioutput regression model as the proportion of the total variation in the set of predicted/dependent variables that is accounted for by the set of observed/independent variables (Dharumarajan et al., 2017).

  $$R^2 = \frac{\sum_{i=1}^{n}(p_I - \overline{p_I})^2}{\sum_{i=1}^{n}(o_I - \overline{o_I})^2} \quad (8.4)$$

Where p_I and o_I are the predicted and observed values, and $\bar{p}$ and $\overline{o_I}$ are the means of the predicted and observed values.

A model's accuracy is indicated by the nearness of its R^2 to one. Conversely, the R^2 value becomes zero in the absence of any linear relationship between the sets of response and predictor variables. However, this metric poorly handles addition of new predictor variables to the model.

- Adjusted R-Squared: The adjusted R-Squared, ${R^2}_{adj}$ is another metric used for assessing the goodness-of-fit of a model. This accuracy metric modifies the R^2 value by compensating for the number of predictor variables included in the model (Montgomery, Peck and Vining 2021). The formula for calculating ${R^2}_{adj}$ from R^2 is shown in Equation 8.5 (Harrell 2017) from which it can be deduced that the ${R^2}_{adj}$ value of a model will always be less than or equal to its R^2.

$$ {R^2}_{adj} = 1 - (1 - R^2)\frac{n-1}{n-x-1} \qquad (8.5) $$

Where n and x are respectively the number of observations and the number of independent variables in the data.

Table 8.4 shows the values of the MAPE, R-Squared and Adjusted R-Squared for all the developed regression models.

Table 8.4: Performance Metrics Values for Developed Regression Models

	Accuracy Metric		
Regression Algorithm	**MAPE (Lower value is desirable)**	**R-Squared (Higher value is desirable)**	**Adjusted R-Squared (Higher value is desirable)**
Decision Tree	13.541%	0.882	0.864
Elastic Net	12.319%	0.931	0.921
Gradient Boosting	10.103%	0.935*	0.925*
KNN	9.394%*	0.863	0.842
LASSO	12.322%	0.931	0.921
Multiple Linear	12.322%	0.931	0.921
MARS	13.814%	0.903	0.887

Random Forest	9.781%	0.924	0.912
Ridge	12.322%	0.931	0.921
Support Vector	10.744%	0.836	0.810

*Best performance with respect to accuracy metric.

Based on the performance evaluation results, Gradient Boosting is observed to be the most adequate for modelling the decommissioning options costs based on its R-squared and Adjusted R-squared values. Although the KNN-based model preformed best in terms of MAPE, Gradient Boosting performed best in terms of R-Squared (and Adjusted R-Squared) which has been identified as being more informative than other accuracy metrics, particularly for regression analysis evaluation (Chicco, Warrens and Jurman 2021). Consequently, the regression model developed using Gradient Boosting algorithm was adopted as the machine learning model for forecasting decommissioning options costs. The python script for developing this model is presented in appendix 7.

8.4. Predicting Decommissioning Options Costs for the Case Study using the Costing Model

From Equation 7.2, the substructure weight, water depth, and age of a platform are the input required by the developed machine learning costing model to predict the costs of decommissioning the platform with different options. These platform features for the case study are

- Substructure weight = 8,774 tons + 2,363 tons = 11,137 tons
- Water depth = 406 feet
- Platform age = 43 years

Inputting these data into the machine learning model yields the costs of decommissioning the case study platform with different decommissioning options as shown in Table 8.5.

Table 8.5: Predicted Decommissioning Options Costs for Case Study

Cost of Complete Removal ($)	Cost of Partial Removal to 85 feet ($)	Cost of Partial Removal to IMO Depth ($)	Cost of Partial Removal to Top of Footings ($)	Cost of Leave in Place ($)
77,931,854	63,816,150	69,470,612	69,693,463	55,745,763

With the decommissioning costs for the case study platform forecasted, data scaling was applied to transform these values into a range that is compatible with the LIKERT scale input data of the decommissioning decision model.

8.4.1. Data Scaling of Forecasted Decommissioning Options Costs for the Case Study

Applying the data scaling equation (Equation 3.9) to the decommissioning options cost values for the case study produces the LIKERT-scale equivalent values shown in Table 8.6.

Table 8.6: LIKERT Scale Equivalent of Decommissioning Options Costs

Decommissioning Option	Cost ($)	LIKERT Scale Equivalent
Complete Removal	77,931,854	6.391
Partial Removal to 85 feet	63,816,150	7.070
Partial Removal to IMO Depth	69,470,612	6.798
Partial Removal to Top of Footings	69,693,463	6.788
Leave in Place	55,745,763	7.458

Because cost-savings is desirable during decommissioning, the most expensive decommissioning option in Table 8.6 is observed to be equivalent to the least value on the LIKERT scale while the cheapest option has the highest equivalent value.

The values in Table 8.6 can effectively be inputted into the DDM as a more accurate replacement for the expert opinion data pertaining to the cost criteria as obtained from the decommissioning survey in this research. Thus, demonstrating the model’s capability to support the incorporation of historical data as input as this information becomes available.

8.5. Summary

This chapter discussed the development of a decommissioning options costing model with the aid of machine learning regression algorithm and a decommissioning costing dataset in the public domain. The costing model predicts the decommissioning options costs from the features of the platform to be decommissioned, namely the substructure weight, water depth and age. Results from the graphical and quantitative performance evaluation of the model both indicated a high prediction accuracy. The costing model was used to forecast the costs of using five options for decommissioning the case study platform. These costs were then scaled into their equivalent values in the Likert scale range to facilitate direct integration into the decommissioning decision model. Thus, demonstrating that the decision model supports the integration of historical data when this becomes available.

The next chapter provides a conclusion to this research and recommendations for future research in the knowledge domain.

Chapter 9 : CONCLUSION AND RECOMMENDATIONS

This chapter concludes this report by summarising the information presented in all the preceding chapters and highlighting the golden thread that links all the chapters. It begins by presenting an evaluative summary of the conducted research in form of its conclusions and findings. Next, the impact of the research is discussed to highlight the implications of the conclusions to the broader context within which the research belongs. A critical appraisal of the research limitations and challenges encountered while conducting the research are also outlined. The chapter closes by providing recommendations for future works in the knowledge domain of the research.

9.1. Conclusion and Findings

The overarching aim of this research was to develop decision support for assisting decision-makers to determine the best available option for decommissioning their offshore platform. However, the achievement of this aim entailed meeting several targets as captured by the research objectives. Completion of this research contributes to the body of knowledge by providing a better understanding of the key elements and decision-making process of determining the optimal decommissioning option for offshore platforms. Hence, stating its conclusion requires a careful reflection on the completed work and its significant contributions vis a vis the aim and objectives.

In performing this research, the researcher has

i. Completed a robust literature review of current practices in offshore decommissioning with focus on the main decommissioning options and key considerations for choosing an option for a project. These considerations or decision criteria were identified to be safety, environmental impact, technical feasibility, financial cost, and public perception. Existing approaches for evaluating decommissioning options for offshore platforms and identified their limitations and strengths have also been reviewed.

   Through this critical review, the primary desirable capabilities of a robust decision model for identifying the optimal option for a decommissioning project were also established. These capabilities comprise the ability to account for qualitative and quantitative data, clarity and structure in use of expert opinion when required, and use of Multi-Criteria Decision Analysis. Lastly, the Analytic Hierarchy Process was identified as the most suitable Multi-Criteria Decision Analysis technique for solving the multicriteria problem of decommissioning options evaluation. This technique was combined with Likert scale to overcome the AHP limitations of having a cumbersome number of judgements and matrix inconsistency issues.

ii. Developed a novel decision model for determining the optimal option for decommissioning an offshore platform. Also demonstrated the applicability of the same by applying it to a case study with information from a decommissioning survey as input. This analysis provided better understanding of the decision-making process of options selection and the complex interaction of the decision criteria. The decision model comprises of four phases and supports efficient identification of the optimal decommissioning option for an offshore platform as demonstrated by the result of its application to a case study.

iii. Validated the survey input data, logical structure, and results of applying the decommissioning decision model with the aid of sensitivity analysis, comparison to similar studies and expert opinion, respectively. All three validation schemes yielded positive outcomes, strongly supporting the fitness-for-purpose and fitness-for-use of the developed model. On this basis, the model is proposed for adoption by the decommissioning industry.

iv. Applied machine learning to an existing dataset to develop a model for estimating decommissioning options costs and subsequently integrating historical data into the decision model. The costing model uses the substructure weight, water depth and age of a platform to predict the costs of its decommissioning under five different scenarios with reasonable accuracy. It was implemented by identifying platform features which highly influence choice of decommissioning option for a project and applying machine learning regression with secondary data to these features to develop a decommissioning options costing model with reasonable prediction accuracy. The costs of decommissioning the case study under five different scenarios were then predicted using the developed costing model and integrated into the decision model, thus replacing the survey input data and minimising bias from human judgement.

