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Design-Strategy Planning For Life Cycle Management of Engineering Systems

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Preface

This thesis is the final part of my Master of Science degree with specialisation in Marine Systems Design at the department of Marine Technology (IMT) at the Norwegian University of Science and Technology (NTNU). The work has been entirely written at NTNU during the spring of 2017. The workload corresponds to 30 ECTS.

My intentions with the work I am presenting in this thesis is to contribute in developing frameworks and quantitative methods to support uncertainty management of engineering systems, with a focus on offshore vessels. This serves as an response to the call-for-research by Erikstad and Rehn (2015) which highlighte the need-for-research on quantitative methods for handling uncertainty in the maritime industry. The thesis partially builds on work done in the authors project thesis with the title *Decision Support Under Uncertainty for Ocean Engineering Systems*. The project thesis was written in the fall off 2016, by Carsten Christensen and Morten A. Strøm. The illustrative case presented extends from the work of Rehn et al. (2017b), Rehn et al. (2017a) and Pettersen et al. (2017).

I would like to thank several people for their help and guidance throughout writing this thesis. First, to my supervisor Bjørn Egil Asbjørnslett for steady guidance. I am gratefully to Sigurd Solheim Pettersen, Carl Fredrik Rehn and Jose Jorge Garcia Agis for your bright ideas, interesting discussions, and open-door policy. I will thank Austin A. Kana at Delft University of Technology for giving me my first lecture in Markov decision processes. Finally, to Jon-Erik Hvidsten Remme and Carsten Christensen, I thank you for keeping the spirits up at the office. I am forever grateful.

Trondheim, 2017-06-11

Morten A. Strøm

Summary and Conclusions

The objective of this thesis is to contribute in developing frameworks and quantitative methods to support uncertainty management of engineering systems, with focus on offshore vessels. This thesis starts out with a literature review, drawing insight from engineering, management, product development, finance, operations research, and artificial intelligence. The review highlights that uncertainty is as much related to opportunities as it is to vulnerabilities, and that an active management approach is necessary to mitigate the vulnerabilities and to exploit the opportunities. While the engineering domain recognises designing for changeability (i.e. flexibility, adaptability, robustness and agility) as means for handling uncertainty, the managerial domain recognises strategic flexibility.

We propose the Value-Aptitude-Design-Strategy (VADS) framework as a quasi-mathematical expression of the relationship between a stakeholder's aptitude, a design's configuration and the stakeholder's life cycle strategies, linking them to the system's ability to deliver value (i.e. stay successful). From this, we propose the term strategic system, comprising a specific design-strategy configuration, defined as a set of distinct devices used to handle uncertainty. We emphasise the importance of having the strategic system aligned with stakeholders' aptitude. This extends the traditional system boundary in engineering, from solely focusing on the relationship between design and its surroundings, to include the managerial dimension. Thus, while the literature is primarily focusing on architecting value robust physical systems, this thesis emphasises the need for identifying value robust strategic systems.

We propose Design-Strategy Planning (DSP) as an active, structured, life cycle approach for managing uncertainty. Building on the VADS framework, DSP focuses on developing, implementing and monitoring strategic systems with the means of handling uncertainty that is aligned with stakeholders' aptitude. DSP highlights the importance of dealing proactively with uncertainty by utilising real (in and on) options. The real in options are related to designing for changeability, and the real on options are related to managerial strategies. While some of these options are implemented in the design phase, others are prepared for in the response to various

trigger information. The type of response is pre-defined in a contingency plan. To do so, DSP incorporates a monitoring system to locate trigger situations over the system's life cycle.

A Markov decision process (MDP) methodology is presented to support the design-strategy planning framework. The methodology is based on the work of Niese and Singer (2014). Together, DSP and MDP form a holistic decision analysis framework to support uncertainty management. A key benefit is that this framework can capture the dynamic interaction between the changeable system and managerial strategies. As seen in the illustrative case, this insight can be used to select product platforms, to identify the most promising real in options to incorporate in the design phase, and to develop a contingency plan.

The knowledge from this thesis can be important in life cycle management of high-value, complex, engineering systems, with long lifetime, facing high degree of exogenous uncertainty. Hopefully the proposed Value-Aptitude-Design-Strategy framework, Design-Strategy Planning and the Markov decision process methodology will give valuable insight that enables maritime decision makers to better handle uncertainty.

Sammendrag og konklusjon

Formålet med denne oppgaven er å bidra til å utvikle rammeverk og kvantitative metoder for å støtte usikkerhetshåndtering in den maritime industrien, med fokus på offshorefartøy.

Oppgaven starter med en litteraturstudie som gir innsikt i ingeniørvitenskap, strategisk ledelse, produktutvikling, økonomi, operasjonsanalyse og kunstigintelligens. Litteraturstudiet viser at usikkerhet er like mye knyttet til muligheter som den er til sårbarheter, og at en aktiv tilnærming til usikkerhetshåndtering er nødvendig for å kunne redusere sårbarhetene og dra utnytte mulighetene. Mens ingeniørvitenskapen anerkjenner foranderlighet i designet som en måte å håndtere usikkerhet, er strategisk fleksibilitet anerkjent som en metode innenfor strategisk ledelse.

Vi foreslår Verdi-Evne-Design-Strategi (VEDS) som et kvasimatematisk uttrykk for forholdet mellom en interessenters evne, designet (f.eks. offshorefartøy) sin konfigurasjon og interessentens livssyklusstrategier, og knytter dem opp mot systemets evne til å levere verdi (dvs. være vellykket). Fra dette foreslår vi begrepet strategisk system, som består av en bestemt design-strategi konfigurasjon, og definerer dette som en aktiv metode for å håndtere usikkerhet. Vi legger vekt på viktigheten av å ha det strategiske systemet i samsvar med interessenters evne til å bruke det. Dette rammeverket utvider den tradisjonelle systemgrensen i ingeniørvitenskapen, fra kun å fokusere på forholdet mellom design og dets omgivelser, til å inkludere den strategiske dimensjonen. Mens litteraturen primært fokuserer på å identifisere verdifulle tekniske systemer, fremhever denne oppgaven behovet for å identifisere verdifulle strategiske systemer.

Vi foreslår Design-Strategi Planlegging (DSP) som en aktiv, strukturert, livssyklus tilnærming til håndtering av usikkerhet. Med utgangspunkt i VEDS-rammeverket fokuserer DSP på å utvikle, implementering og overvåking strategiske systemer med evnen til å håndtere usikkerhet. DSP fremhever viktigheten av å handle proaktivt til usikkerhet ved å bruke tekniske «i» og «på» opsjoner. De tekniske «i» opsjonene er relatert til designet sin foranderlighet, mens de tekniske «på» opsjonene er relatert til livssyklusstrategier for å bruke designet. Mens noen av disse op-

sjonene bør implementert i designfasen, bør andre forbedres for å bli benyttet som en mulig respons til ulike triggere. Hvilken respons som skal gis til ulike triggere bør forhåndsdefinert i en beredskapsplan. En del av DSP metoden er og implementerer et overvåkingssystem for å finne slik triggerinformasjon som krever en respons fra beredskapsplanen.

En Markov beslutningsprosess (MDP) metode presenteres for å støtte det foreslåtte Design-Strategi Planleggings rammeverket. Metoden er basert på arbeidet til Niese and Singer (2014). Sammen danner DSP og MDP en helhetlig beslutningsanalyserammeverk for å støtte usikkerhetshåndtering. En viktig fordel med dette rammeverket er at det gir innsikt til det dynamiske samspillet mellom det foranderlige tekniske systemet og ledelsesstrategiene. Som man ser i et presenterte eksempel, så kan denne innsiktet brukes til å identifisere de mest verdifulle produktplattformene, de mest verdifulle «i» og «på» opsjonene, og til å utvikle en beredskapsplan.

Kunnskapen fra denne oppgaven kan være nyttig for usikkerhetshåndtering av kostbare, komplekse, tekniske systemer, med lang levetid, som står overfor høy grad av eksogen usikkerhet. Forhåpentligvis vil de foreslåtte rammeverkene gi verdifull innsikt som gjør det mulig for maritime beslutningstakere å bedre håndtere usikkerhet.

Contents

Chapter 1

Introduction

1.1 Background

The primary objective in conceptual vessel design is to identify value robust solutions (Browning, 2005; Gaspar et al., 2016), that is, vessels able to deliver high value to key stakeholders over its entire life cycle (Ross and Rhodes, 2008b). Unfortunately, due to the long lifetime, high system complexity (Gaspar et al., 2012) and exogenous uncertainties (Erikstad and Rehn, 2015; Agis et al., 2016) it is difficult, if not impossible, to identify which solutions that are in fact value robust, as the operating context, stakeholders needs, and even the design changes over time (Ross and Rhodes, 2008b; McManus et al., 2007).

Even though exogenous uncertainty imposes considerable commercial, operational and technical vulnerabilities to engineering systems, uncertainty might as well lead to unforeseen opportunities (McManus and Hastings, 2005; de Weck et al., 2007; Lorange, 2009; Thanopoulou, H., Strandenes, 2015). Unfortunately, due to the high consequence of failure, the traditional focus in engineering has almost exclusively been on the possible negative outcomes of uncertainty (de Neufville, 2004; Lorange, 2009). Luckily, uncertainty can be managed and it is starting to be recognised as a key for developing vessels that are able to both mitigate the vulnerabilities and exploit the opportunities (McManus and Hastings, 2005).

Unfortunately, it seems like uncertainty management is an inherently challenging task. With over 135 offshore vessels currently [07.06.2017] in layup on the coast of Norway, one can assume this is not solely due to the crack in the offshore market, but also an effect magnified of the inability of maritime decision makers to grasp and handle uncertainty. By the findings of Strøm and Christensen (2016), it seems like too many complex decisions in the maritime industry is based on gut feeling, thereby highlighting the importance of developing rational methods for decision support (Erikstad and Rehn, 2015; Strøm and Christensen, 2016).

This is the core of this thesis, as the objective is to contribute in developing frameworks and quantitative methods to support uncertainty management of engineering systems, with focus on the conceptual design phase of offshore vessels.

1.2 Research Questions

Based on the background for this thesis presented above, the following research questions were set to be answered in the thesis:

- How does the long lifetime, system complexity and exogenous uncertainty affecting the life cycle value of engineering systems?
- How is uncertainty currently managed, and how should it be managed?
- How can Markov Decision Processes (MDP) be used to support uncertainty management?

1.3 Literature Review

The following section presents a review on literature relevant for answering the research questions. First are aspects related to the complexity and uncertainty of engineering systems presented, before the aspect of uncertainty management is treated. Then, a special focus is given on the concept of changeability, strategies and real options. In the end, a review on literature related to Markov decision processes is presented. Part I in this thesis builds on this literature review.

Engineering System & Offshore Vessels

de Weck et al. (2011, 3) define engineering systems as a *class of systems, characterised by a high degree of technical complexity, social intricacy, and elaborate processes, aimed at fulfilling important functions in society*. They further present ideas for how engineering systems can be modelled, analyse and designed. The monograph by Moses (2004), Whitney (2004), de Neufville (2004), Allen et al. (2004), Cutcher-gershenfeld et al. (2004) and Leveson et al. (2003) treats foundational issues related to engineering systems, such as architecture, uncertainty management, the enterprise perspective, and sustainability. Offshore Support Vessels (OSVs) are examples of large-scale, highly complex, cost-intensive engineering systems, operating in a demanding physical environment (Simosys, 2017).

Complexity

The literature recognises the high complexity of engineering systems, and idea rooting from the classical works of Evans (1959). According to Kolmogorov (1983), the more information needed to completely describe the system, the more complex it is. Magee and de Weck (2004) also considers the number of (unique) elements and the nature of their interconnections, and develop a classification scheme for complex systems. They find engineering systems to separate from other complex systems by being human-designed, in addition to have a significant human and technical complexity. Hubka and Eder (1988) proposes to measure the degree of complexity in technical systems in four levels. Rhodes and Ross (2010) presents a five aspects taxonomy of system complexity, comprising structural, behavioural, contextual, perceptual, and temporal aspects. Hagen and Grimstad (2010) emphasise the need to extend the system boundary of ships to better understand their complexity. As a response, Gaspar et al. (2012) addresses complexity in design of engineering systems, and uses the five-aspect taxonomy of Rhodes and Ross (2010) to discuss ship design as a complex problem. Suh (1990) states that to increase the likelihood for the success of a system, the systems complexity should be minimised while keeping its intended functionality.

Uncertainty

Uncertainty can be defined as the *things that are not known, or only known imprecisely* (McManus and Hastings, 2005, 2), the *inability to quantify precisely; a distribution that reflects potential outcomes* (Walton, 2002, 20), or as *inability to determine the true state of affairs of a system* (Haimes, 2009, 255). Even though uncertainty imposes considerably vulnerabilities (or risks) to offshore vessels it may as well lead to as many opportunities (McManus and Hastings, 2005; de Weck et al., 2007; Lorange, 2009; de Neufville and Scholtes, 2011). McManus and Hastings (2005) classifies uncertainty as statically random variables, known unknowns, or unknown unknowns. de Weck et al. (2007) and Lin et al. (2013) classifies sources of uncertainty as either exogenous, endogenous or hybrid, depending on the degree in which they can be managed. Miller and Lessard (2000) states that the uncertainty is *weak* when managers have enough information to structure problems, estimate distribution, and build decision models uncertainty. Otherwise, the uncertainty is *strong*. Thanopoulou, H., Strandenes (2015) deliberates the role of uncertainty in shipping, and propose a classification of uncertainty sources based on their nature and time horizon of their consequence. In relations to system complexity, more uncertainty is imposed to the system when its complexity increases (Skinner, 2009). Further, Dixit and Pindycke (1994), de Weck et al. (2007), Alizadeh and Nomikos (2009), Erikstad and Rehn (2015) and Strøm and Christensen (2016) presents how uncertainty can be quantified and modelled as an attempt to better foresee future events.

Uncertainty Management

In line with Forrester (1977), de Neufville (2004) states that the three common modes of response to uncertainty management are to control the source of uncertainty, to passively protect or to active protect the system against the impact of uncertainty. McManus and Hastings (2005) provides a framework for handling uncertainty, focusing on how "-ilities" can be used to mitigate risk and exploit opportunities. "-ilities" refers to life cycle properties of engineering systems, such as quality, reliability, safety and flexibility. In order to define this abstract concept, McManus et al. (2007) describes the "-ilities" in terms of changes in context, needs and the system itself. In search for better definitions, Ross and Rhodes (2008b) creates a taxonomy of change that consists of a change agent, a change mechanism and change effect. Beesemyer et al. (2012) develops a framework characterising change mechanisms, giving a better understanding of the link between design decisions as enablers for the "-ilities." De Weck et al. (2012) investigates the relationship and semantic sets among these life-cycle properties.

Ringland (1998) presents scenario planning as a means for managing the future by developing scenarios of how the future might turn out to be, and making plans for how the firm should cope with these possible futures. To support scenario planning, Ross and Rhodes (2008a) presents Epoch-Era Analysis (EEA) as an approach to analyse system value over time by decomposing the continuous future into several static epochs. Gaspar et al. (2012) use EEA analysis to handle the temporal complexity in commercial vessels. Building on EEA, Ross et al. (2009) presents the Responsive System Comparison (RSC) method as a stepwise process for evaluating systems temporal performance. Pettersen et al. (2017) presents the use of the RSC method to structure the general ill-structured offshore decision problem. Ricci et al. (2014) extended EEA by the Systems of Systems Architecting with "-Ilities" (SAI) methods, aiming at supporting system architects to incorporating "-ilities" in the conceptual design phase.

Miller and Lessard (2000) presents how managers should strategically manage large engineering projects. de Neufville (2000) presents Dynamic Strategic Planning (DSP) for large-scale engineering systems, which incorporates real options into the plan for making it flexible. Walker et al. (2001) presents Adaptive Policymaking (APM) as a generic approach for uncertainty management, recognising the dynamics of the world, and therefore the need to plan adaptively. Extending this, Kwakkel et al. (2010) proposes the Adaptive Strategic Planning framework, directed towards airports. Hastings (2015) book Physical Asset Management are also relevant on this part. Erikstad and Rehn (2015) presents the state of the state-of-the-art on uncertainty management in marine systems design, with the primary objective of developing methods to identify value robust systems. Extending this, Strøm and Christensen (2016) provides a literature review on quantitative methods to support decision-making under uncertainty for ocean engineering systems. de Neufville and Scholtes (2011) highlights the difficulty of uncertainty management, stating the common obstacles for implementing change to be ignorance, inattention, failure to plan, stakeholders block and external development.

Changeability

Changeability is an umbrella term comprises four "-ilities", namely: robustness, flexibility, agility and adaptability, that enable the system to adapt to changes in context and needs. The idea to *design for changeability* (DfC), as a principle to enable change in system through its life cycle, was first presented by Fricke (1999), and then later extended by Schulz and Fricke (1999) and Fricke and Schulz (2005). Niese and Singer (2014) states that the three dimensions of changeability are the physical performance dimension, the process dimension and the managerial dimension. In the literature, the word flexibility and changeability are often used interchangeably. Saleh et al. (2007) presents a comprehensive literature review on flexibility in engineering systems, separating between flexibility is the *design process* and flexibility in the *design*, for which changeability is related to flexibility in the design. de Neufville and Scholtes (2011) presents a four-phase approach for developing flexible systems, and states that flexibility can improve life cycle performance by 10-30%. Cardin et al. (2013) states that a flexible system comprises two components: a strategy, and an enabler in the design and management, and further presents a five-phase taxonomy of systematic procedure for supporting the design of flexible systems.

Wang (2005) discuss screening methods to identify potential sources of changeability in engineering design, later, de Neufville and Scholtes (2011) argues for the same idea, and give an overview of various screening methods. Design structure Matrix (DSM) is one of these methods, for which Eppinger and Browning (2012) provides an excellent insight into the method and its applications. Extending the DSM, the Engineering System Matrix (ESM) not only focus on technological relationships, but also social and system drivers (Cardin et al., 2013). Kalligeros (2006) propose sensitivity design structure matrix (sDSM) to identify design variables that are most sensitive to changes, this could indicate the design variables that have the most benefit of being flexible. Pierce (2010) developed a framework, based on option theory, for identifying and valuing alternative change options. Carding and de Neufville (2008) survey methodologies for identifying and valuing flexibility in complex systems using option theory. Fitzgerald (2012) focused on the development of metrics for changeability, for which the filtered outdegree (Ross,

2006) is one method for quantifying the level of changeability utilising network theory. Based on the idea of designing for changeability, Rehn et al. (2017a) outlines a generic method for quantifying the level of changeability incorporated by their effect on change costs and time, further stating that the level of changeability, in the same manner as design variables, is an overall design variables that should be decided in the design phase. Rehn et al. (2017b) investigates the technical performance, cost and flexibility of changeable offshore vessels. The vessel's performance is measured using a generalises utility function, and filtered outdegree is used to quantify the level of changeability.