These findings represent a significant advancement on the current understanding of decision-making during the decommissioning of offshore platforms with regards to determining the optimal option for a project. The DDM is valuable for improving the efficiency of future decommissioning projects as demonstrated by its successful application to a case study and positive outcomes from its validation. As such, its industry use is expected to improve decommissioning decision-making in that the model's logical process will infuse engineering rationality into the options assessment process, thus reducing bias and minimising conflicts between project stakeholders.

9.2. Wider Impact of Research

This work represents a novel approach to the optimisation of offshore decommissioning that is focused on decision-making during the project planning stage. Its outcomes improve on existing decommissioning option selection approaches by developing a more efficient approach. It is also expected to reduce the cost of future decommissioning projects by aiding effective and timely estimation of the financial costs of using different options.

There are several significant impacts of the research, some of which are described below.

i. The decommissioning decision model can serve as an unbiased basis for justifying the choice of a decommissioning option for an offshore asset by establishing traceable steps in the decision-making process. Hence, reducing the traditionally rife conflict between stakeholders of decommissioning projects. The model's structured handling of expert opinion minimises the subjectivity of human judgement, thus increasing the likelihood of arriving at a balanced and logically sound decision as demonstrated by the case study analysis. Additionally, the outcome of the decision-making process can be easily traced back to the beginning if there is a need for auditing the decision. Industry adoption of the decision model will result to significant reduction of time, resources and efforts spent in decision-making during decommissioning. The proposed framework for decommissioning option selection streamlines the entire process of identifying the optimal option for a project. Also, the DDM identifies the key elements of the decision-making and their interplay vis a vis decision criteria comparisons and influence on decommissioning options performance for a project. The model is easily adaptable and therefore can be applied to platform wells, subsea tiebacks and bundles, and pipelines with little modification. Given adequate information supply, the model can facilitate detailed decision-making analysis of assets and components that are more complex than the case study used in this research.

ii. The decommissioning options costing model developed using machine learning regression represents a novel contribution. Its use will improve accuracy in early determination of the potential exposure to decommissioning costs for decommissioning, reporting, asset trading and budget purposes. A paramount aspect of the costing model's novelty relates to its capacity to predict the costs of using five different options for decommissioning a platform while only requiring the substructure weight, water depth, and age of the platform as input. Hence, it is expected to be a game-changer in the decommissioning industry due to its usefulness, particularly at the preliminary stages of decommissioning projects when data is scarce and cost estimates are highly uncertain. Moreover, the model represents the first attempt to concurrently predict the costs of using five different options for decommissioning a platform. Hence, it is expected to be extremely useful to asset owners for preliminary cost evaluation purposes prior to detailed engineering cost estimation.

iii. The elaborate literature review of offshore decommissioning and comparison of decommissioning perception by individuals in different offshore regions can serve as a catalyst for driving policymakers to improve upon existing decommissioning legislation and practices. Highlighting differences in legislations of countries is likely to increase the possibility that governing authorities will identify and correct flaws in their state's current approach to decommissioning. The wide variation in the location of the decommissioning survey participants was invaluable in this regard, especially considering the fragmented nature of decommissioning practice in the world. Even more, this research can support decommissioning policy formulation by countries like Nigeria with ageing infrastructure but no comprehensive decommissioning regulation system.

iv. The relative comparison which established weights of decision criteria and sub-criteria for the case study can support asset owners to effectively develop a scale of preference for these decision elements, and subsequently optimise resource allocation to aspects of the data gathering. Moreso, this research represents a pioneering effort to prioritise platform features in terms of their relevance to decommissioning options selection and relating the prioritised features to options cost. This streamlines data gathering for supporting decommissioning decisions and contributes towards valuable use of historical data. The AHP hierarchy structure used for applying the DDM to the case study was developed from extensive review of literature. It provides a template for collection of decommissioning information from completed projects and using these to realise process improvements in future projects. This is likely to benefit platform owners by improving the efficiency of knowledge transfer between their projects. It can also benefit the offshore decommissioning industry by fostering information sharing which is likely to catalyse process improvements.

v. The completed research work as documented in this report represents the addition of an educational reference to the existing body of offshore decommissioning knowledge. The review of literature pertinent to offshore decommissioning, decision model development, analysis of the case study and integration of historical data to improve the accuracy of decision-making are some of the obvious areas where this work will benefit future research endeavours.

Therefore, this research represents an original contribution to the domain of offshore decommissioning despite making use of existing research elements. This is encapsulated in both the methodological context (i.e., unique combination of quantitative and qualitative research tools to optimise offshore decommissioning), and the application context (i.e., novel approach to decommissioning options selection that builds on the limitations of existing works, is reusable across various locations, and supports integration of historical data) of the research.

9.3. Critical Appraisal of Completed Work

Throughout the conduction of this research, considerable effort was directed towards ensuring achievement of the aim and systematic integration of different expert opinions to arrive at consensus that mitigates extreme outcomes. In this regard, an assessment of some issues of concern in the research is subsequently presented.

i. DDM applicability to more complex scenarios than the case study: Several types of offshore platforms are in existence (see Figure 2.1), but the developed decision model was only applied to a single fixed-steel jacket platform in this research. This limited example is acknowledged as a potential source of bias in determining the usefulness of the model and its application to a more complex platform (and varying legislative requirements) is likely to be more cumbersome. Notwithstanding, the decision model's flow process is generic and hence readily adaptable to varying complexities and levels of analysis detail, provided that sufficient data is made available to the decision-maker. For example, it is expected that the decision criteria will always remain the same when applying the DDM although there might be need to consider a wider range of sub-criteria than those considered in the case study analysis depending on the application context. In essence, the decision-maker's requirements, platform features and available information influence the accuracy of the DDM results.
ii. Use of Work Experience to gauge expertise level of survey respondents: In determining the relative importance or priorities of platform features to decommissioning option selection, the opinion of survey respondents with more years of work experience was weighed more than those of individuals with less work experience. This assumption is a possible source of bias because some individuals who have worked for a limited number of years may possess extensive knowledge of decommissioning from other formal or informal sources. Conversely, it is possible that an individual with more work experience only possesses knowledge of decommissioning relating to a very specific part of such projects. In retrospect, the survey analysis would have benefitted from using a factor which combines the respondent's Work Experience, Level of Education, and Perceived Level of Confidence in Judgement instead of Work Experience alone.
iii. Appropriateness of DDM and Results Validation: Despite the efforts that have been made to logically develop and validate the decommissioning decision model, it is worth noting that the model still possesses some level

of subjectivity. This, however, does not diminish the value of applying the model to decommissioning option selection. As highlighted by the literature review in Chapter two, MCDA approaches are suited for decommissioning decision-making due to vast knowledge gaps even though complete verification of the accuracy of the results obtained from such approaches is impossible due to their conceptual nature.

iv. Research Challenges: Two major challenges were encountered during this research due to the uniqueness and relative infancy of the research domain.

- Scope definition challenge: Decommissioning is multifaceted. It can be viewed from engineering, social, economics, policy-making and environmental science perspectives and each of these perspectives have their unique considerations. Additionally, there is a wide range of offshore structures and each of these, to an extent, has varying decommissioning procedures. Moreso, developing a solution that is reusable across various locations is not straightforward because of the regional differences in decommissioning practice in terms of regulations and perspectives of stakeholders. Hence it was challenging to define boundaries for this research. Addressing this challenge necessitated a careful trade-off between the breadth and depth of analysis in this research. Literature review guided the researcher to choose to focus on fixed-steel platforms located in California while developing a robust solution that is reusable for other offshore structures and adaptable to other locations. In addition, the location-based differences in stakeholders' approach to offshore decommissioning was explored during analysis of the industry survey carried out as part of this research.
- Data-related challenges: Obtaining either live project or historical decommissioning data to support the analysis in this research proved to be an arduous task. Where such data existed for public use e.g., UKCS publicly available decommissioning data (https://www.gov.uk/guidance/oil-and-gas-decommissioning-of-offshore-installations-and-pipelines), there were significant inconsistencies in the procedure followed and documented results. Also, it was observed that data for furnishing most qualitatively

assessed decision criteria and sub-criteria were non-existent despite being mentioned in the literature, possibly because these had neither been adopted by the offshore industry nor documented for past projects. Adopting the workaround strategy of demonstrating the decommissioning decision model's applicability using a theoretical case study and input data from a decommissioning survey enabled the researcher to overcome this challenge. Also, in developing the decommissioning options costing model, the researcher used secondary data from literature and was able to apply machine learning regression despite the limited volume of this data by incorporating the Leave-One-Out cross validation technique.