Strategy

In the classical work on competitive strategy, Porter (1980) states that suppliers, potential entrants, buyers, substitutes and rivalry among existing firms are the five forces drives industry competition. Porter (1980) then examines the way companies strategically should compete to gain competitive advantage. Lorange (2009) present how focused strategies are enablers for gaining competitive advantage in the volatile maritime industry. Georgzén and Palmér (2014) analyse the interplay between managing strategy and flexibility for Swedish companies, and Eriksson and Lutteman (2015) presents a study of strategy within shipping. In their book on *shipping and logistics management*, Lun et al. (2010) devotes a chapter to business strategy in shipping. Sharma (2010) reviews the development of flexibility related to, among other, technical, organisational, operational aspects. He states that there is a critical cap in flexibility research, as flexibility is not only related to technical aspects, but also the managerial processes of the organisation. Khatri and Ng (2010) surveyed senior managers in a variety of industries to examines the role of intuition is strategic decision-making, and find that intuition plays a vital role. Unfortunately, intuition is flawed (Kahneman, 2011). Nemeth (2012) presents an overview of the biases of intuition at both the individual and group level. Payne et al. (1996) goes in-depth on decision process affected by the opportunity-cost pressure. In high-volatile markets, such as the case or offshore shipping, Payne et al. (1996) state that decision makers should focus on generating multiple alternatives actions before deciding on a final one. Mikaelian et al. (2009) propose the Integrated Real Option framework (IRF) to support strategy generation through identification and valuation of real options in enterprise architecture. Cardin et al. (2013) proposes *ex-*

plicit training and prompting as a procedure for understanding uncertainty drivers, identifying strategies, and how to incorporate flexibility in design.

Real Options

As already noted, both the concept of changeability and managerial flexibility (i.e. strategies) are related to real options theory. Quite similar as financial options, real options can be defined as the right, but not the obligation, to exercise actions or to make specific project decisions at a future time (Berk and DeMaro, 2014). Wang and Neufville (2004) distinguished between real *on* options and real *in* options. While real in options concerns changes in the physical system, and is therefore related to changeability, *on* options concerns managerial flexibility treating the physical system as a black box. Recently, Christensen (2017) presented a new classification scheme for real options, stating that real *on* options should be regarded as an overarching class of option, further separated into *build-in design options* and *design change options*. Puisa (2015) presents real option evaluation as a method of integrating market uncertainty in ship design specifications. Trigeorgis (1997), Dixit and Pindycke (1994) and Nembhard and Aktan (2010) are excellent books for gaining deep insight into the world of real options, the latter having a special focus on applying real options in shipping.

Markov Decision Processes

Markov decision processes (MDPs) (Bellman, 1954) is a state-based method of modelling sequential decision-making under uncertainty. Puterman (2005), Mausam and Kolobov (2012) and Hu and Yue (2008) are only some of the books devoted to this topic. Alagoz et al. (2010) provides a tutorial for how to construct and evaluate MDPs, on a sequential medical treatment problem. Previous research using MDP applied to vessel design included analysis of ballast water treatment methods and design for energy efficiency design index (Niese, 2012; Niese and Singer, 2013, 2014), and retrofitting decisions concerning engines to meet new environmental regulations (Kana et al., 2015). Niese and Singer (2014) propose a MDO methodology that combine Markov decision processes, life cycle simulation, and metrics for assessing system changeability.

Backward dynamic programming (BDP) is a standard method for solving finite horizon, discrete-time MDPs. Approximate (or adaptive) Dynamic Programming, commonly referred to as Reinforcement Learning (RL), is an emerging solution method overcoming the struggles BDP often faces when applied on large scale, complex problems (Powell, 2007; Powell., 2009; Gosavi, 2009). Powell. (2009) provides a brief overview of*what you should know about Approximate Dynamic Programming*, and Powell (2007) provides an extensive insight into ADP. Gosavi (2009) give a tutorial survey ADP, aimed at uncovering its mathematical roots to gain a clearer understanding of the core concept. In general, ADP is an umbrella term comprising numerous modelling and algorithmic strategies for solving MDP, one of which are the well-known Q-learning algorithm (Watkins, 1989). Watkins and Dayan (1992) presents a proof of convergence for the Q-learning algorithm, later extending by Tsitsiklis (1994).

1.4 Expected Research Contributions

Based on the research questions and the literature review, the following points present the expected research contributions of this thesis:

- Highlight the importance of an active managerial approach, on both the operational, tactical and commercial level, to handle uncertainty. Thereby expanding the traditional system view to not only consider the engineering dimension, but also to consider the managerial dimension.

- Propose a framework linking a system's value robustness to the physical system design, stakeholders strategies for utilising the design configuration and stakeholder's ability to align its design and strategy.

- Propose a framework for managing value robust systems, building on the ideas from the two points above. This framework should consider the development of value robust systems, the implementation of the systems, and the life-long process of monitoring it.

- Present a Markov Decision Processes Methodology as a quantitative method to support the framework presented above. This should form a holistic decision analysis framework to support uncertainty management.

1.5 Limitations

There are three main limitations affecting the work in this thesis. First, starting off this work in January, the author had zero knowledge about Markov decision processes, in addition there are none with extensive knowledge of the method at the NTNU. This affected the time and effort spent on learning the method, also limiting the ability of peer control. Secondly, the limited amount of relevant data available affected the case study. Since the objective of this thesis was mainly on developing methods, little time was devoted on finding real data so the case data was taken from the literature, mainly from Rehn et al. (2017b,a) and Pettersen et al. (2017). Finally, the wide scope of this thesis serves as a limitation in itself as it became difficult to go in-depth on all the relevant aspects. Further research on this topic is therefore encouraged to divide and conquer, instead of attempting to win the entire war at once.

1.6 Structure of the Report

The report is structured in three parts.

Part I extends the literature review presented in the introduction, giving an in-depth review on the core topics in this thesis. This is to lay the foundation for the research contributions presented in part II.

- **Chapter 2** defines engineering systems and presents their complexity, relating it to offshore vessels. The section on complexity builds on the work of Strøm and Christensen (2016).
- **Chapter 3** presents the uncertainty related to engineering systems, and how it can be managed. This chapter builds on the work of Strøm and Christensen (2016).
- **Chapter 4** and **5** extends the topic of uncertainty management in chapter 3, presenting the how changeability and strategy are engineering and managerial approaches for handling

uncertainty, respectively.

- **Chapter 6** presents Markov decision processes (MDP) as a modelling and solutions technique for sequential decision problems. As MDP still is unfamiliar to most students and professors at NTNU, the primary objective of this chapter is to work as an introduction to this field of operations research.

Part II builds on the knowledge gained in part I, and present the key research contributions.

- **Chapter 7** presents the Value-Aptitude-Design-Strategy (VADS) framework, expressing the dynamic relationship between the stakeholders aptitude and strategy, in addition to the design configuration, linking them to the system's ability to deliver value.

- **Chapter 8** presents the Design-Strategy Planning (DSP), as a structured life cycle approach for managing uncertainty. The chapter also presents a Markov decision processes methodology for supporting DSP.

- **Chapter 9** illustrates the use of Design-Strategy planning and the Markov decision process methodology on an offshore case. The illustrative case is based on the work of Rehn et al. (2017a), Rehn et al. (2017b) and Pettersen et al. (2017).

Part III ends off this thesis by first presenting the discussion in **chapter 10**, before presenting the conclusion and recommendations for further work in **chapter 11**.

Part I - Literature Review

Chapter 2

Engineering Systems & Offshore Vessels

2.1 Defining System & Engineering Systems

The word system originates from the Greek word *sustēma* meaning a *unified whole*[1]. de Weck et al. (2011, p. 32) defines system to be *a set of interacting components – technical artifacts – with well-defined behaviour and well-defined function or purpose*.

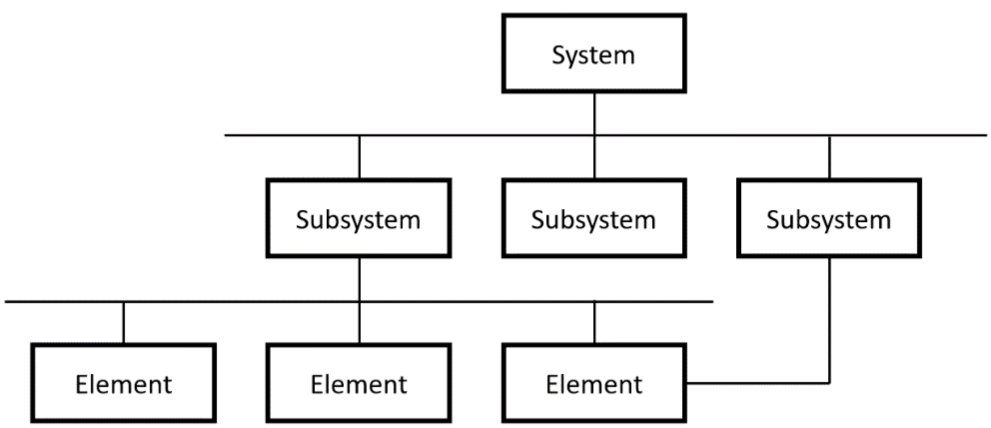


Figure 2.1: Illustration of a system hierarchy (Fet, 1997)

Figure 2.1 illustrates that a system consists of *elements* (or components) interacting to form sub-systems; *attributes*, which are properties of the elements indicating their contribution to the sub-system; and *interconnections*, which are the relationships linking resources, elements and

[1] `https://www.merriam-webster.com/dictionary/system` [20.01.17]

subsystems together to form the total system (i.e. the unified whole) (Blanchard and Fabrycky, 2011; Fet, 1997). The total system can for instance be an offshore vessel, consisting of subsystems such as engines, cranes, and pumps. These subsystems are themselves assembles by gears, propellers, screws, shafts, bolts, tubes, plates, etc. For the system to successfully perform its intended purpose, each of its subsystems and elements must properly interact (Kossiakoff et al., 2011).

In addition to the internal interaction, the system itself interacts with its surroundings. The surroundings might be stakeholders, process, social, political, economic, institutional, and other physical systems (Fet, 1997; de Weck et al., 2011). The system affects the surroundings, and the surroundings affect the system (Fet, 1997). Traditionally, systems engineers have had a limited focus on this interaction. As to be discussed, this thesis emphasises the need to extend the traditional system boundary, to not only consider the physical system and its behaviour, but also to consider its surroundings.

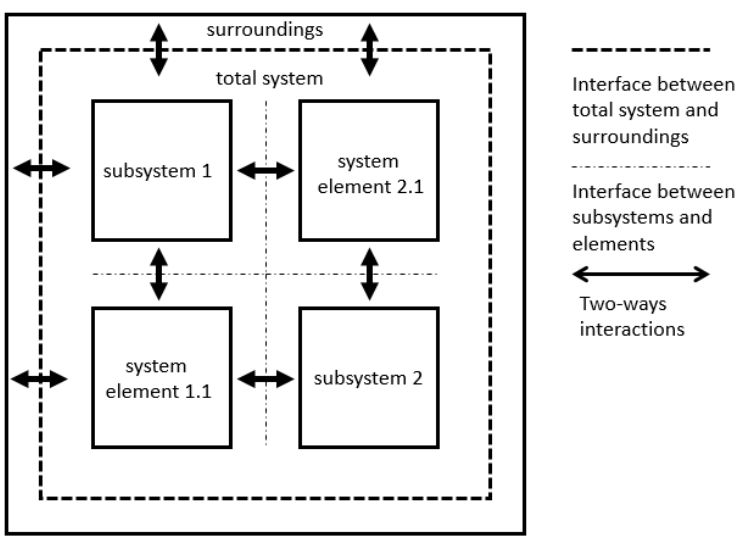


Figure 2.2: Illustration of the interactions between system elements, subsystems, the total total system and its surroundings (Fet, 1997)

Engineering systems are *a class of systems, characterised by a high degree of technical complexity, social intricacies, and elaborate processes, aimed at fulfilling important functions in society* (de Weck et al., 2011, 31). Further, engineering systems can be characterised by their (I) existence in the real world (II) artificiality (III) dynamic properties (IV) a hybrid state space and (V) some degree of human control (de Weck et al., 2011). Engineering systems operating in the ocean environment are often referred to as ocean engineering systems[2]. By this definition, offshore vessels are ocean engineering systems. They are real, human-made systems (hence, are artificial), with changeable system configurations (hence, have dynamic properties). Further, offshore vessels have a hybrid state space since some states are continuous (e.g. sailing and operation), while others are discrete (e.g. a subsystem can be both on and off), and they are influenced by human control over its entire life cycle, which is addressed in section 2.3.

[2] `https://www.merriam-webster.com/dictionary/ocean%20engineering` [20.02.2017]

2.2 Complexity in Engineering Systems

2.2.1 Defining Complexity

One of the key concepts in engineering systems is complexity. As stated by (Evans, 1959, 671-672):

> "Ships and aircraft are examples of extremely complex problems. Not only are they structures, but vehicles as well. Furthermore, they are vehicles whose efficiency, or in fact, whose very ability to perform at all, is strongly dependent on weight economy."

Fundamentally, complexity can be related to the amount of information necessary to completely describe the system (Kolmogorov, 1983). Magee and de Weck (2004) also considered the number of (unique) elements and the nature of their interconnections, defining complex systems to be: *a system with numerous components and interconnections, interactions or interdependencies that are difficult to describe, understand, predict, manage, design, and/or change.*

Increasing system complexity makes it harder to handle all relevant parameters and their interactions (Fricke et al., 2000), enabling more points of failure to occur. Hence, in order to maximise the probability of system success, a system's complexity should be minimised while still providing its functionality. (Suh, 1990)[3]. Unfortunately, it is difficult to find this balance (Moses, 2004).

2.2.2 Level of Complexity

Hubka and Eder (1988) proposes a framework to measure the level of complexity in technical systems in four levels (ref. table 2.1). Complexity level I represent the simplest systems, such as the system elements that often can be produced without assembly operations. On the other end, complexity level IV represents the most complex systems. These are highly complicated, multifunctional systems that consists of several subsystems. In relations to figure 2.1 in section 2.1, the more complex the system is, the further up in the system hierarchy it is. Extending

[3]This is referred to as the *information axiom*

Hubka and Eder (1988), Gaspar et al. (2012) stated that some systems can be regarded as even more complex than level IV, as they are *systems of systems*.

Table 2.1: Level of Complexity in Technical Systems (Hubka and Eder, 1988)

Level of Complexity	**Technical system**	**Characteristics**	**Examples**
I (Simplest)	Part, component	Elementary system produced without assembly operations	Bolt, bearning sleeve, spring, washer
II	Group, mechanism sub-assembly	Simple systems that can fulfil some higher functions	Gear box, hydraulic drive, spindle head, brake unit, shaft, coupling
III	Machine, apparatus, device	System that consists of sub-assemblies and parts that perform a closed function	Lathe, motor vehicle, electric motor
IV	Plant, equipment, complex machine unit	Complicated systems that fulfils a number of functions and that consists of machines groups and parts that constitutes a function and spatial unity	Hardening plant, machine transfer line, factory equipment

2.2.3 Five Aspects of Complexity

Rhodes and Ross (2010) propose the five major aspects of complexity affecting engineering systems to be: *structural, behavioural, contextual, temporal* and *perceptual*. By doing so, they extended the traditional system boundary (consisting of the structural and behavioural aspects) of engineering systems, thereby increasing the amount of information needed to completely describe the system, hence, resulting in more complex systems (ref. Kolmogorov (1983)). Note that table 2.1 is in line with the traditional system boundary, by only consider the structural and behavioural aspect of complexity.

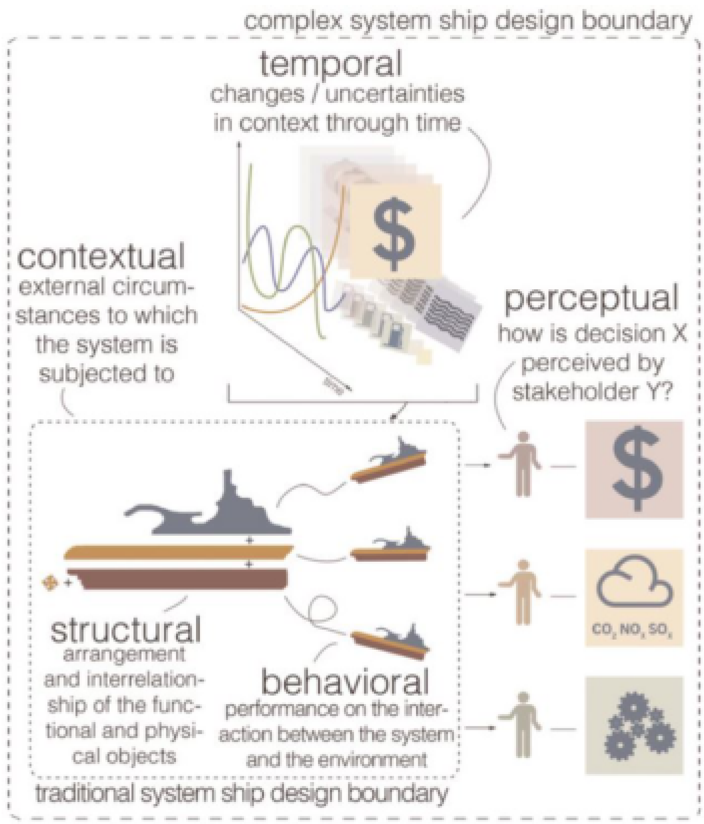


Figure 2.3: Five Main Aspects of Complexity in Offshore Vessels (Gaspar et al., 2012)

The structural aspect of engineering systems has already been treated in section 2. The structural aspect is related to the form of the vessel, and the interconnection and interactions between the function and physical objectives (i.e. subsystems and components) of the vessel. As a complete and self-contained system, all the functions of the vessel (e.g. producing propulsion and electricity, providing accommodation, carry food and water, firefighting, etc.) must be provided by the vessel itself (Hagen and Erikstad, 2014). Due to the strict volume restrictions imposes by the hull, subsystems interactions are tightly coupled. The degree of structural complexity increases when considering change options in the system (Pierce, 2010).