9.4. Recommendations for Future Research

Despite the achievements of the current work, prospects for further research in offshore decommissioning abounds. Hence, some recommendations are presented for future research endeavours in this knowledge domain.

i. Research is needed in understanding the implications of the currently ongoing energy industry net-zero transition to offshore decommissioning. Offshore platforms are a significant contributor to atmospheric emissions due to their running and maintenance operations, and their removal will result to a decrease in the generation of greenhouse gases although the machinery used for such projects also emit pollutant gases. Research in this area can focus on development of more environmental-friendly decommissioning procedures and options. It can also be directed towards catalysing the adoption of repurposing as an alternative to complete platform removal during decommissioning.
ii. In future research, it would be interesting to apply the developed decision model to the decommissioning of other types of offshore structures like concrete gravity-based platforms, FPSO platforms, and tension leg platforms. More decommissioning options such as toppling and deep-sea disposal can also be investigated for platforms as there are countries where the overseeing regulations permit these options. Also, future research can apply the DDM to a platform with similar features to the case study platform in this research but situated in a different location such as the North Sea.

Comparing the outcomes will help to unlock a deeper understanding of the differences in approaches to offshore decommissioning by different countries alongside the attendant strengths and weaknesses.

iii. In the future, the DDM and the options costing model developed in this research can be adapted to a software tool which implements their functionality with minimum human interference. Such tool was not developed in the current work due to time constraints but is expected to be economically viable and beneficial to the decommissioning industry.

iv. Future research is required in developing innovative strategies to promote data sharing and improving the consistency of documenting decommissioning projects. Progress in this area will likely result to improvements to the current decommissioning practices by fostering more objective research and development of innovative solutions. Given adequate access to industry data, it would be interesting to investigate the application of the decision model to an actual project and objectively quantify how much improvement can be realised through its use as compared to a similar project completed with the current industry approach.

v. As more decommissioning data becomes available, future research in platform features prioritisation will benefit from taking the more formal computing approach of principal component analysis (Jolliffe and Cadima 2016). This technique is useful for reducing the dimensionality of large datasets and increasing their interpretability while concurrently minimizing information loss. Similarly, gradient boosting algorithm was identified in this research to be the best algorithm for developing a decommissioning options cost forecasting model. However, due to time constraints the model developed from this algorithm was not optimised before using it to forecast costs. Future research can investigate optimisation of the costing model through hyper-parameters tuning to improve its prediction accuracy.

In summary, the aim of this research has been achieved. The research, despite its completion at this stage, has created opportunities for further research in other areas of decommissioning decision-making. Therefore, there is room to extend and build upon the findings from this research towards further optimisation of offshore decommissioning.

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APPENDICES

Appendix 1: Dataset for Derivation of the Features of the Case Study Platform from Features of Platforms in Pacific Outer Continental Shelf, California

Platform_Name	Age_(Years)	Conductors_Weight_(t)	Topsides_Weight_(t)	Jacket_Weight_(t)	Piles_Weight_(t)	Substructure_Weight_(t)	Structural_Weight_(t)	Water_Depth_(ft)	Distance_from_Shore_(miles)
A	53	1,439	1,357	1,500	600	2,100	3,457	188	5.8
B	53	1,502	1,357	1,500	600	2,100	3,457	190	5.7
C	44	2,261	1,357	1,500	600	2,100	3,457	192	5.7
Edith	38	518	4,134	3,454	450	3,904	8,038	161	8.5
Ellen	41	2,065	5,300	3,200	1,100	4,300	9,600	265	8.6
Elly	41	0	4,700	3,300	1,400	4,700	9,400	255	8.6
Eureka	37	4,377	8,000	19,000	2,000	21,000	29,000	700	9.0
Gail	34	7,064	7,693	18,300	4,000	22,300	29,993	739	9.9
Gilda	40	3,251	3,792	3,220	1,030	4,250	8,042	205	8.8
Gina	41	374	447	434	125	559	1,006	95	3.7
Grace	42	4,684	3,800	3,090	1,500	4,590	8,390	318	10.5
Habitat	40	2,047	3,514	2,550	1,500	4,050	7,564	290	7.8
Harmony	32	21,424	9,839	42,900	12,350	55,250	65,089	1,198	6.4
Harvest	36	6,110	9,024	16,633	3,383	20,016	29,040	675	6.7
Henry	42	1,174	1,371	1,311	150	1,461	2,832	173	4.3
Heritage	32	12,996	9,826	32,420	13,950	46,370	56,196	1,075	8.2
Hermosa	36	3,538	7,830	17,000	2,500	19,500	27,330	603	6.8
Hidalgo	35	2,334	8,100	10,950	2,000	12,950	21,050	430	5.9
Hillhouse	52	2,734	1,200	1,500	400	1,900	3,100	190	5.5
Hogan	54	1,426	2,259	1,263	150	1,413	3,672	154	3.7
Hondo	45	5,928	8,450	12,200	2,900	15,100	23,550	842	5.1
Houchin	53	1,388	2,591	1,486	150	1,636	4,227	163	4.1
Irene	36	1,662	2,500	3,100	1,500	4,600	7,100	242	4.7

Mean* (Average Value)	**42**	**3926**	**4,715**	**8,774**	**2,363**	**11,137**	**15,852**	**406**	**7**

*Defines the physical features of the theoretical case study platform

Appendix 2: Questionnaire for Application of the Decommissioning Decision Model to Case Study Platform

Introduction

This survey is part of a doctoral research study aimed at the development of a decision support model for offshore decommissioning options selection. The study is being conducted by Emmanuel Eke at the Robert Gordon University, Aberdeen UK.

You have been selected to take part in this survey because you are deemed to be knowledgeable in the subject matter of offshore decommissioning.

The survey is designed to capture the judgements of decommissioning stakeholders across different offshore regions of the world about the performance of decommissioning options. Additionally, analysis of the results is intended to uncover new insights into the decision-making process of decommissioning options selection for a project.

Your participation in this survey is voluntary, therefore you can decide to discontinue at any stage. If you are happy to take part, kindly answer the questions that follow. Confidentiality is paramount in this study; hence your answers shall be treated as such. There are no ethical concerns with the survey as it does not require any personal information, Nevertheless, such information, if divulged, shall be kept anonymous in any future research-related output.

For further information, kindly contact Emmanuel by email via e.eke@rgu.ac.uk.

This survey should take about 15 minutes to complete. Your input is much appreciated.

Page 2

Section 1: Demographics

The responses to questions from this section are for understanding the composition of survey respondents.

1. Which of the following offshore regions best describes your main geographic region of operation?

- ○ Gulf of Mexico
- ○ Pacific Outer Continental Shelf
- ○ North Sea
- ○ Offshore Africa
- ○ Asian Seas
- ○ Offshore Australia
- ○ Caribbean Seas
- ○ Offshore South America
- ○ Other

1.a. If you selected Other, please specify:

2. What is your highest level of education?

- ○ Vocational/Technical Education
- ○ Secondary School Certificate
- ○ Bachelor's Degree/ Diploma
- ○ Master's Degree
- ○ Doctorate Degree
- ○ Other

2.a. If you selected Other, please specify:

3. How long have you worked in the offshore oil and gas industry?

- ○ 0 – 3 years
- ○ 4 – 7 years
- ○ 8 – 11 years
- ○ 12 – 15 years
- ○ >15 years

4. Which of the following best describes your current organisation's affiliation to offshore decommissioning?

- ○ Operator
- ○ Service Company
- ○ Academia and Research Organisation
- ○ Government Organisation and Regulatory Body
- ○ Interest Group
- ○ Other

4.a. If you selected Other, please specify:

____

5. What aspect of offshore decommissioning would you consider yourself to be most knowledgeable about?

- ☐ Safety
- ☐ Environmental Impact
- ☐ Technical Feasibility
- ☐ Cost
- ☐ Public Perception
- ☐ None of the above

Page 3

Section 2: Comparisons and Judgements

Please use your best judgement to provide responses to the set of questions in Sections 2(A) and 2(B) with reference to a hypothetical case study platform.

A factsheet containing background information about the case study platform is first presented to provide the decision-maker with contextual knowledge of the platform and hence promote an informed opinion.