The behavioural aspect is related to the function of the design. It includes the vessel's performance, operations and reaction. A system is said to be behavioural complex if it is difficult to predict, analyse, describe, or manage its behaviour (de Weck et al., 2011). In general, a structural complex system is often behavioural complex, but not necessarily the other way around (de Weck et al., 2011). The behavioural aspect, along with the structural aspect, is of high importance when considering changeable design concepts, as it tightly constraints which change options that can be incorporated. For instance, one cannot install a larger crane than the vessels stability support.

The contextual aspect is related to the external operating circumstance affecting the system performance, imposing external constraints on the system. Examples of contextual aspects are company strategy, operational profile, contract scenario, competitive factors, demand, technology, regulations and stakeholders' preferences. The conceptual aspect closely relates to the discussion on uncertainty presented in the section to come.

The perceptual aspect is related to how the vessel is viewed in the light of stakeholder preferences and perceptions. It is of high importance to understand the perceptions might differ from stakeholders to stakeholders, and that a stakeholder's perception changes over time. For offshore vessels, the difference between stakeholders needs and requirements at the design stage, and those when the system is demolished, are large (Son and Savage, 2007). This can be due to change in a vessel's behaviour and context, but stakeholder's perception might change even when everything else is fixed (Gaspar et al., 2016).

The temporal aspect is related to the properties of the system over time, and how context and needs will change. As discussed in the next section, the temporal aspects impose uncertainty to the structural, contextual, behavioural, and perceptual aspects, resulting in both considerable risks and opportunities for offshore vessels.

2.3 Offshore Vessels

Offshore vessels are commonly divided into several types depending on their operations. Examples are Platform Support Vessels (PSVs), Anchor Handling Tug Supply Vessels (AHTS), Dive Support Vessels (DVSs) and Offshore Construction Vessels (OCVs). For the reminder of this thesis, Offshore Construction Vessels will be used to exemplify the theory presented.

Offshore construction vessels (OCVs) are multifunctional vessels able to perform a broad range of constructions tanks. This includes IMR operations (Inspection, Maintenance and Repair), SURF operations (Subsea Installation, Umbilical, Risers and Flow-Lines), LWI operations (Light Well Intervention) and DS operations (Dive support operations) (Pettersen, 2015). To perform these operations, OCVs are typically installed with heavy heave-compensated cranes, moonpool, and large stores for pipes and cables, in addition to a large open deck, remotely operated vehicles (ROV) and, in some cases, diving equipment. OCVs are often in need for large Accommodation spaces, not only for the ship crew but also to accommodate the construction workers and clients. Often, OCVs have a landing pad for helicopters to support the exchange of personnel on board. OCVs needs high-level of position accuracy and excellent station keeping capabilities to safely perform these operations. The cranes are installed with heave compensation to ensure safe and accurate loading and offloading operations (Ritchie, 2008; Levander, 2012; Pettersen, 2015).

Figure 2.4 presents the technical drawings in profile for the Offshore Construction and Anchor Handling Vessel Normand installer, built in 2006 by Ulstein[4] for the Norwegian offshore company Solstad Offshore[5] ASA. The vessel has a length over all of 123.65 m, breadth of 28 m, deadweight 9511.8 t, lightship of 10 573.6t, and gross tonnage of 14 506t. Normand installer has an a 350t capacity A-frame over the stern, a 250t heave-compensated offshore crane and a helideck. The total number of bunks are 100. The bollard pull is 308t[6].

[4] `https://ulstein.com/`
[5] `https://solstad.no/`
[6] `https://solstad.no/wp-content/uploads/2014/02/Normand-Installer.pdf`

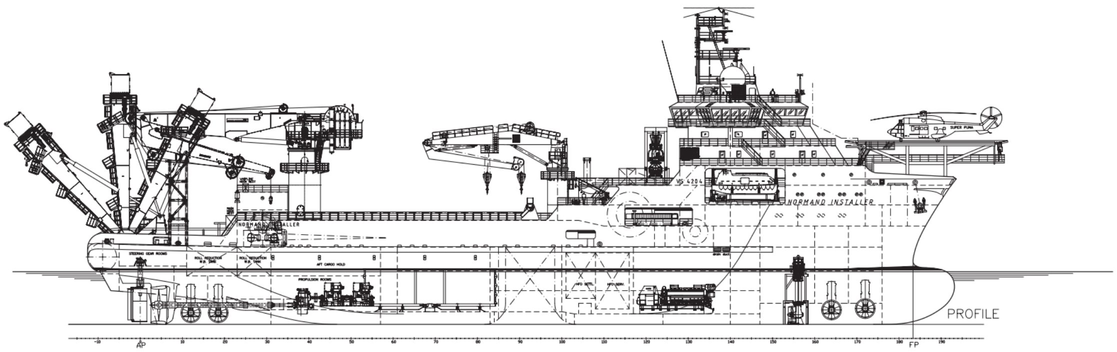


Figure 2.4: Technical drawings (Profile) of the OCV & AHV NORMAND INSTALLER

When analysing engineering systems, it is essential to have a holistic view and understand the systems interconnection with its surroundings. A specific offshore construction vessel, consisting of system elements and subsystem[7]. The *ship related systems*, such as structure, outfitting, accommodation, machinery, tanks and voids, relates to the seaworthiness of the vessel enabling it to properly function as a self-contained system. The *task related systems*, such as cargo spaces, lifting, construction and diving, relates to the specific objectives of the vessel (Levander, 2012). However, the vessel itself is also a sub-system, operating as a part of a fleet in the maritime transportation system, serving a greater logistics chain.

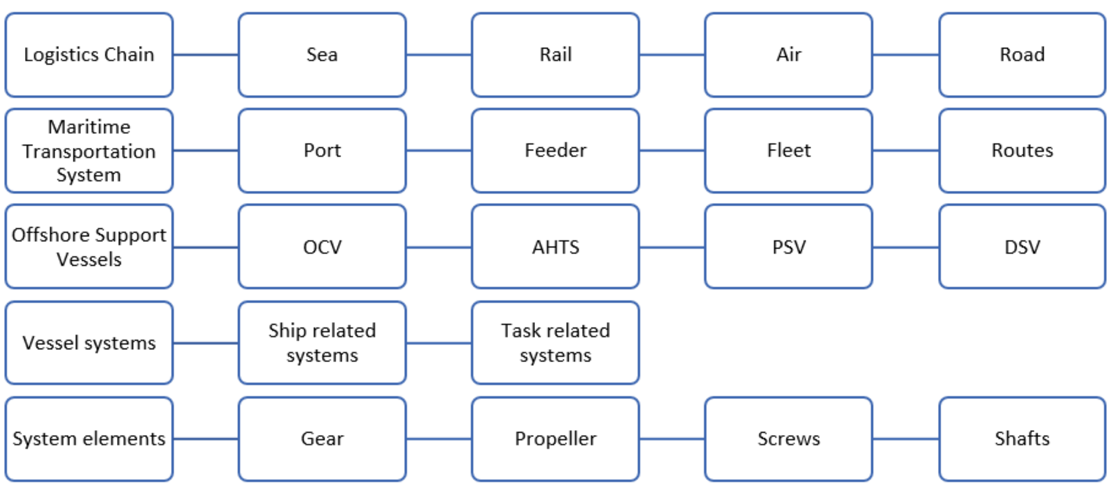


Figure 2.5: A holistic view on Offshore Vessels (based on (Levander, 2012; Gaspar et al., 2012)
)

The life cycle of engineering systems constitutes a series of activities, stretching from its birth to death. For offshore vessels, the life cycle generally divides into four phases (Ayyub et al., 2000):

[7]See appendix C

(I) design phase (II) production phase (III) operations phase and (IV) disposal phase. Figure 2.6 presents a simple illustration of these four life cycle phases, including some of their sub-stages. This thesis will not describe each of the four phases in detail since this would require an entire thesis itself. However, to form the basis for later discussions, the design phase and operational phase is briefly presented below. The reader is advised to Erikstad (1996), Fet (1997), Ayyub et al. (2000) and Hagen and Erikstad (2014) for in-depth view in each phase.

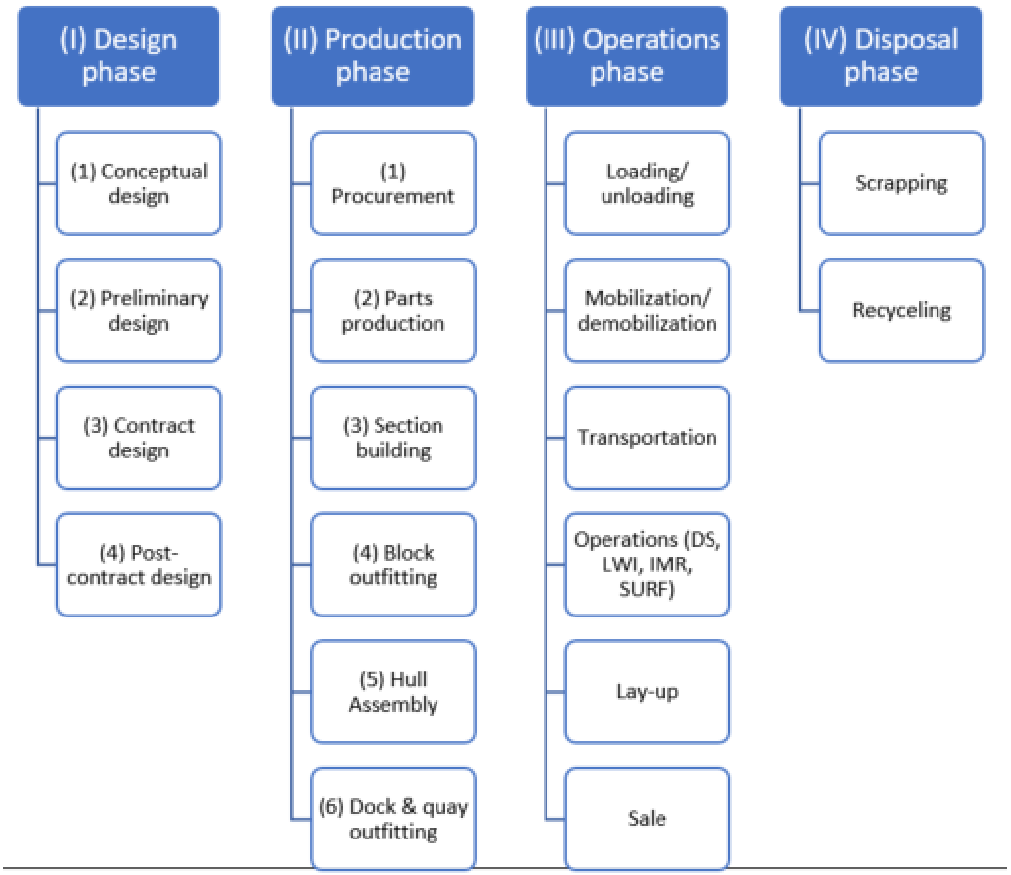


Figure 2.6: Life cycle of Offshore Vessels (based on (Erikstad, 1996; Fet, 1997; Ayyub et al., 2000; Hagen and Erikstad, 2014)

The Design Phase

The design process consists of all activities starting from initiation of the design project to the contract specifications is delivered (Erikstad, 1996). Generally, the design phase is divided into four phases, where the first phase – the conceptual design phase – is the focus in this thesis.

The conceptual design phase is initiated by stakeholders' needs, forming requirements which constraints the design (or solution) space. The objective in the concept design phase is to explore this design space to identify a set of conceptual solutions which meets stakeholders needs (e.g. functional analysis and feasibility analysis). This process can be seen as a high-level function-to-form mapping where the goal is to develop a sufficient functional description of both the overall design and subsystems to meet stakeholders needs (Erikstad, 1996). After a series of analyses and sequential elimination of design concepts, a set of concepts are selected for more detailed development in the subsequent design phases.

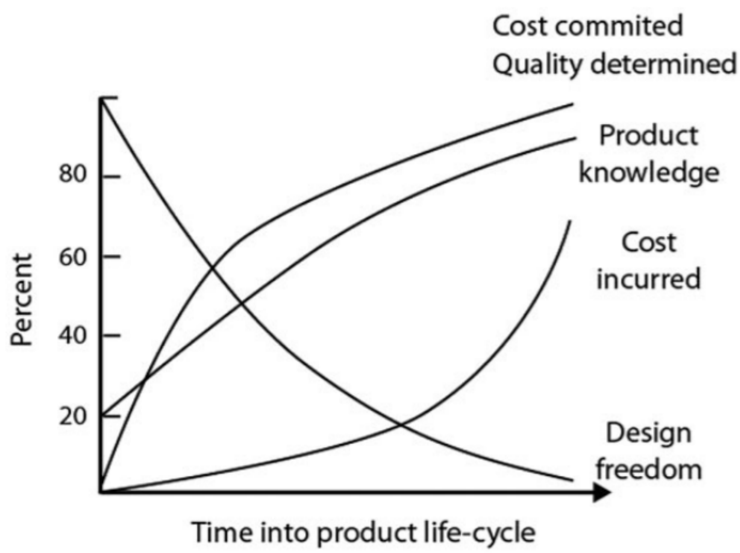


Figure 2.7: Illustration of the costs committed, costs incurred, design freedom and design knowledge over a design life cycle (Karniel and Reich, 2011)

In the primary design phase, the concept design is further analysed, attempting to optimise the life cycle performance of the system, and basic drawing is developed. These drawings highlight the structure of the vessel and its systems. After primary design, the development team should have sufficient information to tender. After the tender is accepted, the final details in the design (such as arrangements and systems) are specified in the contract design. After the contract specifications are agreed upon, the design can go into production. Even during the production phase, some post-contract design will occur. This typically includes work on detailed design of structure and outfit. The reader is advised to Eyres (2007) and Hagen and Erikstad (2014) for more information about the design of offshore vessels.

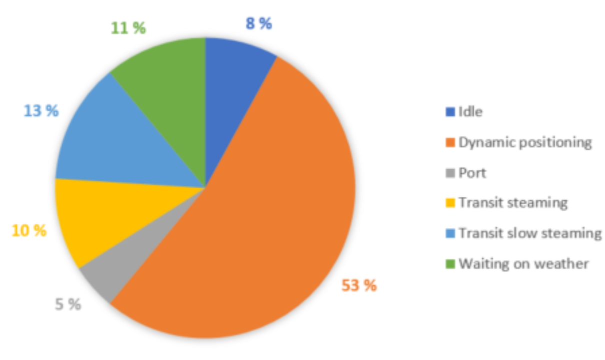
Despite the brief time spent in the conceptual design phase, it is recognised as probably the most critical phase for determining a vessel's success. Figure 2.7 presents one of the key challenges. As seen, for engineering systems in general, 70-80 % of a system's cost is committed during the conceptual phases, despite little actually being incurred (Roy, 2003; Andrews, 2013). Further, the *rule-of-ten* states that the cost of changing a decision already made becomes ten times higher for each subsequent phase. Despite the high consequences of the decision made, the knowledge of the design is at its lowest. This makes it highly important to make good decisions in this phase.

The Operations Phase

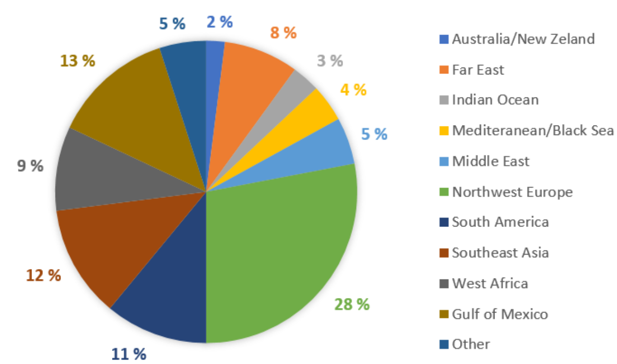
The operational phase is the longest of all the four life cycle phases, typically lasting for 20-30 years. The primary mission of the OSV fleet is to support the Exploration and Production (E& P) activities of offshore oil and gas resources. This includes, the *exploration phase*, consisting of seismic examination, exploratory drilling; the *installation phase*, in which production platform and subsea installations are installed; and the *production phase*, when maintenance, supply and standby services are needed for the oil and gas resources to be extracted.

OSVs are important in the entire E & P process, however, most of the work is done in the operations phase which stretches for decades. While *upstream logistics* in the production phase is about supporting the production operations, *downstream logistics* is about transporting the extracted oil and gas resources onshore. The production requires transportation of personnel and equipment, inspection and maintenance, etc. These operations are performed by various vessels in the offshore fleet. Normally, oil companies do not own these vessels, but charter them from shipowners (Døsen and Langeland, 2015). The chartering cost is a major cost factor in upstream logistics. See Lun et al. (2010), Babicz (2015), and Olesen (2015) for more insight into the value chain for offshore oil and gas.

In order to design successful engineering systems, it is of major importance to have a clear understanding of what the system will encounter in the operational phase and an indication of how the system will perform meeting these encounters. Because E&P activities have unique needs and requirements around the world. For instance, the environmental factors (e.g. wind and sea state) and operational factors (e.g. depth and type of production methods) might differ in various sectors. Figure 2.8a illustrates an operational profile for offshore construction vessels. As seen, most of the time the vessel is spent operating on dynamic positioning. Note that the operational profile varies a lot between vessel types. For instance, in the case of cargo vessels, most of the time would be spent in transit. Figure 2.8b shows the geographical distribution for offshore construction vessels. As seen, Northwest Europa has the largest share of vessels (28 %), followed by the Gulf of Mexico (13%), South Asia (12%) and South America (11%).



(a) Operational Profile for OCVs (Agis, 2017)



(b) Operating Area distribution (Remme, 2017)

Figure 2.8: Operational specific information for Offshore Construction Vessels

Table 2.2 presents some of the functional requirements for various missions offshore construction vessels undertake. Note that this only serves as a general representation, and that there are large variations from mission to mission. In addition, a low functional requirement does not indicate that it is easy to enable the specific capacity. It only serves to indicate that the functional requirement is low compared to the other missions (Remme, 2017).