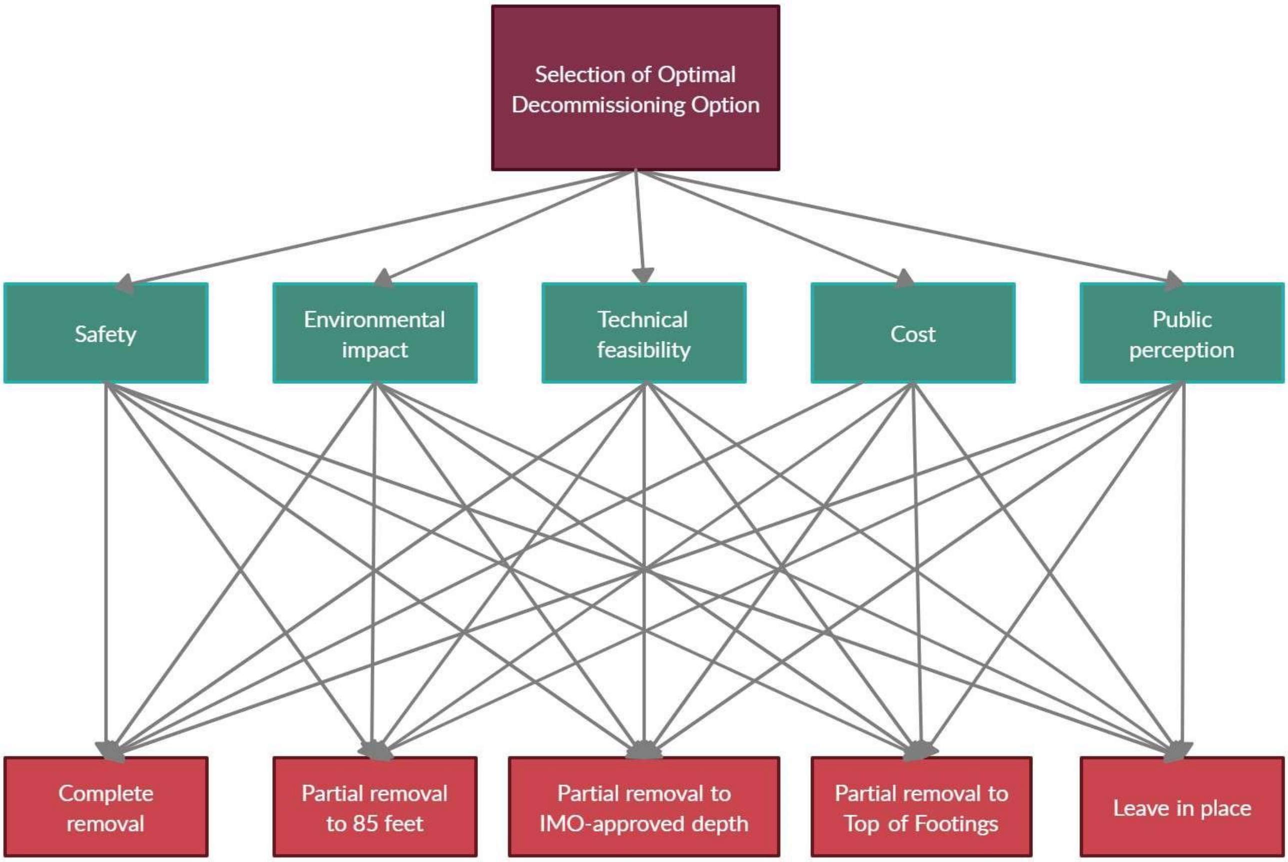
The problem hierarchy structure is also presented to show all relevant elements of the decision-making problem. The goal is to select the optimal decommissioning option from a list of five different options by considering five distinct decision criteria.

Please carefully go through this information before proceeding to answer the next set of questions.

Case Study Platform Factsheet

Location: Pacific Outer Continental Shelf, California	
Platform type: Fixed steel jacket structure	**Water depth**: 406 feet (124 metres)
Topsides weight: 4,715 tons	**Jacket weight**: 8,774 tons
Piles weight: 2,363 tons	**Number of piles**: 16 (8-main and 8-skirt piles)
Conductors weight: 3,926 tons	**Distance from land**: 7 miles (11 kilometres)
Year of installation: 1979 (42 years)	**End of economic life?**: Yes

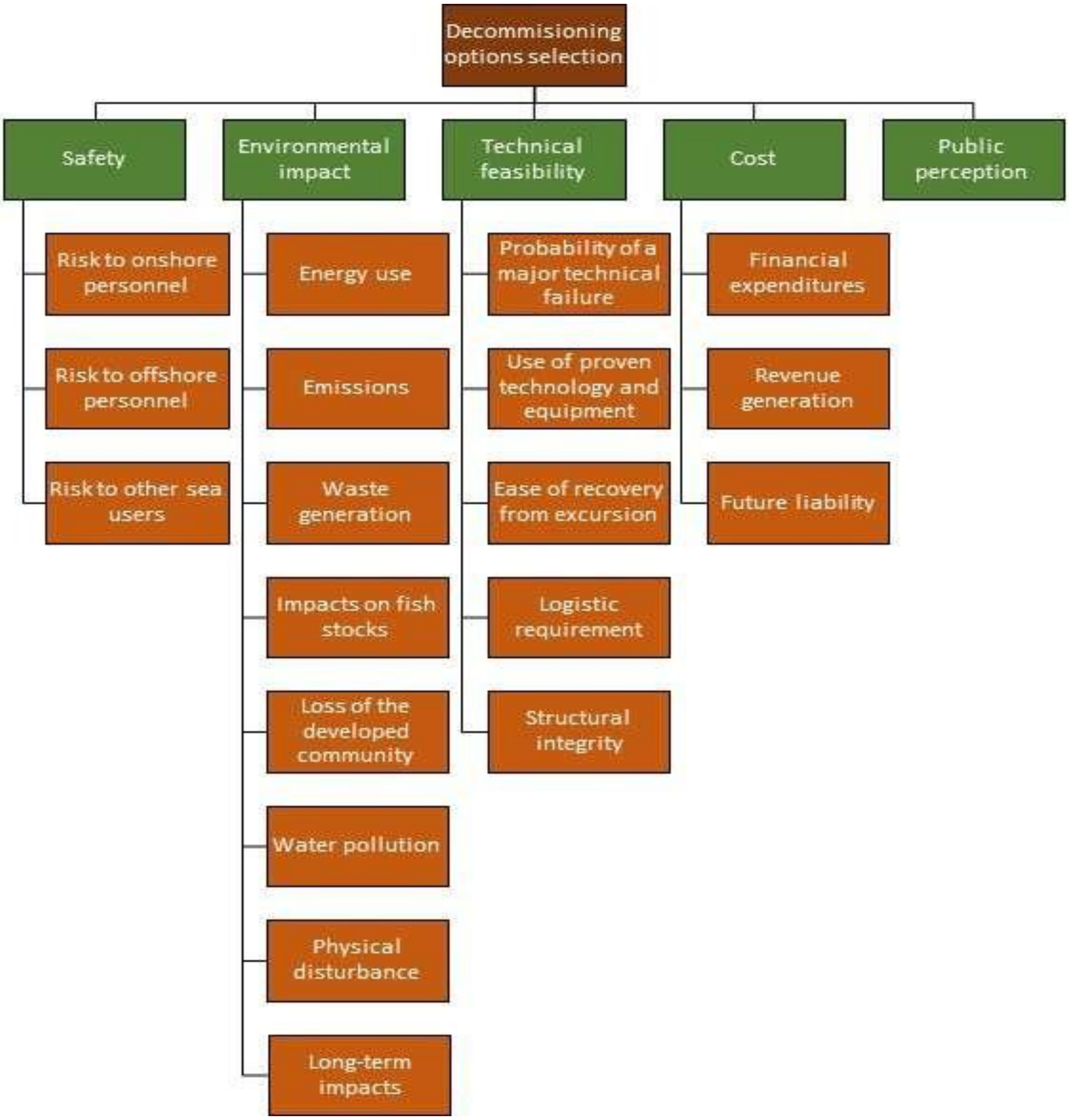
Problem Hierarchy Structure



Section 2(A): Criteria and Sub-Criteria Weighting

The responses to questions from this section are for assigning weights of importance to the decision criteria and sub-criteria. Note that, in order to accommodate situations where there are no differences in perceived importance, the same ranking can be assigned to up to two criteria/sub-criteria for a given question.

Illustration of the Criteria and Sub-Criteria for Decommissioning Options Selection



6. How would you rank the importance of the following criteria in determining the optimal decommissioning option for the case study? ✱ *Required*

	Least Important	Less Important	Moderately Important	Highly Important	Extremely Important
Safety	☐	☐	☐	☐	☐
Environmental Impact	☐	☐	☐	☐	☐
Technical Feasibility	☐	☐	☐	☐	☐
Cost	☐	☐	☐	☐	☐
Public Perception	☐	☐	☐	☐	☐

7. How would you rank the importance of the following sub-criteria in assessing the SAFETY of using a decommissioning option for the case study? ✱ *Required*

	Least Important	Less Important	Moderately Important	Highly Important	Extremely Important
Risk to onshore personnel	☐	☐	☐	☐	☐
Risk to offshore personnel	☐	☐	☐	☐	☐
Risk to other sea users	☐	☐	☐	☐	☐

8. How would you rank the importance of the following sub-criteria in assessing the ENVIRONMENTAL IMPACT of using a decommissioning option for the case study? ✱ *Required*

	Least Important	Less Important	Moderately Important	Highly Important	Extremely Important
Energy use	☐	☐	☐	☐	☐
Air emissions	☐	☐	☐	☐	☐
Waste generation	☐	☐	☐	☐	☐
Impacts on fish stocks	☐	☐	☐	☐	☐
Loss of the developed community	☐	☐	☐	☐	☐
Water pollution	☐	☐	☐	☐	☐
Physical disturbance to the seabed	☐	☐	☐	☐	☐
Long-term impacts	☐	☐	☐	☐	☐

9. How would you rank the importance of the following sub-criteria in assessing the TECHNICAL FEASIBILITY of using a decommissioning option for the case study? ✱ *Required*

	Least Important	Less Important	Moderately Important	Highly Important	Extremely Important
Probability of a major technical failure	☐	☐	☐	☐	☐
Use of proven technology and equipment	☐	☐	☐	☐	☐
Ease of recovery from an excursion	☐	☐	☐	☐	☐
Logistic requirements	☐	☐	☐	☐	☐
Structural integrity	☐	☐	☐	☐	☐

10. How would you rank the importance of the following sub-criteria in assessing the FINANCIAL COST of using a decommissioning option for the case study? ✱ *Required*

	Least Important	Less Important	Moderately Important	Highly Important	Extremely Important
Financial expenditure	☐	☐	☐	☐	☐
Revenue generation	☐	☐	☐	☐	☐
Future liability	☐	☐	☐	☐	☐

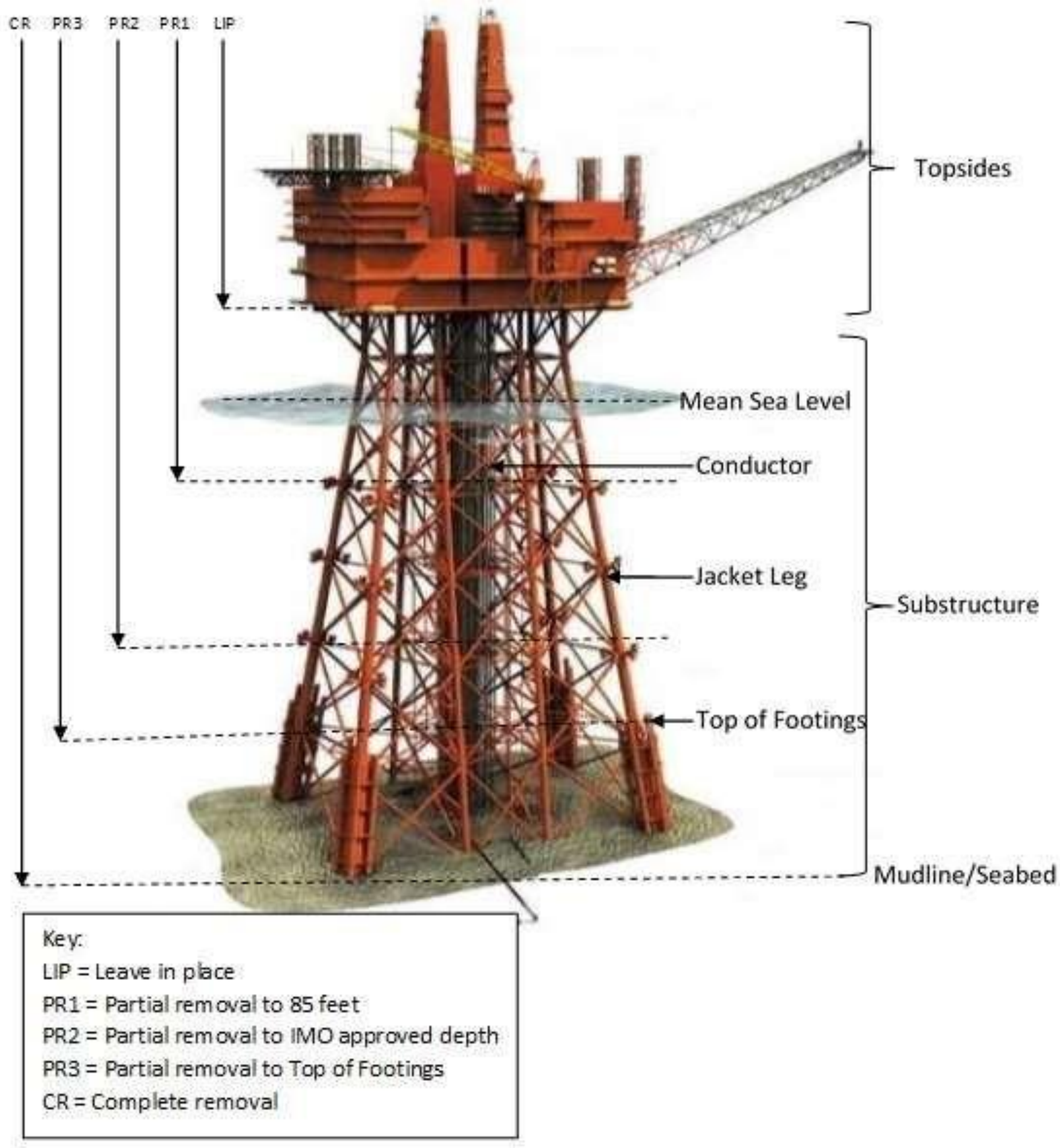
11. How would you rank the importance of the following sub-criteria in assessing the PUBLIC PERCEPTION of using a decommissioning option for the case study?

	Least Important	Less Important	Moderately Important	Highly Important	Extremely Important
Employment	☐	☐	☐	☐	☐
Ocean access	☐	☐	☐	☐	☐
Recreational use	☐	☐	☐	☐	☐
Tax concessions	☐	☐	☐	☐	☐

Section 2(B): Decommissioning Options Scoring

The responses to questions in this section are for assigning scores to the decommissioning options for the case study platform with reference to the decision criteria. Note that no two decommissioning options can have the same ranking for a given criteria as all options are distinct.

Illustration of Differences in Removal Depth of Decommissioning Options



**The removed portion of the platform is assumed to be taken to shore for recycling, reuse or disposal for all scenarios.*

12. With reference to SAFETY, how would you rate the performance of the following decommissioning options for the case study? ✱ *Required*

	Worst	Poor	Medium	Good	Best
Leave in Place	☐	☐	☐	☐	☐
Partial Removal to 85 feet	☐	☐	☐	☐	☐
Partial Removal to IMO-Approved Depth	☐	☐	☐	☐	☐
Partial Removal to Top of Footings	☐	☐	☐	☐	☐
Complete Removal	☐	☐	☐	☐	☐

13. With reference to ENVIRONMENTAL IMPACT, how would you rate the performance of the following decommissioning options for the case study? ✱ *Required*

	Worst	Poor	Medium	Good	Best
Leave in Place	☐	☐	☐	☐	☐
Partial Removal to 85 feet	☐	☐	☐	☐	☐
Partial Removal to IMO-Approved Depth	☐	☐	☐	☐	☐
Partial Removal to Top of Footings	☐	☐	☐	☐	☐
Complete Removal	☐	☐	☐	☐	☐

14. With reference to TECHNICAL FEASIBILITY, how would you rate the performance of the following decommissioning options for the case study? ✱ *Required*

	Worst	Poor	Medium	Good	Best
Leave in Place	☐	☐	☐	☐	☐
Partial Removal to 85 feet	☐	☐	☐	☐	☐
Partial Removal to IMO-Approved Depth	☐	☐	☐	☐	☐
Partial Removal to Top of Footings	☐	☐	☐	☐	☐
Complete Removal	☐	☐	☐	☐	☐

15. With reference to FINANCIAL COST, how would you rate the performance of the following decommissioning options for the case study? ✱ *Required*

	Worst	Poor	Medium	Good	Best
Leave in Place	☐	☐	☐	☐	☐
Partial Removal to 85 feet	☐	☐	☐	☐	☐
Partial Removal to IMO-Approved Depth	☐	☐	☐	☐	☐
Partial Removal to Top of Footings	☐	☐	☐	☐	☐
Complete Removal	☐	☐	☐	☐	☐

16. With reference to PUBLIC PERCEPTION, how would you rate the performance of the following decommissioning options for the case study? ✱ *Required*

	Worst	Poor	Medium	Good	Best
Leave in Place	☐	☐	☐	☐	☐
Partial Removal to 85 feet	☐	☐	☐	☐	☐
Partial Removal to IMO-Approved Depth	☐	☐	☐	☐	☐
Partial Removal to Top of Footings	☐	☐	☐	☐	☐
Complete Removal	☐	☐	☐	☐	☐

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Section 3: Additional Information

The responses to questions in this section are for gaining deeper insights into the decommissioning options selection process from offshore decommissioning experts based on their domain knowledge and expertise.