Table 2.2: Functional specification for missions related to offshore construction vessels (Based on (Agis, 2017; Remme, 2017)

Mission	Accommondation space	Deck area	Bulk cargo	Crane capacity	Ligth well intervention	ROV class	Cabel laying equipemtn	Moonpool	DP class
Subsea Installation and Construction	High	Med-High	Low	High	No	Inspection	No	Yes	DP2/DP3
Inspection Meintenance and Repair	Low	Low	Low	Low	No	Working	No	Yes	DP2/DP3
Light Well Intervention	High	Med-High	High	Med-High	Yes	Working	No	Yes	DP3
Field decommission support	Med-High	Med-High	Med	High	No	Inspection/ working	No	No	DP2/DP3
Offshore Accommodation	High	Low-Med	Low-Med	Low	No	No	No	No	DP2/DP3
Subsea Umbilicals, Risers and Flowlines (SURF): Cable	Low	Low	Low	Low	No	Inspection	Yes	No	DP2/DP3
Subsea Umbilicals, Risers and Flowlines (SURF): Pipe	High	High	Low	High	No	Inspection	yes	No	DP2/DP3
Dive support	Med	Low	Low	Low	No	Working	No	Yes	DP2/DP3
Multipurpose Construction	Med-High	Med-High	Low-High	Med-High	Yes/No	Inspection/ Working	Yes/No	Yes/No	DP2/DP3

Chapter 3

Uncertainty & Uncertainty Management

3.1 Uncertainty

3.1.1 Defining Uncertainty

Uncertainty can be defined as the *things that are not known, or only known imprecisely* (McManus and Hastings, 2005, 2), the *inability to quantify precisely; a distribution that reflects potential outcome*s (Walton, 2002, 20), or as *inability to determine the true state of affairs of a system* (Haimes, 2009, 255).

Figure 3.1 illustrates one major challenge with uncertainty: it causes a gap between foreseen and realised events. Using experience, analysis and simulation, one can anticipate and handle a small set of events to occur over a system's life cycle. Unfortunately, only a subset of these foreseen events will in fact be realised, and many unforeseen events instead will occur. As maritime decision makers needs to consider multiple uncertainty parameters at once, the uncertainty of the parameters forms complex interactions, leading to a wide range of potential future outcomes. It is these unforeseen events that can make an initially good decision end up becoming a bad one (Mao-Jones, 2007). Generally, increased system complexity imposes more uncertainty (Skinner, 2009).

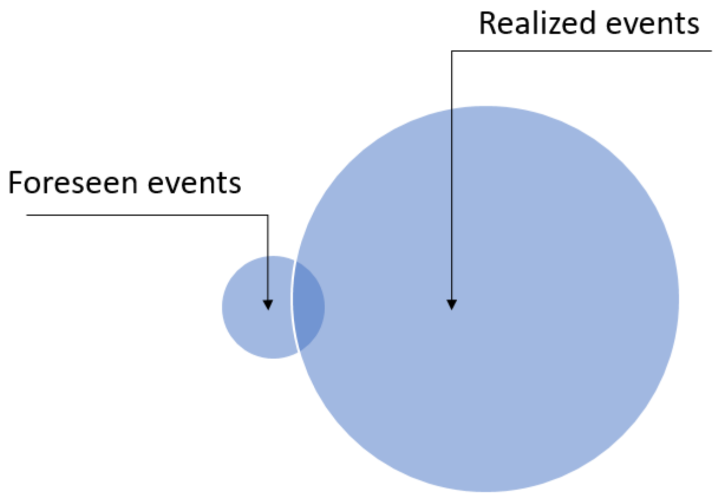


Figure 3.1: Illustration of the difference between foreseen events and realised events

History has shown how large-scale failures (e.g. RMS Titanic[1] (1912), MS Estonia[2] (1994) and Deepwater horizon[3] (2010)), create public pressure on incorporating means to reduce the likelihood for failures to occur. Further, from a financial point of view, ocean engineering systems are high-cost systems, for which its failure can have devastating impacts on the company with possibilities for bankruptcy. These factors, among others, has resulted in an asymmetric focus on uncertainty, where it almost entirely is associated with something negative (referred to as risk or vulnerabilities).

However, uncertainty might as well cause unforeseen opportunities (McManus and Hastings, 2005; de Weck et al., 2007; Lorange, 2009; Thanopoulou, H., Strandenes, 2015). In the maritime industry, some of the potential future opportunities are related to growth in demand for energy, food, resources and transportation, operations in more challenging conditions (deeper waters and harsher environments), emerging markets (e.g. Arctic areas), fast rate of technical innovation, and increased focus on efficiency and eco-friendly solutions (Norwegian Shipowners' Association, 2013; Amdahl et al., 2014).

On a final note, uncertainty can be quantified and modelled in an attempt to better foresee

[1] https://en.wikipedia.org/wiki/RMS_Titanic
[2] https://en.wikipedia.org/wiki/MS_Estonia
[3] https://no.wikipedia.org/wiki/Deepwater_Horizon

future events. The reader is advised to Dixit and Pindycke (1994), de Weck et al. (2007), Alizadeh and Nomikos (2009), Erikstad and Rehn (2015) and Strøm and Christensen (2016) for in depth knowledge in these aspects.

3.1.2 Classification of Uncertainty

From the system engineer's point of view, *lack of knowledge* and *lack of definition* are two overarching classes of uncertainty (McManus and Hastings, 2005). Lack of definition is defined to be *facts that are not known, or are known only imprecisely, that are needed to complete the system architecture in a rational way.* Lack of definition is defined to be *things about the system in question that have not been decided or specified.* The reader is advised to Strøm and Christensen (2016) for exemplifications.

Further, McManus and Hastings (2005) states that lack of knowledge and lack of definition can have several characteristics. They can either be (I) *statically random variables*, which are uncertain variables that can be statically characterised; (II) *known unknowns*, which are things known to be unknown; or as; (III) *unknown unknowns*, which are things not known to be unknown[4]. While statically random variables can, at least to some extent, be modelled, unknown unknowns represent a complete lack of knowledge. Unfortunately, it is difficult to transform class (III) uncertainty into class (II), however, brainstorming might be a method for doing so. Schoemaker (1995)has a similar classification as McManus and Hastings (2005) for degrees of knowledge. His classification includes known unknowns, and unknown unknowns, in addition to known knowns, for which the latter represents a state of complete knowledge.

Sources of uncertainty might be classified as *exogenous, endogenous* or *hybrid*, depending on the degree in which they can be managed (de Weck et al., 2007; Lin et al., 2013). In contrast to endogenous uncertainty, the sources to exogenous uncertainty cannot actively be managed. The sources of hybrid uncertainty can, to some extent, by influenced. While a shipowner is in full control of the technical aspect of the project (endogenous uncertainty), and can choose

[4]Donald Rumsfeld, former U.S. Secretary of Defence, also distinguished between "known knowns", "known unknowns", and "unknown unknowns". See `http://archive.defense.gov/Transcripts/Transcript.aspx?TranscriptID=2636`

structural configuration of his liking, he has only partial influence on the industry dynamics (hybrid uncertainty), and he has no control of the forces in the nature (endogenous uncertainty). Note that this classification is highly case specific. For example, to which degree a shipowner can influence freight rates in the market is depending on the size of his fleet. With a (very) large fleet, the shipowner is partially in control of the vessel supply, and can thereby benchmark the freight rate. The focus in this thesis is on exogenous uncertainty, and how one can (despite not being able to control the source of the uncertainty) can influence the outcome of it.

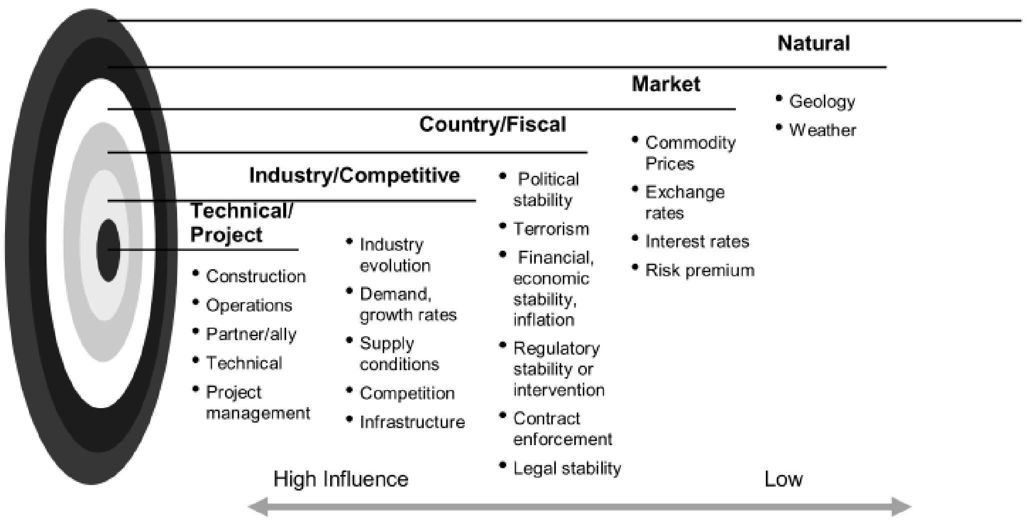


Figure 3.2: Layers of Uncertainty (de Weck et al., 2011)

Related to classification of exogenous, endogenous and hybrid uncertainty, figure 3.2 illustrates a layered representation of uncertainty. A key aspect in this representation is that the ability to influence the uncertainty diminishes when going from the inner to the outer layer. Thus, endogenous uncertainty is mostly located in the inner circles, hybrid uncertainty is mostly located in the middle, while exogenous uncertainty is located close to the outer boundary.

Miller and Lessard (2000) states that the uncertainty is *weak* when managers have adequate information to structure problems, estimate its distribution, and build decision models. When these conditions do not hold, the uncertainty can be said to be *strong*, and the outcome of a decision is ambiguous. In the case of *indeterminacy*, the future outcomes are difficult to assess due to its dependency on exogenous or endogenous events leading to the possibility of multiple outcomes.

Uncertainty can be decomposed into technical, commercial and operational aspects (Ulstein and Brett, 2015; Agis et al., 2016). According to Ulstein and Brett (2015, 54):

- **Commercial aspects** are *all factors/articles/systems that influence the valuation, preferences and exploitation of the vessel during its operational lifetime and increases the returns of the investment.*
- **Operational aspects** are *all factors/articles/systems that influence the performance of different missions, for which the vessel is designed and set to do, improving operational conditions*
- **Technical aspects** are *all factors/articles/systems that influence the intrinsic effectiveness of the vessel over its project life cycle and that affects the design and construction process of the vessel.*

Agis et al. (2016) argues that in the case of commercial vessels, all operational and technical aspects indirectly affects the commercial aspect since they affect the vessels cost and earning capacity. In addition, while technical and operational uncertainties typically are related to the vulnerabilities, the commercial aspect of uncertainty is to a large extent symmetrical, also associated with opportunities. Alternately, Erikstad and Rehn (2015) classifies uncertainty according to economic, technological, regulatory, and physical sources.

Table 3.1 illustrates the variety of uncertainty types in the maritime industry, their nature and time horizon. Note that *Zuellig factors* are defined to be events with accidental character, lack of periodicity, and the absence of links with economic mechanisms (Thanopoulou, H., Strandenes, 2015, 7). Further, figure 3.3 presents the historical development and the prediction for the North sea brent crude oil spot price, representing one of the major uncertain factors in the maritime industry. By 2030, EIA predicts the oil price to be $\$104/b$ in the Reference case, $\$49/b$ in the Low Oil Price case, and $\$207/b$ in the High Oil Price case.

Table 3.1: Types of Uncertainty in the maritime industry, their nature and time horizon (Thanopoulou, H., Strandenes, 2015)

Type of Uncertainty	**Category**	**Time Horizon**		
		Short-term	*Medium-term*	*Long-term*
Operational	delays and disruptions	√		
	bunker	√		
	human factors	√		
Financial	Credit conditions	√	√	
	Currency		√	
Market	Freight rate	√	√	√
	Counterparty	√		
	Trade restrictions		√	√
Competition	Concentration	√		
	Technical innovation		√	√
Regulations			√	√
Technical factors		√		
"Zuellig factors"	war/ embargoes	√	√	
	terrorism/piracy	√	√	
	epidemics	√	√	

Figure 3.3 illustrates that one single factor can have a wide uncertainty associated with it. As maritime decision makers needs to consider multiple of such uncertain factors at once, their complex interactions leading to a wide range of potential future outcomes. This make the decision making process highly difficult. For more in-depth information of uncertainty directly related to the maritime industry, the reader is advised to Stopford (2009), Lorange (2009), Thanopoulou, H., Strandenes (2015), Erikstad and Rehn (2015).

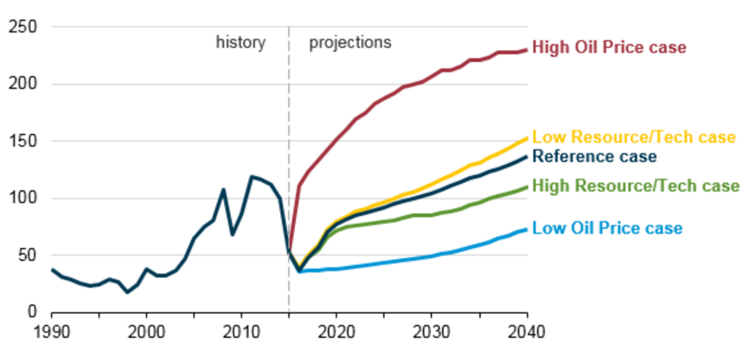


Figure 3.3: North Sea Brent crude oil spot price, 1990-2040 (EIA, 2016)

3.2 Uncertainty Management

As stated in the previous section, uncertainty leads to unforeseen changes disturbing the vessel's ability to deliver value (Walton, 2002; Mikaelian et al., 2009). Thus, if not properly managed, uncertainty can cause vessels that initially are successful to become unsuccessful over time. Luckily, uncertainty can be managed (de Neufville, 2004) and can in many cases be the difference between a company staying in business or bankruptcy (Lorange, 2009). Uncertainty management should therefore be incorporated at all levels in the firm (de Neufville, 2004).

3.2.1 Introducing Uncertainty Management

In general, management is *the act or manner of managing; handling, direction, or control*[5]. de Neufville (2004, 3) refers to management as *the active direction of the evolution of the engineering project*, indicating that management of engineering systems consists of planning, design and implementation of means for handling changes in context and needs for throughout the system's entire life cycle.

Miller and Lessard (2000) distinguishes between two broad categories for approaching to uncertainty management: *decisioneering* and *managerial approaches*. Decisioneering assumes that the future is probabilistic, and therefore deterministic analysis (e.g. NPV calculations and linear optimisation) can be used to find the expected optimal solutions. The managerial approach recognises that the future is unpredictable, or at least, highly uncertain. In this approach, managers should use analysis tools that incorporates uncertainty into the calculations (e.g. simulation and stochastic optimisation), in addition to using various life cycle strategies to influence the outcome. The managerial approach is more appropriate in indeterminate futures, in which both exogenous and endogenous events affects its outcome making it difficult, if not impossible, to assess (Miller and Lessard, 2000).

Generally, uncertainty management can be viewed in terms of the well-known SWOT analysis. This analysis gives insight into the external opportunities (O) which the company can ex-

[5] `http://www.dictionary.com/browse/management` [04.03.17]

ploit, and the external threats (T) (or vulnerabilities) that the company must mitigate. For offshore vessels, these opportunities and threats can be highly uncertain. This uncertainty must be identified, modelled and quantified in the analysis. Further, the SWOT analysis gives insight into the company's internal strengths (S) and weaknesses (W). Strengths are capabilities that can be used to handle the opportunities and threats. Weaknesses are limitations making the company vulnerable for the threats and unable to exploit the opportunities. Figure 3.4 illustrates the SWOT-matrix, a common way of presenting the results from a SWOT analysis, for a hypothetical offshore shipping company evaluating the possibility to seize opportunities in the emerging offshore aquaculture industry by retrofitting an OCV. The insight gain from such an analysis could be used to align manager's strengths and weaknesses with the possible opportunities and threats, both current and those emerging.

Figure 3.4: Illustration of SWOT matrix for a hypothetical offshore shipping company case

Despite traditionally being designing to meet fixed specifications (Levander, 2012; Nembhard and Aktan, 2010), uncertainty management has always been a bedrock in engineering design. Unfortunately, due to the asymmetric view of uncertainty, the focus in uncertainty management has almost exclusively been on preventing the possible negative outcomes of uncertainty, especially on risk management of technical failures (Moses, 2004; de Neufville, 2004; McManus and Hastings, 2005). Often, this results in robust designs, with high margins that are able to perform adequately in a broad range of future context and needs (Andrews and Erikstad, 2015; Agis et al., 2016). As stated by Andrews and Erikstad (2015, 3): the focus on robust designs reflects a *bunker mentality*, focusing on the systems survivability in the future. However, with the goal of maximising life cycle value of the vessel, risk management fails due to the narrow view on uncertainty as the opportunities, especially in the operational and commercial side of uncertainty, often is forgotten (Pierce, 2010; Browning, 2005; Andrews and Erikstad, 2015; Agis et al., 2016).

Luckily, a greater attention has recently been given to the exploitation of possible opportunities that lies in uncertainty. Designing with both risk and opportunities in mind, thereby capturing the full extent of uncertainty, might lead to different solutions than those that only focus on the risk. (de Neufville, 2004)[6].

3.2.2 Three Modes of Response to Uncertainty

de Neufville (2004) states the three basic modes of managing uncertainty:

(I) To control the source of uncertainty

(II) To passively protect the system against the impact of uncertainty

(III) To actively protect the system against the impact of uncertainty

These are further presented below.

Mode I: Controlling the Source of Uncertainty

In relations to the classification of uncertainty, endogenous uncertainty and, to some degree, hybrid uncertainty can be influenced and controlled. For instance, the building cost of a vessel is a hybrid uncertainty that can be partially controlled by improved planning of the building

[6]The Systems Engineering Advancement Research Initiative (SEAri) group at MIT has been a driver in this work. `http://seari.mit.edu/research.php`

process. However, despite the depth of planning, there will always be unforeseen factors affecting the building cost. This is partially due to the structural complexity of engineering systems, making it difficult to assess major cost factors, such as work hours and amount of steel needed.

Forecasting is another means of controlling the source uncertainty, as it tries to clarify how uncertain information will develop. However, as stated by de Neufville and Scholtes (2011) *forecasts are "always wrong"*, a statement especially true in highly volatile markets. Despite this, de Neufville and Scholtes (2011) emphasises the importance of having information when making decisions, and recognises the role of forecasting in information gathering. This double-edged sword is referred to as the *forecasting paradox* (Stopford, 2009), stating that it is a paradox that demand for forecast is so high, when it is always wrong.

Mode II: Passive Protection Against the Impact of Uncertainty

The passive approach is coherent with the traditional ship design methodology, in which the system is designed for the most likely scenario. The idea is to incorporate measures that functions without significant intervention from the manager, thus the goal is often to make it insensitive for industrial dynamics (Forrester, 1977) (i.e. *bullet-proof the system* (de Neufville, 2004)), designing it to handle the most extreme conditions (Nembhard and Aktan, 2010). Such bullet-proof solutions are often referred to as *robust*. This approach can result in two extremes, either (Niese and Singer, 2014):

(I) An under-specified design, requiring large investments to adapt to changing operational contexts, or

(II) An over-specified design, that easily can adapt to changing operational context, but which needs to carry unused equipment over large parts of its life cycle.

In offshore shipping, the latter seems to currently be preferred. While it has the capacity to meet changes in context and needs (i.e. able to take the upside in the uncertainty), it also has a large exposure to the downside of uncertainty as the high-spec systems comes with a high-carrying cost. The high carrying cost, in addition to the drawback of not being specialised, has made many multifunctional vessels ending up becoming multi-useless. (Ulstein and Brett, 2015)

For a passive system, uncertainty can lead to asymmetric returns (de Neufville et al., 2006). Because, while the passive system has a limited ability to take the upside of uncertainty, it can be victim to the entire downside. This is often referred to as the “flaw of the averages.”[7] which can be expressed using Jensen’s Inequality (Jensen, 1906):

$$\gamma(\mathbb{E}[X]) \leq \mathbb{E}[\gamma(X)]$$

Where γ is a convex function, X is a random variable and $\mathbb{E}[\cdot]$ is the expectation of the term inside the brackets. Jensen’s inequality states that the function of the expected value is less or equal to the value of the convex function. Thus, a decision bases on average values are not representative for that actual outcome. For instance, a vessel designed with a crane capacity based on the most likely demand has a limited ability to take the upside if demand increases, as it is expensive, and possibly impossible, to increase the crane size. On the other side, the vessel will be subject to the entire downside of demand falls since it has expensive, unused capacity. Thus, the vessel has an asymmetric relation to the outcome of this uncertainty. Still, the passive managerial approach remains well suited for systems operating in relatively stable environments in which forecast adequately predicts the future (Pierce, 2010).

Mode III: Active Protection Against the Impact of Uncertainty

McManus and Hastings (2005) proposes a framework to handle uncertainties by incorporating "-ilities" to mitigate the vulnerabilities and exploit the opportunities. The term “-ilities”, referring to life cycle properties such as: quality, reliability, safety, flexibility and robustness (de Weck et al., 2011). Note that they often, but not always, ends with “-ility”. These life cycle properties extend the traditional set of properties for engineering systems, such as function, performance and cost (Moses, 2004), and are starting to be recognised as highly important enablers for successful engineering systems. Generally, “-ilities” are most important in systems characterised by high complexity, long lifetime, dynamic operational context, and high cost of errors (Fricke and Schulz, 2005). This thesis focuses on one of these "-ilities", namely changeability, presented

[7] `http://web.stanford.edu/~savage/flaw/`

in the section to come. The proposed framework is presented below.

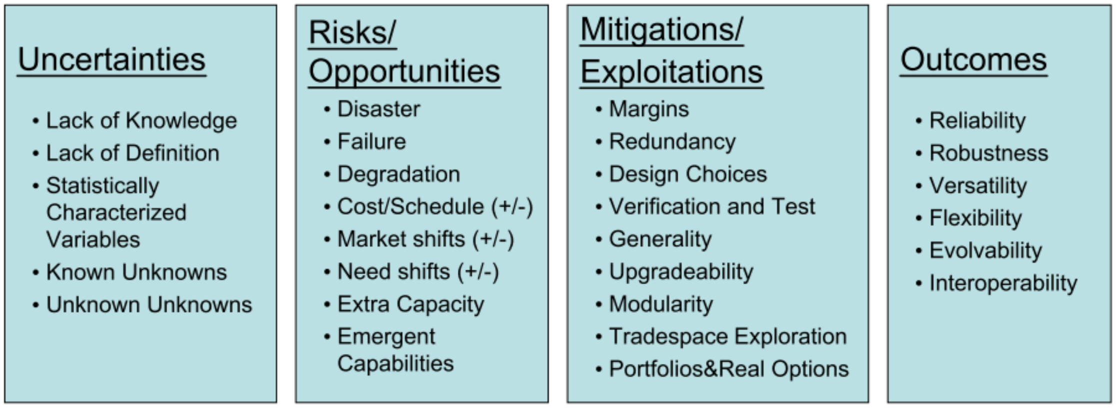


Figure 3.5: Framework for handling sources of uncertainty and their outcomes (McManus and Hastings, 2005)

Readers can recognise the previous classifications of uncertainties. In relations to the traditional passive approach for uncertainty management, to handle *unknown unknowns* systems engineer could invest in margins and redundancy to get a reliable and robust design, which is able to mitigate the downside of uncertainty (e.g. system failure and degradation). However, with an active approach, the systems engineer could invest in modularity to get a flexible design, able to reconfigure as a means to mitigate risk (e.g. change failed components), but also exploit opportunities (e.g. switch functionality to operate in more favourable markets).

This approach broadens the view of uncertainty, considering the entire range of possible outcomes (i.e. both the vulnerabilities and opportunities). Instead of designing for a given set of specifications, this approach incorporates changeability into the system to enable redesign to handle changes (Forrester, 1977; de Neufville, 2004). As stated by Andrews and Erikstad (2015, 3) *we "design to specification" when we should "design for variation."*

Comparing the Passive and Active Approach

Figure 3.6 illustrates the difference between an active and passive approach for managing uncertainty. The figure presents the temporal evaluation of changes in stakeholder's expectations and operation context, and the performance of a vessel in each epoch. An epoch is defined as a static representation of context and expectations (or needs).

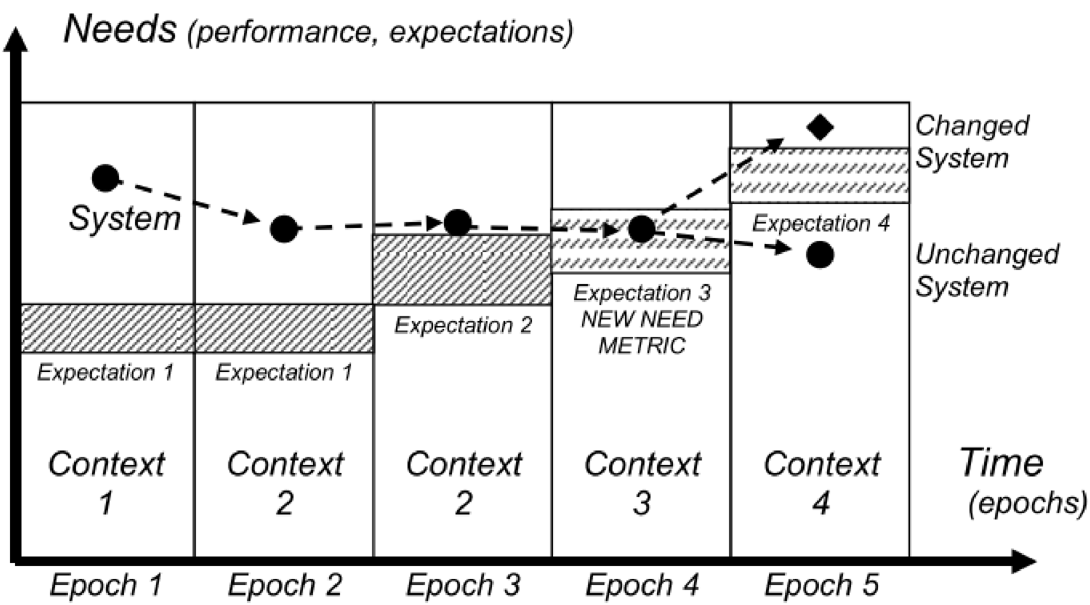


Figure 3.6: Illustration of the temporal evaluation of a system needs and contexts change. (McManus et al., 2007)

As seen, in Epoch 1 (comprising context 1 and expectation 1) the system's performance exceeds stakeholders' expectations. In Epoch 2 (consisting of context 2 and expectation 1), the system's performance is reduced, however, it still meets stakeholders' expectations. The vessels also perform within stakeholders' expectations in Epochs 3 and 4. However, as Epoch 5 emerges, the performance of the unchanged system falls below expectations, while the changeable system can adapt to the new set of contexts and needs. Thus, while the passive approach (represented by the robust/unchangeable system) is unsuccessful in epoch 5, the active approach (represented by the adaptable/changeable system) is able to stay successful over its entire life cycle.

Chapter 4

Changeability

4.1 Introducing Changeability

In engineering, changeability can be defined as *the ability of the system to change* (Fitzgerald, 2012, 23). In relation to the active approach for uncertainty management (de Neufville, 2004), incorporating changeability in system architecture is recognised as an active method to manage uncertainty (Fricke and Schulz, 2005).

Changeability is an umbrella term that comprises of the four life cycle properties: robustness, flexibility, agility and adaptability (Schulz and Fricke, 1999; Fricke and Schulz, 2005). Robustness is the ability to be insensitive towards changing environments; Flexibility is the ability to be changed easily; Agility is the ability to be changed rapidly; and Adaptability is the ability to adapt itself towards changing environments (Schulz and Fricke, 1999).

Robustness represents a passive approach for handling change, as it requires no changes from sources outside the system boundary. Flexibility, on the other hand, is an active approach, requiring implementation of changes from sources outside the system boundary. As with robustness, adaptability requires no changes from sources outside the system boundary, however, an adaptable system changes itself, and is therefore recognised as an active approach. Thus, whether a system is passive or active depends on the location of the system boundary. As with flexibility, agility requires implementation of changes from external sources, but includes the time used to change, not only the ease of change. Note that whether a change is quick is highly subjective, and will therefore vary between stakeholders.

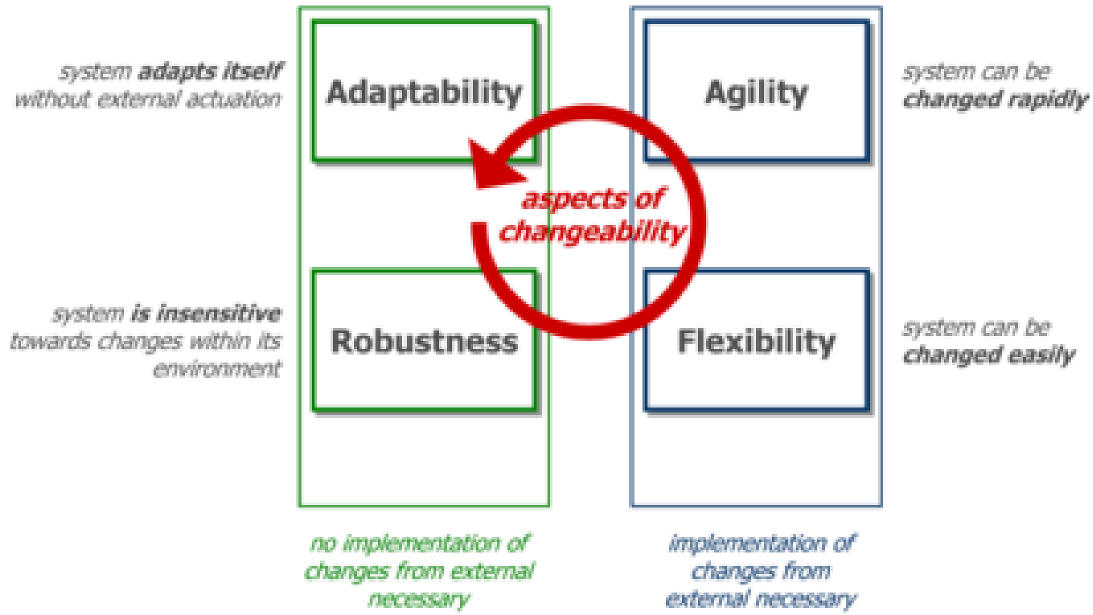


Figure 4.1: Illustration of the relationships between the four aspects of changeability: robustness, flexibility, adaptability and agility (Fricke and Schulz, 2005)

4.1.1 Dimensions of Changeability

Niese and Singer (2014) perceives the notation of system changeability to include three dimensions: (I) the physical performance dimension (II) the process dimension, and (III) the managerial dimension. The physical performance dimension concerns the physical design's ability to change its system state. This is related to the system's robustness, adaptability, flexibility and agility (the standard focus in changeability literature). The process dimension focuses on the utilisation and the timely execution of the changeability. Niese and Singer (2014) argues that the process dimension is related to the concept of *lean-ness* and *just-in-time delivery*. The managerial dimension focuses on the managers (or more generally stakeholders) ability to manage change. In that regard, it is important to understand that different stakeholders have different abilities to recognise the need to change, and varying capacity to plan, implement and monitored the change. As stated by Niese and Singer (2014), the manager dimension is an area of need-for-research in the changeability literature - and an area of focus in this thesis.

4.1.2 Principles of Changeability

The principles of changeability are enablers for incorporating changeability in system design. Figure 4.2 presents the *aspect-principle-correlation matrix* indicating which principle influence which aspect of changeability (e.g. robustness, flexibility, adaptability and agility). As seen, the *basic principles* (ideality/simplicity, independence, modularity/encapsulation) contribute to all four changeability aspects, while the *extended principles* (integrability, autonomy, scalability, non-hierarchical integration, decentralization, redundancy) only contribute to a set of them. These principles interact creating both harmful interactions (leading to undesired effects), or useful interactions (leading to desired effects). It is therefore important to carefully consider which principles to incorporate enabling the desired changeability.

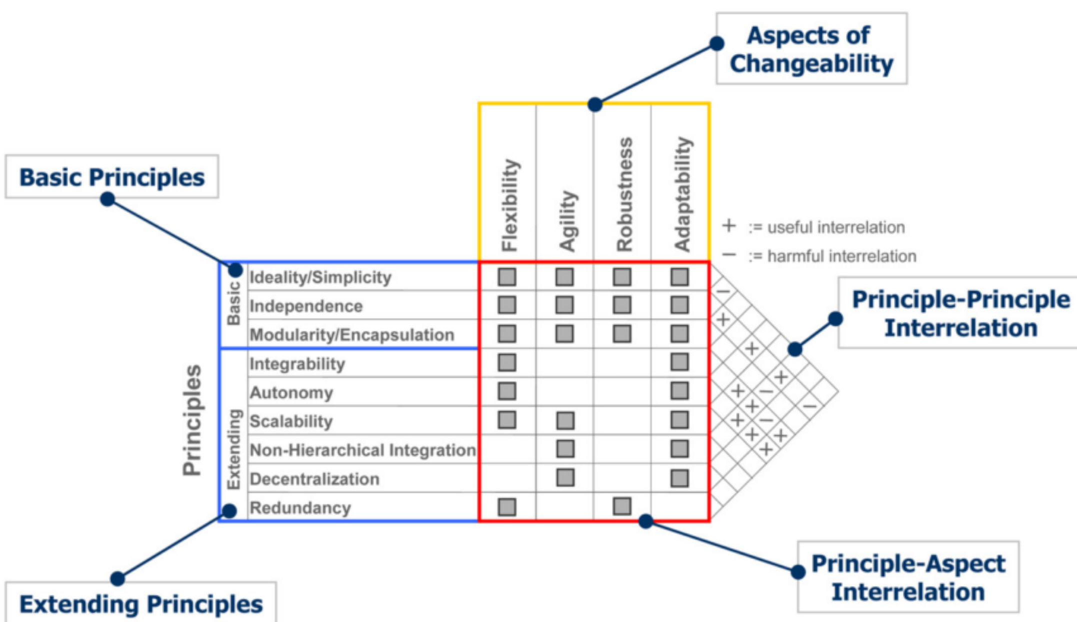


Figure 4.2: The aspect-principle-correlation matrix (Fricke and Schulz, 2005)

The reader is advised to Schulz and Fricke (1999) and Fricke and Schulz (2005) for thorough presentation of both the basic and extended principles of changeability. As the basic principles are related to all four aspects of changeability, they are briefly presented below.

Ideality/simplicity is about minimising system complexity, for instance by reducing the number of interconnections between systems, and reducing the number of secondary functions in a system (Fricke and Schulz, 2005). This is closely related to the information axiom (Suh, 1990) highlighting the importance of minimising the information context in design. As seen in figure 4.2, ideality has a harmful interaction with the principle of independence.

Independence is about having a system structure in which changing one parameter does not affect the related design parameters. According to the independence axiom (Suh, 1990), each system function ideally should be performed by one independent design parameter. This is related to the simplification of the function-to-form mapping. As seen in figure 4.2, independence has a useful interaction with the principle of modularity since independence between modules is a key in architecting modular designs.

Figure 4.3: Example of Modularity: Module switching (From Fricke and Schults, 2005)

Modularity is increasingly used in shipbuilding, both in the design and in the production (Hagen and Erikstad, 2014; Erikstad, 2009). In a modular design, a set of the systems functions with strong coupling is clustered in modules. Ideally, this results in weak coupling between the modules themselves. Figure 4.3 presents the concept of having a modular design (A) that can change its system configuration by switching between three different modules (A, B or C). As a result, numerous different system configuration can be combined (A & A, A & B, or A & C). The modular design can be an offshore construction vessel, and the modules can be for instance different crane suited to conduct various operations. With such a design, rather than having all three cranes installed at all times, the cranes can be added when needed. The idea is to have distinct, self-sufficient modules that builds up the total system, and that can be switched to change the system's functionality. This is closely related to portfolio theory, and product platforms (Erikstad and Levander, 2012).