17. Suggest additional SAFETY sub-criteria that should be included in the decision support model.

18. Suggest additional ENVIRONMENTAL IMPACT sub-criteria that should be included in the decision support model.

19. Suggest additional TECHNICAL FEASIBILITY sub-criteria that should be included in the decision support model.

20. Suggest additional FINANCIAL COST sub-criteria that should be included in the decision support model.

21. Suggest additional PUBLIC PERCEPTION sub-criteria that should be included in the decision support model.

Appendix 3: Likert-AHP Calculations

Pre-Processing of Likert Scale Input Data

A. Calculation of Relative Ratings (R_i/R_{i-1})

A1. Weighting of Decision Criteria

	Rating*	Relative Rating
Safety	8.2673	-
Environment	6.8016	0.8227
Technical	6.4642	0.9504
Cost	4.9862	0.7714
Public	4.2251	0.8474

B. Development of Suggestion Matrices**

Decision Criteria	Safety	Environment	Technical	Cost	Public
Safety	1.0000	1.2155	1.2789	1.6580	1.9567
Environment	0.8227	1.0000	1.0522	1.3641	1.6098
Technical	0.7819	0.9504	1.0000	1.2964	1.5300
Cost	0.6031	0.7331	0.7714	1.0000	1.1801
Public	0.5111	0.6212	0.6536	0.8474	1.0000

A2. Scoring of Decommissioning Options*** for the Decision Criteria

-with reference to Safety

	Rating	Relative Rating
LIP	3.3994	-
PR1	4.6000	1.3532
PR2	5.2215	1.1351
PR3	4.5719	0.8756
CR	2.5315	0.5537

Safety	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.7390	0.6511	0.7436	1.3428
PR1	1.3532	1.0000	0.8810	1.0062	1.8171
PR2	1.5360	1.1351	1.0000	1.1421	2.0626
PR3	1.3449	0.9939	0.8756	1.0000	1.8060
CR	0.7447	0.5503	0.4848	0.5537	1.0000

-with reference to Environmental Impact

	Rating	Relative Rating
LIP	2.9022	-
PR1	4.7194	1.6262
PR2	5.4293	1.1504
PR3	4.5785	0.8433
CR	2.7756	0.6062

Environment	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.6149	0.5345	0.6339	1.0456
PR1	1.6262	1.0000	0.8692	1.0308	1.7003
PR2	1.8708	1.1504	1.0000	1.1858	1.9561
PR3	1.5776	0.9702	0.8433	1.0000	1.6496
CR	0.9564	0.5881	0.5112	0.6062	1.0000

-with reference to Technical Feasibility

	Rating	Relative Rating
LIP	5.3750	-
PR1	5.7445	1.0688
PR2	5.2917	0.9212
PR3	3.8307	0.7239
CR	1.5098	0.3941

Technical	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.9357	1.0157	1.4031	3.5600
PR1	1.0688	1.0000	1.0856	1.4996	3.8048
PR2	0.9845	0.9212	1.0000	1.3814	3.5048
PR3	0.7127	0.6668	0.7239	1.0000	2.5372
CR	0.2809	0.2628	0.2853	0.3941	1.0000

-with reference to Cost

	Rating	Relative Rating
LIP	6.0308	-
PR1	5.8832	0.9755
PR2	5.4604	0.9281
PR3	3.6441	0.6674
CR	1.3385	0.3673

Cost	LIP	PR1	PR2	PR3	CR
LIP	1.0000	1.0251	1.1045	1.6550	4.5055
PR1	0.9755	1.0000	1.0774	1.6145	4.3953
PR2	0.9054	0.9281	1.0000	1.4984	4.0794
PR3	0.6042	0.6194	0.6674	1.0000	2.7224
CR	0.2219	0.2275	0.2451	0.3673	1.0000

-with reference to Public Perception

	Rating	Relative Rating
LIP	1.2129	-
PR1	3.3124	2.7311
PR2	5.1463	1.5536
PR3	6.6289	1.2881
CR	6.8951	1.0402

Public	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.3662	0.2357	0.1830	0.1759
PR1	2.7311	1.0000	0.6436	0.4997	0.4804
PR2	4.2431	1.5536	1.0000	0.7763	0.7464
PR3	5.4655	2.0012	1.2881	1.0000	0.9614
CR	5.6850	2.0816	1.3398	1.0402	1.0000

*Aggregation of the numerical equivalent of survey responses, calculated as the geometric mean of the values

**Developed from applying transitivity and reciprocity rules to the relative ratings, replaces the AHP Pairwise Comparison Matrices

***Decommissioning Options Key

LIP Leave in place
PR1 Partial removal to 85 feet
PR2 Partial removal to IMO-approved depth
PR3 Partial removal to top of footings
CR Complete removal

Synthesis of AHP Pairwise Comparisons Matrices (i.e., Suggestion Matrices)

Matrix size = 5

Standardised Matrix*

A1. AHP Matrix for Weighting of Decision Criteria

	Safety	Environment	Technical	Cost	Public
Safety	1.0000	1.2155	1.2789	1.6580	1.9567
Environment	0.8227	1.0000	1.0522	1.3641	1.6098
Technical	0.7819	0.9504	1.0000	1.2964	1.5300
Cost	0.6031	0.7331	0.7714	1.0000	1.1801
Public	0.5111	0.6212	0.6536	0.8474	1.0000
Column Total	*3.7188*	*4.5202*	*4.7561*	*6.1659*	*7.2767*

Decision Criteria	Safety	Environment	Technical	Cost	Public	Priority (W_i)**
Safety	0.2689	0.2689	0.2689	0.2689	0.2689	0.2689
Environment	0.2212	0.2212	0.2212	0.2212	0.2212	0.2212
Technical	0.2103	0.2103	0.2103	0.2103	0.2103	0.2103
Cost	0.1622	0.1622	0.1622	0.1622	0.1622	0.1622
Public	0.1374	0.1374	0.1374	0.1374	0.1374	0.1374

A2. AHP Matrix for Scoring of Decommissioning Options*** for the Decision Criteria

-with reference to Safety

	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.7390	0.6511	0.7436	1.3428
PR1	1.3532	1.0000	0.8810	1.0062	1.8171
PR2	1.5360	1.1351	1.0000	1.1421	2.0626
PR3	1.3449	0.9939	0.8756	1.0000	1.8060
CR	0.7447	0.5503	0.4848	0.5537	1.0000
Column Total	*5.9787*	*4.4183*	*3.8925*	*4.4455*	*8.0285*

Safety	LIP	PR1	PR2	PR3	CR	Priority (S_{ij})
LIP	0.1673	0.1673	0.1673	0.1673	0.1673	0.1673
PR1	0.2263	0.2263	0.2263	0.2263	0.2263	0.2263
PR2	0.2569	0.2569	0.2569	0.2569	0.2569	0.2569
PR3	0.2249	0.2249	0.2249	0.2249	0.2249	0.2249
CR	0.1246	0.1246	0.1246	0.1246	0.1246	0.1246

-with reference to Environmental Impact

	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.6149	0.5345	0.6339	1.0456
PR1	1.6262	1.0000	0.8692	1.0308	1.7003
PR2	1.8708	1.1504	1.0000	1.1858	1.9561
PR3	1.5776	0.9702	0.8433	1.0000	1.6496
CR	0.9564	0.5881	0.5112	0.6062	1.0000
Column Total	*7.0309*	*4.3237*	*3.7583*	*4.4567*	*7.3516*