On a final note, the *principles* of changeability correspond with what Ross et al. (2009) and (Beesemyer et al., 2012) call *path enablers.* In contrast to design variables (e.g. length, breath, depth), the design principles (e.g. structural reinforcement and modularity) do to not drive value delivery, but rather enables changeability. In the section to come, it is said the path enablers enable the *mechanism* of change.

4.2 Taxonomy of Change

McManus et al. (2007) states that change is the common concept with the "-ilities." In general, change can be defined as *the transition over time of a system to an altered state* (Ross and Hastings, 2006). McManus et al. (2007) describes and distinguish the "-ilities" in terms of changes in the system's operating context, stakeholders need and changes in the physical system itself. Note that change implicitly implies a four dimension, namely time.

To better clarify the definition of the abstract "-ilities," Ross and Rhodes (2008b) creates a framework to define change. In this framework, every change is defined as a transition between states using three elements: (I) a change agent (II) a change mechanism, and (III) the effect of change. Every change can be described using a specific agent-mechanism-effect composition, as illustrated in figure 4.4 for one specific change.

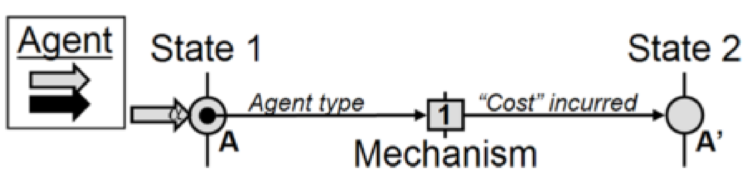


Figure 4.4: Illustration of the agent-mechanism-effect framework for a single change (Ross and Rhodes, 2008b). "A" represents the system state prior to change, while "A'" represents the state after the change has occurred.

The change agent is the force (e.g. human or nature) initiating the change. It can either be internal or external to the system. If the change agent is internal, the change is the adaptable-type;

if the change agent is external, the change is the flexible-type. Thus, depending on the change under consideration, the system can both be flexible and adaptable. This coincides with the definitions of flexibility and adaptability presented in section 4.1.

The mechanism of change represents in what way the system changes from one system state to another, defining a particular transition path for the change. A change mechanism can for instance be a modular configuration on a vessel, enabling it to change its configuration relatively easily. The transition path includes a description of the cost committed by changing. Cost refers to the resources needed for changing, including both monetary and non-monetary value. In addition to the monetary cost of executing the change, there might also be some cost associated with implementing the change mechanism in the first place (e.g. in the design phase), and cost associated with maintaining the ability to change. In addition, the time it takes to perform the change is linked to the system's *agility*. In relations to this, Rehn et al. (2017a) states that all systems are inherently changeable, *it just a matter of how much effort it will take to change.*

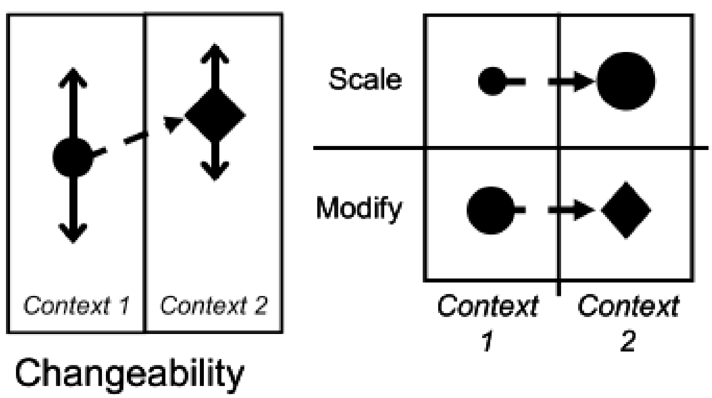


Figure 4.5: Illustration of the effects (scale and modify) of change. A change is represented by a change in the systems "icon." The vertical axis represents the variability in systems performance in a specific context (McManus et al., 2007)

The effect of change is the resulting difference between the initial and ending state of the system's parameters after a change. Note that the effect of change can be related to the systems form, function and operations. Figure 4.5 illustrates some of the effects of change. The circle represents the original form of the system, while a diamond represents the form after change. A system is scalable if the levels of the systems parameter changes (e.g. size of a vessel's tank capacity). Note that a system can both be increased and reduced in size (Fricke and Schulz, 2005). A system is *modifiable* if the system can change the set of system parameters (e.g. switch modules on the vessel). A system is *robust* if the system maintains constant system parameters in the presence of changing forces (Ross et al., 2008; McManus et al., 2007). The vertical arrows represent the variability in the system performance. As seen in the figure to the left, in context 2, the changed system configuration (diamond) has a higher performance, and a lower performance variability.

The agent's response is triggered by a perturbation, and one can therefore view change pathways in a perturbation-agent-mechanism-effect framework (Ross and Rhodes, 2011)[1]. A perturbation defined as *any unintended state change of a system's form, operations, or context which could jeopardise value delivery* (Mekdeci et al., 2012, 508). Table 4.1 presents a taxonomy of perturbations, which can be used to help identifying potential ways that a system can lose value (Ricci et al., 2014).

Table 4.1: The Taxonomy of Perturbation (Ricci et al., 2014)

Perturbation	**Type**	**Space**	**Origin**	**Intentional**	**Nature**	**Consequence**	**Effect**
Name	Disruption Disturbance Shift	Design Context Need	Internal External Either	Yes No Either	Nature Artificial	Positive Negative Either	Various

As seen, perturbation is divided into *disruption*, *disturbance* and *shift*. Disruption is defined as *an unintended, instantaneous, discontinuous state change of a system's form, operation, or context, which could jeopardise value delivery* (Mekdeci et al., 2012, 507). Thus, a sudden failure of the propulsion system is a disruption. A disturbance is defined as *an unintended finite duration, continuous state change of a system's form, operation, or context, which could jeopardise value delivery* (Mekdeci et al., 2012, 508). Thus, going from port without a low level of fuel left is a disturbance. If the disturbance's duration becomes zero, it is a disruption. A shift represents a change in context and/or need (such as changes in technology and regulations) (Ricci et al., 2014).

[1] See figure 3 page 2 in Ross and Rhodes (2011).

Figure 4.6 expands figure 4.4 by including multiple pathways of change. The number of possible pathways of change is determined both by the number of available change mechanisms, and the number of possible end states (Ross et al., 2008). In general, the more change paths available the more changeable the system is. This is referred to as the systems *degree of changeability* (Ross and Rhodes, 2011). The figure also illustrates how an internal (black arrow) and external (grey arrow) change agent initiates a flexible and adaptable change-type, respectively. Notice how an internal change agent results in an adaptable change, which can use change mechanism [2] to either transfer the vessel to state A' or C' with two different costs associated with it. This would lead to change effect A-A' or A-C', respectively.

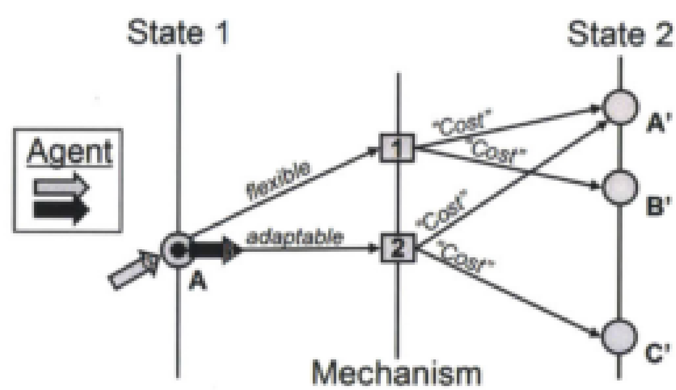


Figure 4.6: Illustration of the agent-mechanism-effect framework for multiple changes (Ross et al., 2008). A grey arrow and black arrow represents an external and internal change agent, respectively. "A" represents the initial system state. "A', B' and C'" represents possible post states.

Rehn et al. (2017a) adapts the *Design for Changeability (DfC)* (Fricke and Schulz, 2005), stating that a system's level of changeability is, in the same manner as design variables (e.g. length, breath, depth), an overall system design variable to be decided in the design phase. Table 4.1 exemplifies the idea of DfC level for a vessel. As seen, the DfC level is a variable (i.e. 0, 1, 2, 3) and comprises various path-enablers (e.g. structural reinforcement, modular interfaces, ice class capacity). In contrast to a low DfC level, a high DfC level has associated a high investment and carrying cost, but has in the same time a lower cost associated with executing the change option.

Table 4.2: Exemplification of the Design for changeability (DFC) level for an offshore vessel (Rehn et al., 2017a)

DFC level	Path enablers	Inv. Cost	Carry Cost
0	Base case (none).	-	-
1	Structural reinforcement.	Low	Low
2	Structural reinforcement and modular interfaces.	Medium	Medium
3	Structural reinforcement, modular interfaces and ice class capability.	High	High

4.3 Changeability as Real Options

In 1984, Myer introduced the concept of *real options*. Quite similar as financial options[2][3], real options can be defined as the right, but not the obligation, to exercise actions or to make specific project decisions at a future time (Berk and DeMaro, 2014). The main difference is (as the name indicates) that real options concern decisions regarding real assets (e.g. offshore vessels and technology) rather than financial assets (e.g. stock and commodity). Examples of real options can be to expand the fleet by buying a new vessel in the second-hand market, or to switch the modular configuration on a vessel. In contrast to financial options, real options are not necessarily a legal contract traded over the counter (Wang, 2005; Mikaelian et al., 2011), as it can simply be a decision affecting the real asset.

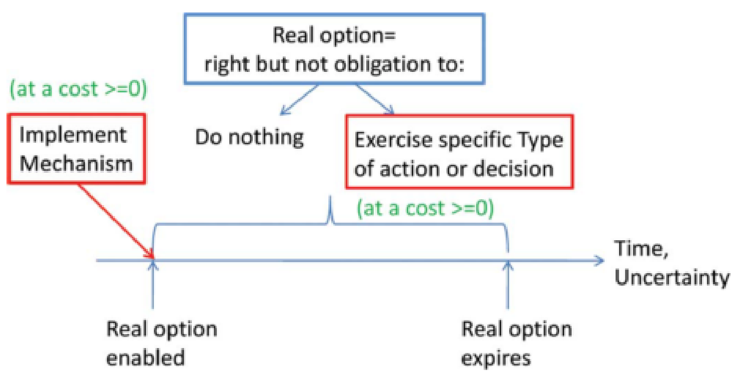


Figure 4.7: The Anatomy of a real option (Mikaelian et al., 2011)

Figure 4.7 illustrates the anatomy of real options. The *mechanism* is the action, decision, or entity that enables the real option. The real option type refers to the action or decision that is

[2]Financial options were first traded in 1973 at the Chicago board of Exchange. See `http://www.investopedia.com/articles/optioninvestor/10/history-options-futures.asp` [20.06.2017]
[3]The reader is advised to Berk and DeMaro (2014) for insight financial options

enabled by the mechanism, which can be exercised at a future time. For instance, investing in a modular design can be a mechanism for change, enabling the future flexibility by easily changing vessel functionality.

Wang and Neufville (2004) distinguishes between real options *in* and *on* the system. While real *in* options concerns changes in the physical system, real *on* options concerns the flexible management of the system treating the physical system as a black box. Examples of on options are shipowners right to sell or layup the vessel if the market situation is unfavourable. Examples of in options could be to install a new crane, or to change the modular configuration in the vessel. Since changing the modular configuration impacts the vessels stability, power requirements, space, maintainability, etc., knowledge of the technological aspects of the real system is needed to execute the option. In contrast to real *on* options which can be legal contracts, real *in* options are hard to identify as there are a wide range of possibilities for architecting changeability into the system. In addition, there is less data available to evaluate real *in* options than the case is for real *on* options and financial options. Real *on* options are traditionally considered to be in the domain of management, while in options are in the engineering domain (Mikaelian et al., 2011).

Table 4.3: Examples of "In" Real options in Shipping (Rehn, 2015)

***In* Options**	**Description**
Expand capacity	Option to physically expand the capacity of a particular ship by retrofit, such as midship elongation.
Switch Scope	Option to switch between different modes of operation or between different chartering contracts offer a certain level of flexibility ship operations and charterers.
Switch fuel	Option to alter or change the fuel of engine systems. This may be to change from normal diesel (MGO) to liquefied natural gas (LNG), which involves different fuel tanks, cryogenic systems and other engine properties.
Capacity retrofit	Option to add or change the capabilities of the ship, for example by installation of a crane or ROV systems on an offshore construction vessel.

Christensen (2017)[4] propose a new option classification system, extending the traditional real

[4]The author is gratefully to his classmate Carsten Christensen for collaboration on the project thesis, and all discussions related to option theory and stochastic processes.

in/*on* option view (Wang and Neufville, 2004). In this system, real *on* options is regarded as an overarching option, further separated into *Built-in Design Options* and *Design Change Options*.

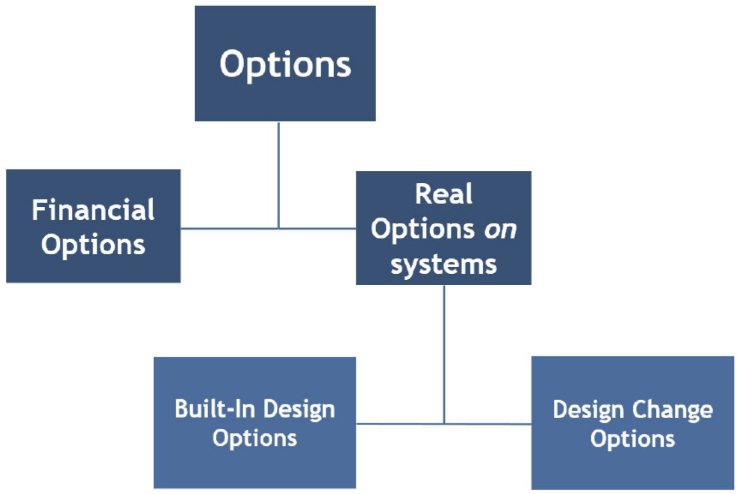


Figure 4.8: Classification of Options (Christensen, 2017)

Built-in Design Options representing options implemented in the design, such that the design itself can its form, function or operations without external influence. The author sees this as closely related to the concept of *robustness* and *adaptability*. Example of a *built-in design option* for an OCV is moonpool and structural reinforcement making the vessel able to perform light well intervention (LWI) operations, which can be utilised through equipment. This option has a cost associated with implementing the moonpool and structural reinforcement in the design phase, in addition to the exercises cost through equipment. Commonly for build-in design options, the exercise cost is lower than the cost of implementing, and the options can often be executed a number of times.

Design Change Options represent options for which external influence is needed for the change to occur. The author sees this as closely related to the concept of *flexibility* and *agility*. In contrast to the build-in design options, these options are often only exercised once-in-a-lifetime, with an associated exercising cost often exceeding the initial cost - if any at all.

The redesign of Vestland Cygnus[5] is an example of such a design change option. With no initial build-in design options, the platform supply vessel was retrofitted into a wind farm Service vessel just months after being built. The retrofitting included an accommodation module for 134 people, a footpath system for transferring personnel to offshore installations, and a 100-ton, 40-metres range offshore crane. To do so, the vessels stability had to be increased, therefore sponsors of 1.2 metres were added on each side, in addition to reinforcing the deck where the crane was placed. The original cost of Vestland Cygnus was around 320 mNOK.[6], the retrofitting cost around 150 mNOK.[7]. By rather having some of the changes incorporated at the design phase (i.e. being a *built-in design option*) the cost of retrofitting the vessel would probably be less than 150 mNOk. However this would tie up capital, which would be lost of the option was not executed. This represents the trade-off between whether or not to build in the option.

[5] http://www.swzonline.nl/news/7482/vestland-Cygnus-be-converted-wind-farm-service-vessel [06.05.2017]
[6] http://www.skipsrevyen.no/ms-vestland-cygnus/ [06.05.2017]
[7] https://www.tu.no/artikler/offshoreskipet-ble-levert-i-april-allerede-na-bygges-det-om-til-vindkraft 275722 [06.05.2017]

Chapter 5

Strategy

5.1 Introducing Strategy

Academia has many different descriptions of what strategy means. The word strategy originates from the Greek word *stratēgia*, meaning a military leader[1]. A strategy can be defined as a *co-ordinated set of decisions* (Skinner, 2009, 329). The Merriam-Webster dictionary[2] defines it as a *careful plan or method: a clever stratagem (trick); the art of devising or employing plans or stratagems towards a goal*, and Mieghem and Allon (2015, 7) simply defines it as a *specific plan of action to reach a particular objective*.

According to Lun et al. (2010), developing strategies involves answering the interrelated questions: what to do, when to do it, and how to do it? After being developed, the strategies need to be implemented, and then monitored. Georgzén and Palmér (2014) highlights three fundamental approaches to strategy, namely: strategy as a *plan*, strategy as a *pattern* and strategy as a *practice*. This thesis focuses on the approach of strategy as a plan.

Strategy as a plan is based on the ideas of Michael Porter's classical book from 1980 on *Competitive Strategy*. According to Porter (1980, xviii), competitive strategy (I) examines the way in which a firm can compete more effectively to strength its market position (II) to state the goals

[1] `https://en.oxforddictionaries.com/definition/strategy` [05.05.2017]
[2] `https://www.merriam-webster.com/dictionary/strategy` [05.05.2017]

for of the company, and (III) the means of getting there. A special focus in Porter (1980) is how a firm can create a unique competitive advantage. Porter's five forces model (Porter, 1980, 4) states that the (I) suppliers (II) potential entrants (III) buyers (IV) substitutes and (V) rivalry among existing firms are the five forces driving competition in an industry. By examining this competitive environment, a company can understand how to gain competitive advantage.

5.2 Five Components of Strategy

Lun et al. (2010) presents (I) scope (II) goals and objectives (III) resource deployment (IV) competitive advantage and (V) synergy at the five basic components that should be a part of a strategy. *Scope* refers to the type of industry and market segment that the firm operates in or plans to enter, and is closely related to a firm's vision. A strategic scope could be to enter the OSVs segment in the North Sea Market. *Goals* deal with the aspects leading up to managing the scope, and *objectives* states the desired level of accomplishment of each of the objectives. For instance, a firm's goals and objectives could be to have a five percent market share of the North Sea PSV market within the next three years. *Resource deployment* deals with the ensuring that the firm have the required resources to achieve the goals and objectives. This can be to invest in OSVs with the capacities required to operate in the North Sea. The *competitive advantage* specifies how the firm intents to compete in the market. As mentioned in the previous section, the goal of *Porter's five forces* is to examine how to gain such a competitive advantage. Focusing on low day rates could be a strategy related gaining competitive advantage. Finally, *Synergies* are related to which degree the various resources deployed complement and reinforces each other.

5.3 Strategic Hierarchy

In general, there are various levels of interrelated strategies that companies implement in different levels in the organisation. The hierarchy often divides into three levels: (I) corporate strategy (II) business strategy and (III) functional strategy (Barnes, 2008; Lun et al., 2010; Georgzén and Palmér, 2014). Each of these strategies needs to be aligned with each other, which in itself is a complex task (Georgzén and Palmér, 2014).

Corporate strategies are high-level strategies, setting long-term directions and scope for the entire firm. These are often expressed in vision and mission statements. A corporate strategy can for instance state which markets a unit of the firm should enter, and how resources should be divided in between each of the firm's units. These strategic decisions have a long-term impact on the firm, and some of them might even be irreversible.

Business strategies focus on what objectives a specific unit of the firm should have, how it should compete in its market and what value-adding activities to perform. The business strategy is constraints by the corporate strategy. In firm of only a single unit, the business strategy is equivalent to the corporate level strategy. In the maritime industry, such strategic decisions can for instance be which vessel to build, and what functionalities and life cycle properties to vessel should hold. Further, these decisions could consider which market segments to operate the vessel, which contracts to take (short-term or long-term), and which vessel configuration to have at a specific time. These decisions are bases on a medium-term view of the further contexts and needs. Since it much resources (time, money and efforts) are committed when making these decisions, their decisions can have a medium-term impact on the firm.

Functional strategies support the business strategy, focusing on how a unit's individual functions and resources should be aligned to support the business strategy. Functional strategy is often associated with operational decisions. Operational decisions focus on immediate concern, often on the day-to-day operations of the vessel. Such a decision could be how to utilise the systems installed, such as cranes, ROVs, winches, to most effectively perform a specific offshore operation (DS, LWI, etc.).

5.4 Strategies as Real Options

The concept of real options has already been presented in sections 5.4. Recall that real *in* options are related to concepts of designing for changeability, and real *on* options are related to strategic decisions made by the managers. The latter is the focus in this chapter.

The table below presents some examples of real *on* options in shipping. Note that some of these options are relevant at several levels in the organisation. For instance, on a commercial level, one can expand the firm's operations to new markets. On a business level, one can expand the fleet to increase the presence in the market (an "on" option), or can expand a vessel's size and capacity (an "in" option). On the functional level one can abandon a contract/ operation. In contrast to the real *in* options presented in section 5.4, these options do not necessarily need to be bought upfront, such as the option to abandon an a new building project. The reader is advised to Dixit and Pindycke (1994), Wang and Neufville (2004) and Alizadeh and Nomikos (2009) for more on the concept of real *on* options.

Table 5.1: Examples of real on options in shipping (Rehn (2015), based on Alizadeh and Nomikos (2009)

***On* Options**	**Description**
Abondon	Option to sell the assets and exit the market, which can be valuable when the market is volatile and there is substantial uncertainty about its future direction.
Expand fleet	Option to expand in operational and investment projects introduces the flexibility to have limited involvement initially, and to increase the involvement once the conditions are right.
Lay-up	Option to delay certain decisions and projects. For example, if local market imbalances occur, the actors experiencing the downside from this effect can wait for more favourable market conditions before fixing a contract.
Other	Options may also be embedded in contracts, which are often used without proper valuation. Without going in details, these can for example be time-charter (TC) extensions, new building options, purchase options on TC contracts or options related to debt.

Chapter 6

Markov Decision Processes (MDP)

This section presents Markov Decision Processes (MDP), a modelling and solution technique for Sequential Decision Problems. As Markov decision rocesses still is unfamiliar to most students and professors as NTNU, the primary objective of this chapter to introduce the reader to MDP, hopefully motivate further studies in this area of operations research. In this thesis, MDP is used to support the proposed Design-Strategy Planning (DSP) procedure presented in chapter 8.

The chapter is primarily based on the extensive works of Watkins (1989), Puterman (2005) and Powell (2007) and Powell. (2009), supported by the work of Watkins and Dayan (1992), Mausam and Kolobov (2012), Gosavi (2009), Marescot et al. (2013), and Kochenderfer et al. (2015). Since the MDP community has not settled on a notation form, the author chooses to use the notation from operations research. This is in line with the work of Powell Powell (2007) and Powell. (2009). On a final note, the literature seldom treats finite decision problems. Due to the temporal aspect of complexity affecting the problems treated in this thesis, the author has fitted the notation and equations to include the aspect of time (i.e. finite-horizon problems).

6.1 Sequential Decision Problems

Figure 6.1 presents the symbolic representation of sequential decision-making. For each point in time, an decision maker finds himself in a decision epoch, where he, based on the state of the system, chooses an decision from a set of available decisions. When making the decision, it is assumed that the current system is fully known to the decision maker. The consequence of the decision is two folded; first: the decision maker receives an immediate contribution (which can be both positive, negative or zero); secondly: the system transits to a new state. Afterwards, the procedure is repeated. The action made by the decision maker is bases on a *decision rule*. A sequence of decision rules is called a *decision policy*.

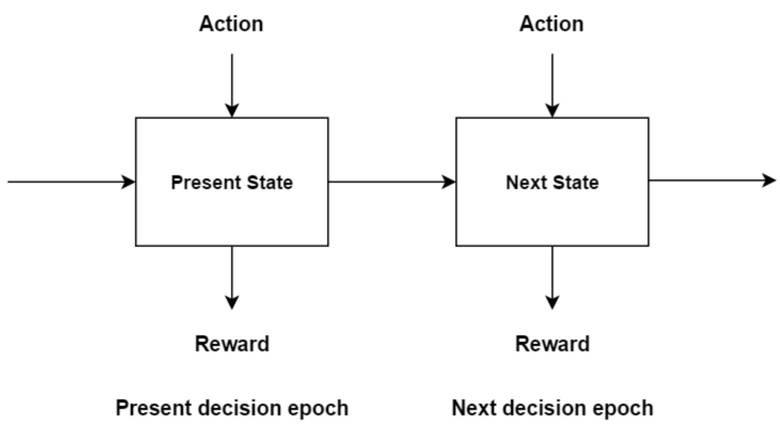


Figure 6.1: Symbolic representation of a sequential decision problem (Puterman, 2005)

The goal of sequential decision problems is to find the *optimal policy* (i.e. the optimal decision to be made inn every state) which maximises (or minimises) the contribution of the system over its lifetime[1]. The optimal policy is often expressed in a decision matrix (ref. figure 6.2). For the optimal policy, the benefit of the decisions might not be immediately clear, but it is the one that ensures the highest expected contribution over the system's lifetime.

Depending on the nature of the problem, the sequential decision problem continues for a finite of infinite time. The state, action and time space can be discrete or continuous. The contribution can be conditioned both on the current state, the chosen action, and/or the state the system ends up in. In addition, the contribution and the transition probability can be stochastic or deterministic. In this thesis, the focus is on stochastic, finite horizon processes, with discrete state, decision and time space.

[1]Two common metric for evaluating the performance of a policy is the *discounted contribution* and the *average contribution*. See section 6.2.2 for more on this

		System Space			
		State 1	**State 2**	**...**	**State |S|**
Time Space	**t = 1**	Decision II	Decision XI	...	Decision X
	t = 2	Decision I	Decision I	...	Decision IV
	...	...	...	...	...
	t = |T|	Decision XI	Decision XX	...	Decision I

Figure 6.2: Illustration of a decision matrix

Decision trees is a common way of modelling sequential decision-making problems (Phillips et al., 1987). A decision three illustrates how the sequence of actions and outcomes unfolds. Unfortunately, as the number of possible decisions in each decision node increases and/or the transitions between states are stochastic, decisions trees no longer are effective in modelling the situation. It rather ends up becoming a textitmessy bush. Markov Decision Processes (MDP) is a method of modelling sequential decision-making under uncertainty (Puterman, 2005) that might better handle the complexity in the problem.

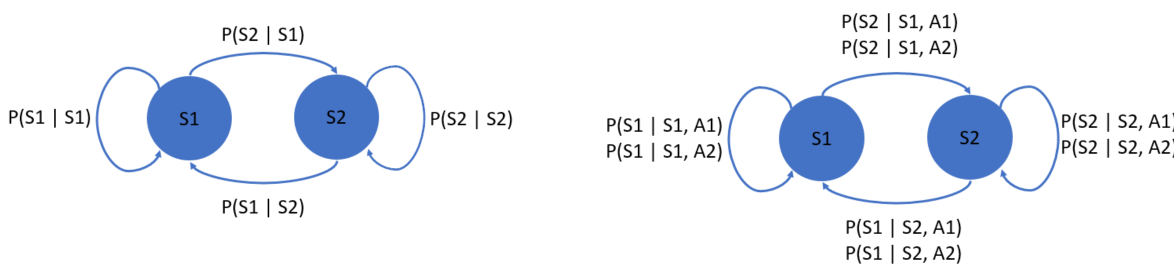
6.2 Markov Decision Processes

In general, a MDP consists of a (I) Markov reward process (MRP), and (II) a decision-making process. In a pure Markov chain, a system go through a sequence of transitions from state to state based on a transition matrix. The probability of transition from one system state to another is only dependent on the current state of the system. That is, the process is *memoryless*[2]. In a Markov reward process, there is in addition a reward associated with each state. By including the decision-making process, MDP extends a general MRP by allowing decisions to be made in each state that affect the outcome of the next transition.

Figure 6.3 presents the basic structural representation of Markov decision processes, in addition to highlighting the fundamental difference between a Markov chain and a Markov decision process. Figure 6.3a illustrates a Markov Chain where S_1 and S_2 are the two possible system states, and $P(S_i \mid S_j)$ is the probability of transition to state S_i given currently is in state S_j. As-

[2]The *first order* Markov assumption

sociate with each state is a reward for being in that state. The same goes for figure 6.3b, but the transition probability depends both on the system state and the action taken (A_1 or A_2).



(a) Markov Chain

(b) Markov Decision Process

Figure 6.3: Illustration of a Markov Chain (MC) and Markov Decision Process (MDP).

6.2.1 The Notation of Markov Decision Processes

More formally, in a Markov decision process the system is, at time t, in a state $s \in S_t$. In this state, often referred to as decision epoch[3], the decision maker has to make a decision $x_t \in X_t$. When making the decision, the decision maker is assumed to have full knowledge of the current system state[4]. In this thesis, it is assumed that the state space is discrete and small enough to enumerate. After the decision is made, the system transits to a new state, S_{t+1}, in the next time step. Which state the system enters is determined by the transition function, S^M, often referred to as the *system model*. The transition function is expressed as (Powell, 2007):

$$S_{t+1} = S^M(S_t, X_t, W_{t+1}) \tag{6.1}$$

W_{t+1} is the exogenous information revealed to the decision maker first after the decision is made[5]. Thus, the decision maker is not fully in control of the system's transitions[6]. The fact

[3]The decision maker only have to make a decision in a subset of the states. These states are classed as *decision-making states* or *decision epochs*. In MDP, it is sufficient to only consider transitions from one decision-epoch to another. Thus, in this thesis, the general term *state* referees to decision epochs

[4]There are many problems where it is not possible to precisely know the state the systems. These problems are referred to as partially observable Markov decision processes (POMDP). In many applications, this generalisation is important. Readers with interest are encouraged to explore the rich area of literature treating this subject.

[5]W is therefore indexed with $t+1$ to indicate that it is not known at time t, but is revealed during the interval $(t, t+1]$.

[6]Since the transition function only depends on the current state, the decision taken, and future exogenous information, and not on previous states, the transition function maintains the *Markov property*.

that the decision must be made before all relevant information is known stands as the key challenged of the decision maker in the sequential decision problem under uncertainty[7]

In each time step, the contribution function, $C_t(S_t, x_t)$, determines the cost incurred or the reward received for making the decision. The contribution might for instance be expressed in purely monetary terms, such as rewards, profits and revenues, but also non-monetary terms, using e.g. an utility function. The probability of transition from state S_t to S_{t+1} is given by the one-step transition matrix, $\mathbb{P}(S_{t+1} \mid S_t, X_t)$, depending on the system's current state and the decision made. The following figure illustrates the relationship between the components of the Markov decision process.

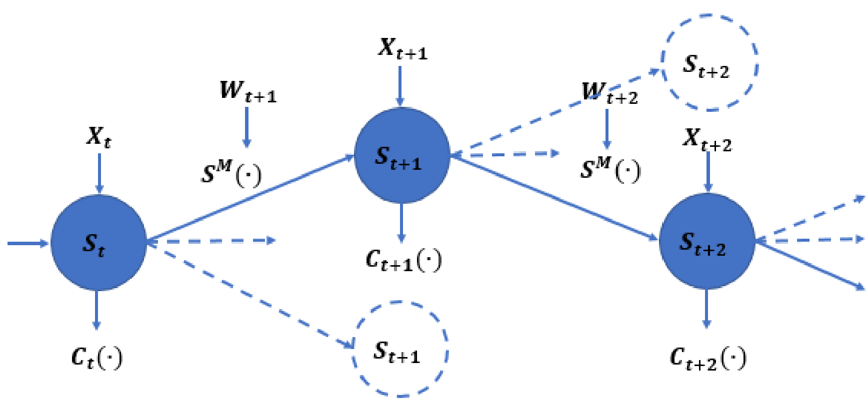


Figure 6.4: Illustration of the components in a Markov Decision Process.

The policy, $\pi \in \Pi$ is a function $\pi_t : S_t \rightarrow X_t$ that for each time step t, links all state, S_t to an decision, x_t. $X_t^{\pi}(S_t)$ expresses the decision choose in state S_t under policy π. Note that everything is indexed by time which is appropriate for finite-horizon problems. If the problem in stationary, the time indexes can be neglected. In offshore shipping, non-stationary processes are common. Changes in stakeholders perception, technical requirements, operating context, and fuel prices are examples of factors making transitions in offshore shipping non-stationary (Kana et al., 2015). To summarise, table 6.1 presents the notation and description of the compo-

[7]For deterministic problems, W_{t+1} is assumed to be known when taking the decision. Thus, when taking the decision under certainty, the decision maker knows for sure which state the system enters at the next time step. This is similar to taking decisions under endogenous information.

nents of the a Markov decision process presented above.

Component	Notation	Description
Time space	$t \in T$	A finite, discrete and countable time-space where decisions are made. Often referred to as *decision epochs*
System space	$s \in S_t$	A finite, discrete and countable set of all possible system states at time step t. The state of the system is what everything else (e.g. decision space, transition function, etc.) is centred around.
Decision space	$x_t \in X_t$	A finite, discrete and countable set of all possible decision to make in the current system state.
Contribution function	$C_t(S_t, x_t)$	The contribution to the system of making a particular decision, x_t, is a given state, S_t.
Stochastic variable	W_{t+1}	Exogenous information revealed after a decision is made. This represents the source of uncertainty in the problem.
Transition function	$S^M(S_t, X_t, W_{t+1})$	Describes how the system evolves from system state to system state under the influence of the decisions made, X_t, and exogenous information W_{t+1}. Often referred to as the *system mode.*
Transition Probability	$\mathbb{P}(S_t \mid S_{t+1}, X_t)$	The probability of transition from system state S_t to system state S_{t+1} when decision X_t is made.

Table 6.1: The Notation and Description of the Components of a Markov Decision Process (based on (Powell, 2007)

)

6.2.2 Performance Metrics & Objective Function

Performance metrics represent the performance of a policy. The goal of a decision maker is to find the policy that maximised the value of a chosen performance metric. Generally, the value of a performance metric depends on the decision made, the contribution, the horizon of the problem, and whether or not no include the time value of the contribution (i.e. discounting).

In this thesis, the performance metric chosen is the expected discounted contribution over the problem's time horizon. By discounting, the contribution received in the future is less worth than the immediate contribution received from making the decision (i.e. *the time value of money*). For a specific policy π starting in state i, the discounted contribution is:

$$\psi_i^\pi \equiv \mathbb{E}\left\{\sum_{t=0}^{T} \gamma^t C_t^\pi(S_t, X_t^\pi(S_t)) \mid S_0 = i\right\} \tag{6.2}$$

where γ is the discount factor. The expectation is over the uncertainty in the contribution function.

By using the discounted contribution as a metric for evaluating the performance of a policy, the objective function can be expressed as (Powell, 2007):

$$\underset{\pi}{max} \quad \mathbb{E}\left\{\sum_{t=0}^{T} \gamma^t C_t^\pi(S_t, X_t^\pi(S_t))\right\} \tag{6.3}$$

Thus, the objective of the decision maker is to identify the policy $\pi \in \Pi$, that maximises the expected discounted contribution over the entire life cycle of the system. The optimal policy manages to balance the immediate contribution of the current decisions, and the contributions from future opportunities.

6.3 Solving Finite-Horizon Markov Decision Processes

Solving equation 6.3 can be difficult or even impossible to do (Powell, 2007). Luckily there methods for coping with this: Let $V_{t+1}(S_t)$ be the value of making the optimal decision, $x_t^*(S_t)$, in state S_t. This function is referred to as the *Value function*. The value function is given by Bellmans's equation (in *standard form*) (Powell, 2007):

$$V_t(S_t) = \underset{x_t \in X_t}{max} \quad \left(C_t(S_t, x_t) + \gamma \sum_{s' \in S} \mathbb{P}(S_{t+1} = s' \mid S_t, x_t) V_{t+1}(s')\right) \tag{6.4}$$

Mathematical equivalent, the value function can also be expressed using the *expected form* of Bellman's equation (Powell, 2007):

$$V_t(S_t) = \max_{x_t \in X_t} \left(C_t(S_t, x_t) + \gamma \mathbb{E}\left\{ V_{t+1}(S_{t+1}) \mid S_t \right\} \right) \tag{6.5}$$

Where the expectation is over the random variable W_{t+1} in the transition function $S_{t+1} = S^M(S_t, X_t, W_{t+1})$. These two forms of the value functions is the key of solving Markov decision problems. While the standard form is typically used in the standard work on Markov decision processes, e.g. backward dynamic programming, the expected form is more applicable when working on approximated dynamic programming (ADP).