Environment	LIP	PR1	PR2	PR3	CR	Priority (S_{ij})
LIP	0.1422	0.1422	0.1422	0.1422	0.1422	0.1422
PR1	0.2313	0.2313	0.2313	0.2313	0.2313	0.2313
PR2	0.2661	0.2661	0.2661	0.2661	0.2661	0.2661
PR3	0.2244	0.2244	0.2244	0.2244	0.2244	0.2244
CR	0.1360	0.1360	0.1360	0.1360	0.1360	0.1360

-with reference to Technical Feasibility

Technical	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.9357	1.0157	1.4031	3.5600
PR1	1.0688	1.0000	1.0856	1.4996	3.8048
PR2	0.9845	0.9212	1.0000	1.3814	3.5048
PR3	0.7127	0.6668	0.7239	1.0000	2.5372
CR	0.2809	0.2628	0.2853	0.3941	1.0000
Column Total	*4.0468*	*3.7865*	*4.1106*	*5.6783*	*14.4068*

Technical	LIP	PR1	PR2	PR3	CR	Priority (S_{ij})
LIP	0.2471	0.2471	0.2471	0.2471	0.2471	0.2471
PR1	0.2641	0.2641	0.2641	0.2641	0.2641	0.2641
PR2	0.2433	0.2433	0.2433	0.2433	0.2433	0.2433
PR3	0.1761	0.1761	0.1761	0.1761	0.1761	0.1761
CR	0.0694	0.0694	0.0694	0.0694	0.0694	0.0694

-with reference to Cost

Cost	LIP	PR1	PR2	PR3	CR
LIP	1.0000	1.0251	1.1045	1.6550	4.5055
PR1	0.9755	1.0000	1.0774	1.6145	4.3953
PR2	0.9054	0.9281	1.0000	1.4984	4.0794
PR3	0.6042	0.6194	0.6674	1.0000	2.7224
CR	0.2219	0.2275	0.2451	0.3673	1.0000
Column Total	*3.7071*	*3.8001*	*4.0944*	*6.1352*	*16.7027*

Cost	LIP	PR1	PR2	PR3	CR	Priority (S_{ij})
LIP	0.2697	0.2697	0.2697	0.2697	0.2697	0.2697
PR1	0.2631	0.2631	0.2631	0.2631	0.2631	0.2631
PR2	0.2442	0.2442	0.2442	0.2442	0.2442	0.2442
PR3	0.1630	0.1630	0.1630	0.1630	0.1630	0.1630
CR	0.0599	0.0599	0.0599	0.0599	0.0599	0.0599

-with reference to Public Perception

Public	LIP	PR1	PR2	PR3	CR
LIP	1.0000	0.3662	0.2357	0.1830	0.1759
PR1	2.7311	1.0000	0.6436	0.4997	0.4804
PR2	4.2431	1.5536	1.0000	0.7763	0.7464
PR3	5.4655	2.0012	1.2881	1.0000	0.9614
CR	5.6850	2.0816	1.3398	1.0402	1.0000
Column Total	*19.1248*	*7.0026*	*4.5072*	*3.4992*	*3.3641*

Public	LIP	PR1	PR2	PR3	CR	Priority (S_{ij})
LIP	0.0523	0.0523	0.0523	0.0523	0.0523	0.0523
PR1	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428
PR2	0.2219	0.2219	0.2219	0.2219	0.2219	0.2219
PR3	0.2858	0.2858	0.2858	0.2858	0.2858	0.2858
CR	0.2973	0.2973	0.2973	0.2973	0.2973	0.2973

*Calculated for each cell in the standardised matrix by dividing the corresponding cell value in the AHP pairwise matrix by its column total

**Calculated for each row in the standardised matrix as the average of row values

***Decommissioning Options Key

LIP	Leave in place
PR1	Partial removal to 85 feet
PR2	Partial removal to IMO-approved depth
PR3	Partial removal to top of footings
CR	Complete removal

Calculation of the Weighted Scores of Decommissioning Options

Decision Criteria	**Weight of Importance** (W_i)
Safety	0.269
Environment	0.221
Technical	0.210
Cost	0.162
Public	0.137
Total	**1.000**

Criteria \ **Option**	**Leave in Place**		**Partial Removal - 85ft**		**Partial Removal - IMO**		**Partial Removal - Top of Footings**		**Complete Removal**	
	Option score (S_{ij})	Weighted score (W_iS_{ij})	Option score (S_{ij})	Weighted score (W_iS_{ij})	Option score (S_{ij})	Weighted score (W_iS_{ij})	Option score (S_{ij})	Weighted score (W_iS_{ij})	Option score (S_{ij})	Weighted score (W_iS_{ij})
Safety	0.167	**0.045**	0.226	**0.061**	0.257	**0.069**	0.225	**0.060**	0.125	**0.033**
Environment	0.142	**0.031**	0.231	**0.051**	0.266	**0.059**	0.224	**0.050**	0.136	**0.030**
Technical	0.247	**0.052**	0.264	**0.056**	0.243	**0.051**	0.176	**0.037**	0.069	**0.015**
Cost	0.270	**0.044**	0.263	**0.043**	0.244	**0.040**	0.163	**0.026**	0.060	**0.010**
Public	0.052	**0.007**	0.143	**0.020**	0.222	**0.030**	0.286	**0.039**	0.297	**0.041**
Weighted Score $\sum(W_iS_{ij})$	0.1793		0.2299		0.2492		0.2129		0.1287	

Appendix 4: Calculated Sub-Criteria Weights for the Case Study

Decision Criteria	Sub-Criteria	Local Priority	Local Rank
Safety	Risk to onshore personnel	0.3037	3
	Risk to offshore personnel	0.3876	1
	Risk to other sea users	0.3088	2
Environmental Impact	Energy use	0.0938	8
	Air emissions	0.1120	5
	Waste generation	0.1328	3
	Impacts on fish stocks	0.1229	4
	Loss of the developed community	0.1098	6
	Water pollution	0.1717	1
	Physical disturbance to seabed	0.0953	7
	Long-term impacts	0.1617	2
Technical Feasibility	Probability of a major technical failure	0.2687	1
	Use of proven technology and equipment	0.1839	3
	Ease of recovery from excursion	0.1722	4
	Logistic requirement	0.1446	5
	Structural integrity	0.2305	2
Cost	Financial expenditure	0.4030	1
	Revenue generation	0.2091	3
	Future liability	0.3879	2
Public Perception*	-	-	-

* No suitable sub-criteria were identified from the literature for this criterion.

Appendix 5: Questionnaire for Validation of Decommissioning Decision Model Logical Structure

Part A: Details of Respondent

Profession:	
Academic Qualification:	
Current Job Designation:	
Years of Decommissioning-Related Work Experience:	

Section B: Responses

Question	Options	Tick/Comment as Appropriate
Does the model address an important issue in offshore decommissioning?	a) Yes, quite significant	
	b) Yes, but not significant	
	c) No, would make no difference	
	d) Not sure of its significance	
	Comments (if any):	
Accuracy: How closely do the obtained results match what, in your best knowledge, would have been obtained from evaluating decommissioning options for the case study?	a) Very close	
	b) Slightly close	
	c) Not close	
	d) Not sure of the match	
	Comments (if any):	

Completeness: How complete is the model's flow process with respect to the problem it seeks to solve?	a) Very complete	
	b) Somewhat complete	
	c) Incomplete	
	d) Not sure of its completeness	
	Comments (if any):	
Comprehensibility: Do you think the model simple, clear, and easy to understand and use with little or no practical difficulties?	a) Yes	
	b) No	
	Comments (if any):	
Cost-effectiveness: What is your opinion on the resources needed to implement the model in actual decommissioning projects?	a) Would be too costly to implement	
	b) Benefits of using the model justifies any resource requirements	
	Comment (if any):	
Please provide any other comments that you have on the model or suggestions for its improvement	Comment (if any):	

Thank you very much for your time.

NB: Confidentiality and anonymity are guaranteed as no personal data will be publicly divulged. All information collected will conform to the University's Human Research Ethical procedure.

Appendix 6: Decommissioning Options Costs for Platforms in Pacific Outer Continental Shelf, California

Platform_Name	Complete_Removal_($)	Partial_Removal_to_85ft_($)	Partial_Removal_to_IMO_Depth_($)	Partial_Removal_to_Top_of_Footings__($)	Leave_in_Place_($)
A	44,170,000	35,350,000	42,860,000	34,190,000	29,900,000
B	39,470,000	30,830,000	38,190,000	29,810,000	25,620,000
C	38,350,000	30,460,000	37,160,000	29,680,000	26,280,000
Edith	45,080,000	41,000,000	45,080,000	38,270,000	35,310,000
Ellen	46,170,000	38,090,000	41,690,000	40,220,000	32,630,000
Elly	42,900,000	38,780,000	40,380,000	39,730,000	36,390,000
Eureka	132,100,000	72,010,000	80,550,000	119,060,000	61,160,000
Gail	116,260,000	61,680,000	68,350,000	105,130,000	52,750,000
Gilda	59,880,000	52,970,000	57,440,000	52,440,000	46,330,000
Gina	26,320,000	25,990,000	26,320,000	26,320,000	23,700,000
Grace	55,860,000	45,050,000	48,410,000	49,670,000	39,790,000
Habitat	45,610,000	39,590,000	41,600,000	41,710,000	36,300,000
Harmony	190,000,000	70,170,000	78,510,000	175,480,000	58,350,000
Harvest	112,620,000	64,320,000	70,910,000	101,720,000	55,600,000
Henry	35,490,000	33,130,000	35,490,000	32,090,000	30,120,000
Heritage	172,320,000	71,130,000	78,410,000	158,480,000	59,960,000
Hermosa	109,230,000	62,850,000	70,380,000	97,350,000	53,290,000
Hidalgo	88,670,000	61,260,000	67,700,000	78,190,000	52,980,000
Hillhouse	40,170,000	31,650,000	39,040,000	30,660,000	26,610,000
Hogan	38,400,000	35,280,000	38,400,000	32,780,000	30,330,000
Hondo	108,350,000	64,320,000	68,960,000	100,540,000	57,960,000
Houchin	37,540,000	34,320,000	37,540,000	32,340,000	29,730,000
Irene	48,950,000	42,040,000	45,130,000	43,170,000	37,190,000

Appendix 7: Python Script for Machine Learning Model Development from Cost Data with Gradient Boosting Algorithm

```python
# -*- coding: utf-8 -*-

#Gradient Boosting Regression
#Importing the Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import ensemble
from sklearn.multioutput import MultiOutputRegressor
from sklearn.model_selection import LeaveOneOut

#Importing the dataset
dataset = pd.read_csv("Decom_Data2.csv")
X = dataset.iloc[:, [1,3,4]].values
y_cost = dataset.iloc[:, 5:10].values

#Executing Leave-One-Out Cross-Validation
loo = LeaveOneOut()
loo.get_n_splits(X)
predictions = []
for train_index, test_index in loo.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_cost_train, y_cost_test = y_cost[train_index], y_cost[test_index]
    regressor = ensemble.GradientBoostingRegressor(random_state = 0)
    regressor = MultiOutputRegressor(regressor)
    regressor.fit(X_train, y_cost_train)
    y_pred = regressor.predict(X_test)
    predictions.extend(y_pred)
predictions = np.array(predictions)

#Assigning variable names to the decommissioning options costs
#Complete Removal
CR = predictions[:, 0]
#Partial Removal to 85ft
PR1 = predictions[:, 1]
#Partial Removal to IMO-approved Depth (55m/180ft)
PR2 = predictions[:, 2]
#Partial Removal to Top of Footings
PR3 = predictions[:, 3]
#Leave in Place
LIP = predictions[:, 4]

#Evaluating the Accuracy of Model Predictions
#Quantitative Model Evaluation
#Calculating R-Squared and Adjusted R-Squared Values
from sklearn.metrics import r2_score
rsquared = r2_score(y_cost, predictions, multioutput='variance_weighted')
print('R-Squared Value: %.3f' % rsquared)
Adj_rsquared= 1 - (1-rsquared) * (len(y_cost)-1)/(len(y_cost)-X.shape[1]-1)
print('Adjusted R-Squared Value: %.3f' % Adj_rsquared)
#Calculating MAPE
MAPE = np.mean(np.abs((y_cost - predictions)/y_cost))*100
print('Mean Absolute Percentage Error: %.3f' % MAPE, "\b%")
```

```python
#Graphical Model Evaluation
#Crossplotting actual vs predicted decommissioning options costs
model="Gradient Boosting Regression"
plt.figure(figsize=(15,10))
plt.rcParams["font.weight"] ="bold"
plt.rcParams["axes.labelweight"] ="bold"
plt.scatter(CR, y_cost[:, 0], marker='x', label='Complete Removal')
plt.scatter(PR1, y_cost[:, 1], marker='8', label='Partial Removal to 85ft')
plt.scatter(PR2, y_cost[:, 2], marker='P', label='Partial Removal to IMO')
plt.scatter(PR3, y_cost[:, 3], marker='*', label='Partial Removal to ToF')
plt.scatter(LIP, y_cost[:, 4], marker='X', label='Leave in Place')
plt.title(model,fontweight = 'bold', fontsize = 20, loc='center')
plt.xlabel('Actual Cost ($)', fontweight = 'bold', fontsize = 18)
plt.ylabel('Predicted Cost ($)', fontweight = 'bold', fontsize = 18)
plt.legend(fontsize = 16, loc='lower right')
plt.xlim(left=0, right=2E8)
plt.ylim(bottom=0, top=2E8)
plt.plot([0, 2E8], [0, 2E8])
plt.savefig(model, bbox_inches = 'tight')
plt.show()

#Predicting Decommissioning Options Costs for the Case Study platform
features = [[43, 11137, 406]]
costs = regressor.predict(features)
print('The cost of decommissioning the platform with', "\n",
      'Complete Removal: $', costs[0,0], "\n",
      'Partial Removal to 85 Feet: $', costs[0,1], "\n",
      'Partial Removal to IMO Depth: $', costs[0,2], "\n",
      'Partial Removal to Top of Footings: $', costs[0,3], "\n",
      'Leave in Place: $', costs[0,4])
```

Appendix 8: Glossary

A_i	Weighted score of decommissioning option i
BTC_i	Benefit-to-cost ratio of decommissioning option i
CI	Consistency index
$Cost_i$	Financial expenditure from using decommissioning option i for a project
CR	Consistency ratio
CR_X	Cost incurred in project phase x when decommissioning the platform with a Complete Removal option
E_{ij}	Value of the element in cell in row i and column j of matrix E
$f(\text{Substructure weight, water depth, platform age})$	Mathematical function which requires as argument the substructure weight, water depth and age of the platform to be decommissioned.
J	Number of judgements for populating a matrix
$MAPE$	Mean Absolute Percentage Error
n	Number of elements in a comparison matrix
$NMAX_i$	Maximum scaled value of parameter i
$NMIN_i$	Minimum scaled value of parameter i
NPV_i	Net present value of decommissioning option i
$OMAX_i$	Maximum actual value of parameter i
$OMIN_i$	Minimum actual value of parameter i
P	Priority vector
PR_X	Cost incurred in project phase x when decommissioning the platform with a partial removal option
R^2	Coefficient of determination
$R^2{}_{adj}$	Adjusted coefficient of determination

RI_n	Random index number
RM_X	Cost avoided in project phase x due to leaving some residual materials
$Score_{i,j}$	Performance score of decommissioning option i, with reference to criterion (or sub-criteria) j
S_{ij}	Performance rating or Score of decommissioning option i with reference to criterion j
U_i	Scaled value of element i
V	Actual value of a parameter
V'	Scaled value of a parameter
$\%Weight$	Factor which represents the weight proportions of the platform components
X_{best}	Best possible value of element i
X_i	Actual value of element i
X_s	Scaled value of parameter X
X_{worst}	Worst possible value of element i
W_j	Weight of importance of criterion j

Greek Symbols

$\epsilon_{i,j}$	Error term which accounts for noise and randomness in the data.
λ_{max}	Maximum eigenvalue

Appendix 9: Publications

1. EKE, E., IYALLA, I., ANDRAWUS, J. and PRABHU, R., 2020. Optimising Offshore Structures Decommissioning-A Multicriteria Decision Approach. In: *SPE Nigeria Annual International Conference and Exhibition*. OnePetro.
2. EKE, E., IYALLA, I., ANDRAWUS, J. and PRABHU, R., 2021. Optimisation of Offshore Structures Decommissioning–Cost Considerations. In: *SPE Nigeria Annual International Conference and Exhibition*. OnePetro.
3. EKE, E., IYALLA, I., ANDRAWUS, J. and PRABHU, R., 2022. Investigating Decommissioning Options Selection: A Survey-Driven Approach. In: *Structures in the Marine Environment 2022, Edinburgh.*