By knowing the value function in the previous time step for all possible transition states the optimal decision, $x_t^*(S_t)$, can be calculated. This is done by finding the argument of the maxima of the following equation (Powell, 2007):

$$x_t^*(S_t) = \underset{x_t \in X_t}{argmax} \left\{ C_t(S_t, x_t) + \gamma V_{t+1}(S_{t+1}) \right\} \tag{6.6}$$

6.3.1 Backward Dynamic Programming

In backward dynamic programming (BDP) the value function, $V_t(S_t)$ (ref. eg. 6.5), is recursively computed. The idea behind this procedure is simple: Assuming that the value function in the previous states,$V_{t+1}(S_{t+1})$, the probability matrix, $\mathbb{P}(S_{t+1} = s' \mid S_t, x_t)$, and the contribution function, $C_t(S_{t,t})$, for all time steps are known, the values in the current states, S_t, can be computed using the following algorithm (Powell, 2007):

Step 0. Initialization:

Initialize the terminal contribution $V_T(S_T)$

Set t = T - 1

Step 1. Calculate:

$$V_t(S_t) = \max_{x_t \in X_t} \left(C_t(S_t, x_t) + \gamma \sum_{s' \in S} \mathbb{P}(S_{t+1} = s' \mid S_t, x_t) V_{t+1}(s') \right)$$

for all $S_t \in S$

Step 2. if $t > 0$, decrement and return to step 1. Else stop.

As seen, the procedure is quite simple: Start in the last time step, T, in which the value function, $V_T(S_T)$, for all states, is assumed to be known [8]. Then, one step backward in time to compute $V_{T-1}(S_{T-1})$ using equation 6.4. By continuing this backward stepping process, the value function for all time-periods can be calculated. When this is done, the optimal decision, x_t^* can be calculated using equation 6.6.

A drawback with backward dynamic programming is that the procedure requires the value function in a given time step to be computed for all possible transition state (Powell, 2007). This might become computational difficult for models with large state spaces (i.e.*the curse of dimensionality*). In addition, even small problems might be hard to solve due to the limited ability to model the information process (i.e. *the curse of modelling*). This is the case when the transition function, S^M, is unknown. For more information regarding the obstacles of BDP, the reader is advised to Powell (2007). These drawbacks motivated the author to look into newer methods, such as approximate dynamic programming, to solve MDPs.

[8] Note that V_T can be regarded as the sunset value. See Strøm and Christensen (2016) and Alvarez et al. (2011)

6.3.2 Approximate Dynamic Programming

In general, the principle of approximate dynamic programming is as follows (Powell, 2007; Powell., 2009): Instead of stepping *backward* in time, approximate dynamic programming steps *forward* in time[9]. The path the system follows is given by a sample path $\omega \in \Omega$ which represents a sequence of exogenous information revealed throughout the process. An illustration of such sample paths for the oil price is presented in table 6.2. When stepping forward in time, the *true* value of being in a specific state, $V_t(S_t)$, is not known, and is therefore replaced with an *approximation*, $\bar{V}_t(S_t)$. There are many ways to estimate the value function, but the simplest way is using a *look-up table*, where a estimation is known up front. The approximated value function is estimated iteratively. Everything is therefore indexed by the iteration counter n. For instance, $\bar{V}_t^n$ represents the value function at time t for iteration n, and, w^n represents the sample path for the system at iteration n.

	t					
Ω	$t=1$	$t=2$	$t=3$	$t=4$	...	$t=\lvert T\rvert$
$\omega=1$	50.01	49.09	49.06	49.06	...	60.01
$\omega=1$	51.04	51.01	49.09	50.00	...	63.06
...	...	...	...	...	...	...
$\omega=\Omega$	47.01	47.03	47.04	47.04	...	44.07

Table 6.2: Illustration of a sample path, ω, for the oil prise [$] over time.

Assuming that the system currently is in iteration n: From iteration $n-1$ the value of being in that state is approximated to be $\bar{V}_t^{n-1}(S_t)$. The approximation is now used to make a decision x_t^n. After the decision is made three things occurs: first, an immediate contribution, $C_t(S_t, x_t)$, is received; secondly, the approximation of the value function is updated; then, exogenous information is revealed W_{t+1}^n. Bases on this new information, the transition function, $S_{t+1} = S^M(S_t, X_t, W_{t+1})$, determines the next system state. This process continuous until the horizon of the process is met (at $t = T$). At the end of the horizon, the iteration counter is updated ($n = n+1$) and the process starts all over again (now from t = 0). The algorithm continuous until $n = N$, where N is a pre-defined number of iterations to be conducted. By iteratively learning the value of being in different states by taking various actions each time the state is encountered, the algorithm learns which action that gives the highest expected contribution. Below,

[9]The procedure is therefore often referred to as *forward dynamic* programming.

a general algorithm for ADP using the one-step transition matrix presented (Powel, 2008,97):

Step 0. Initialization:

Step 0a. Initialize $\bar{V}_t^0$ for all states S_t

Step 0b. Choose an initial state S_0^1

Step 0c. Set n = 1.

Step 1. Choose a sample path ω^n

Step 2. For t = 0, 1, 2, ..., T do:

Step 2a. Solve

$$\hat{v}_t^n = \max_{x_t \in X_t^n} \Big(C_t(S_t^n, x_t) + \gamma \sum_{s' \in S} \mathbb{P}(s' \mid S_t^n, x_t)) \bar{V}_{t+1}^{n-1}(s')) \Big). \tag{6.7}$$

and let x_t^n be the value of x_t that solves the maximisation problem

Step 2b. Update $V_t^{n-1}(S_t)$ using

$$V_t^n(S_t) = \begin{cases} \hat{v}_t^n & S_t = S_t^n \\ V_t^{n-1}(S_t) & otherwise, \end{cases} \tag{6.8}$$

Step 2c. Compute $S_{t+1}^n = S^M(S_t^n, x_t^n, W_{t+1}(\omega^n))$.

Step 3. Let n = n + 1. If n < N, go to step 1.

Note that the initial approximation (at $n = 0$) for the value function, $\bar{V}_t^0$ is assumed known. Often, this value is put to zero. Also, notice that the approximated value function is only updated for the states the system visits (determined by the sample path). As a result, since each system state will be visited different number of times, this is a form of *asynchronous* dynamic programming. Despite the forward stepping procedure, this algorithm is quite similar to the one for backward induction earlier presented. This algorithm still leaves some challenges to handle.

First, the one-step transition matrix is used. As earlier mentioned, computing the transition matrix might be difficult and even impossible. Secondly, despite not visiting every state, there is a need to know the value of the states that the procedure might visit. Thirdly, the procedure might end up only visiting states already visited. Assuming the initial value function is set to zero, and the states visited in the first iteration all gave a positive contribution, then the same states would be visited in the next iteration as they look relative good (compared to all the states not visited since they have a value of zero). It is therefore a need for a search procedure that also takes decisions that currently are not optimal, to investigate if they might escape a local optimum.

There are many methods for conducting approximate dynamic programming. The reader is directed to the reference literature to see get a grasp of the richness of this area of research literature. In this thesis, the choice fell on the Q-learning strategy, one of the fundamental algorithms in ADP.

6.3.3 Q-learning: A form of Approximate Dynamic Programming

Q-learning[10] (Watkins, 1989) is a method of coping with many of the limitations of Backward Dynamic programming. It does so by iteratively solving the Bellman equation to find the optimal policy, without initially knowing the contribution function, $C(\cdot)$, and the transition matrix, $\mathbb{P}(\cdot)$ (Powell, 2007). Because of this, Q-learning is classed as model-free reinforcement learning (Watkins and Dayan, 1992).

As illustrated in figure 6.5, the Q-learning strategy creates an artificial post-decision state (S, x), represented by S_t^x, and defines an associated post-decision value function, $Q(S, x)$ (referred to as *Q-values* or *Q-functions*). An illustration of the Q-states in a non-stationary context is given in figure 6.6. As seen, the Q-states are defined by the decision space and the state space, and must also be defined in the time space if the problem is non-stationary.

[10]The Q-learning algorithm can be derived via the Robbins-Monroe algorithm (Robbins and Monro, 1951) where the transition matrix is bypassed using stochastic approximation. See Gosavi (2009). In order to do so, the bellman equation must be expressed on the expected form of the Bellman equation(ref. eq. 6.5).

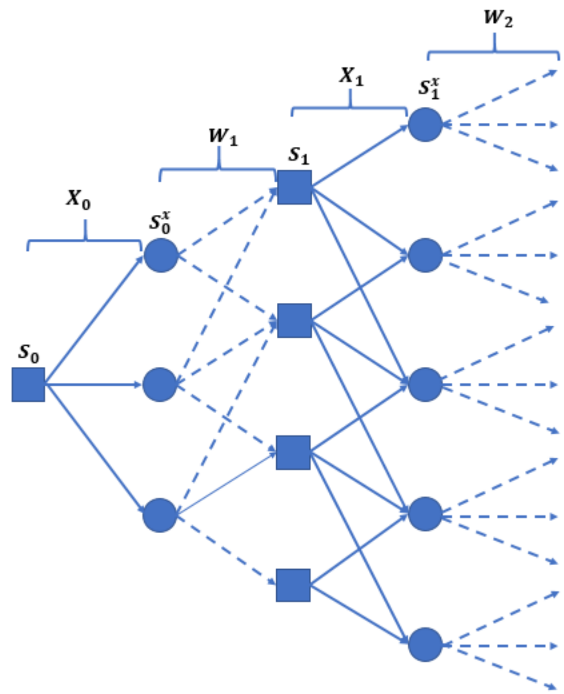


Figure 6.5: Illustration of an decision tree, presenting the decision nodes (squares) and the outcome nodes (circles). Solid lines represent decisions, and the dotted lines represents random outcomes (Powell, 2007)

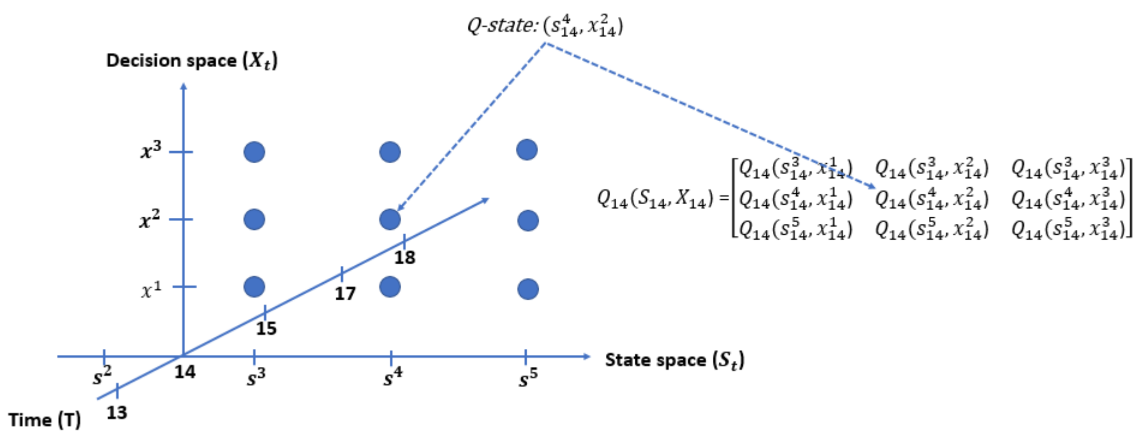


Figure 6.6: Illustration of the Q-states in a non-stationary context.

The Q-value is defined as the *expected* discounted contribution of taking decision, x_t, in state S_t:

$$Q_t(S_t, x_t) = \mathbb{E}\left\{C_t(S_t, x_t) + \gamma \max_{x_{t+1} \in X_{t+1}} Q_{t+1}(S_{t+1}, x_{t+1})\right\} \tag{6.9}$$

where the expectation is over the exogenous information. The first term inside the brackets is the immediate contribution, while the second term is the Q-value in the next post-decision state visited, (S_{t+1}, x_{t+1}). The value function, $V(S_t)$, is then:

$$V(S_t) = \max_{x_t \in X_t} Q_t(S_t, x_t) \tag{6.10}$$

Instead of estimating the value in the pre-decision state S, this approach estimated the value of being in the post-decision state, S_t^x. The optimal decision is the one that maximized that equation:

$$x_t = \underset{x_t \in X_t}{argmax}\, Q_t(S_t, x_t) \tag{6.11}$$

In light of the approximate dynamic programming procedure, the *approximation* of the *true* Q-value, as used in this thesis, in iteration n at time step t is expresses as:

$$\underbrace{\bar{Q}_t^n(S_t^n, x_t^n)}_{\text{New estimate}} = (1-\alpha_{n-1})\underbrace{\bar{Q}_t^{n-1}(S_t^n, x_t^n)}_{\text{Old estimate}} + \alpha_{n-1}\overbrace{\left[C_t(S_t^n, x_t^n, S_{t+1}^n) + \gamma \underbrace{\max_{x_{t+1} \in X_{t+1}} \bar{Q}_{t+1}^n(S_{t+1}^n, x_{t+1}^n)}_{\text{Estimated optimal future value}}\right]}^{\text{Learned value}} \tag{6.12}$$

Where α is the *learning rate*, treated in sections to come, represent how much the *learned value* in iteration n should be counted for in the new estimate of the Q-function. The Q-learning strategy learning the Q-value by taking subsequently $(t = 0, 1, 2, ..., |T|)$ decisions, x_t and learning the consequence of them. After doing so for a sufficient amount of iterations, N, the algorithm has learned which decisions to make in each state.

The Q-learning algorithm used in this thesis have the following format (based on (Powell., 2009) and (Gosavi, 2009)):

Step 0. Initialize

Step 0a. Set $Q_t^0(S_t, X_t) = 0$ for all $t \in T$.

Step 0b. Set N = Max number of iterations

Step 0c. Set n = 1

Step 0d. Initialize S_0^1

Step 1. Choose a sample path ω^n

Step 2. For t = 0,1,2,...,T do:

Step 2a. Choose which decision,x_t,to make. Use procedure (I) with probability ϵ_n, otherwise use procedure (II):

(I) Select x_t randomly with probability $1/|X_t|$

(II) $x_t = argmax_{x_t \in X_t} Q_t^n(S_t, x_t)$

Step 2b. Simulate the outcome of the decision,$S_{t+1} = S^M(S_t^n, x_t^n, W_{t+1}^n)$

Step 2c. Estimate the contribution, $C_t(S_t, x_t, S_{t+1})$

Step 2d. Update the Q-value approximation, using equation 6.12.

Step 3. Increment n by 1. If $n \leq N$ go to Step 1. Otherwise, go to step 4.

Step 4. Create the policy, π, by finding $x_t = argmax_{x_t \in X_t} Q_t^n(S_t, x_t)$

As seen, the Q-learning starts from an arbitrary initial Q-function Q_0 and updates it without requiring a model (e.g. transition probability). Instead is uses the observed transitions and rewards of following the sample path, w. Is well known that the simulation of complex systems is considerably easier than generating the TPs of the system. The algorithm is run iteratively, every run indexed by n. After each transition, the approximated Q-function is updated. See appendix F.8 for the Matlab implementation of this algorithm used to solve the illustrative case presented in section 9.

Selection of actions to take

As seen in the Q-learning algorithm, the selection procedure of which actions to take in each time step is important in the ADP. This is particularly important in regards to the comment to convergence of ADP given later, as it is important for the agent to be able to take all decisions in every encountered state in order to have prof of convergence. Before presenting some selection procedures, a short comment on the concept of exploration and exploiting is necessary.

Exploration strategies refer to action selection strategies which seeks to get better information of the value of being in a particular state, regardless of whether that state appears to be the best state to actually visit. Contrary, exploitation strategies refer to action selection strategies which seeks to find the best action given the current information (ref. equation 6.6). In a pure exploration strategy, one selecting a particular decision x_t with probability $1/|X_t|$ (i.e. equal probability). With such a strategy, it is guaranteed that every state has a chance of being visited. A problem with exploration is that many times the decision provides no important information at all. Such a pure exploration strategy will require many iterations before converging, and will only work in small state spaces. Thus, in order to have algorithms that works in practice, on also need to exploit. In a pure exploiting strategy, the agent always selects the action with the highest expected value (i.e. $argmax_{x_t \in X_t} Q_t(S_t, x_t)$). Note that, given that the initial approximation for the Q-values were zero (step 0a. in the Q-learning algorithm), and that the contribution for visiting states is purely positive, the states not visited will have a value of zero. Thus, with a pure exploitation strategy, the same states would be visited in all iterations as they would be the only one to look favourable. This will lead the to algorithm to end up in local optimums. These drawbacks with pure exploration and exploitation strategies implies the need to have mixed between exploration and exploitation to guide the decisions. The trade-off between exploration and exploitation is one of important unsolved problems in ADP (Powell, 2007).

There is an vast amount of methods proposed for mixing exploration and exploitation. In this thesis, the author ended up selecting a simple mixing-strategy, for which the exploration rate ϵ ($\epsilon_n \in (0,1)$) indicating the fraction of iterations where the action chooses is to be random (i.e. exploration probability. While, $1-\epsilon$ indicates the fraction of iterations where the action choose is to be based on a greedy strategy (i.e. exploitation probability). While ϵ_n can be constant, the author selected a stepwise reduction in its value. Starting with $\epsilon_n = 1$ for $n = [0, 0.1 * |N|]$, $\epsilon_n = 0.9$ for $n = [0.1 * |N| + 1, 0.2 * |N|]$, $\epsilon_n = 0.8$ for $n = [0.2 * |N| + 1, 0.3 * |N|]$ and so on, until $\epsilon_n = 0.1$ for $n = [0.9 * |N| + 1, |N|]$, where N is the number of interations (e.g.10,100, 1000, 10000,....). As seen in figure 6.7, in the beginning the algorithm follows a pure exploitation strategy, but as times goes by the algorithm starts exploiting more and more. The author recognizes this as an *undirected exploration strategy*. There are more *advanced directed* strategies where the exploited action selected is not selected at random, rather e.g. based on the number of previous occurrences or its value.

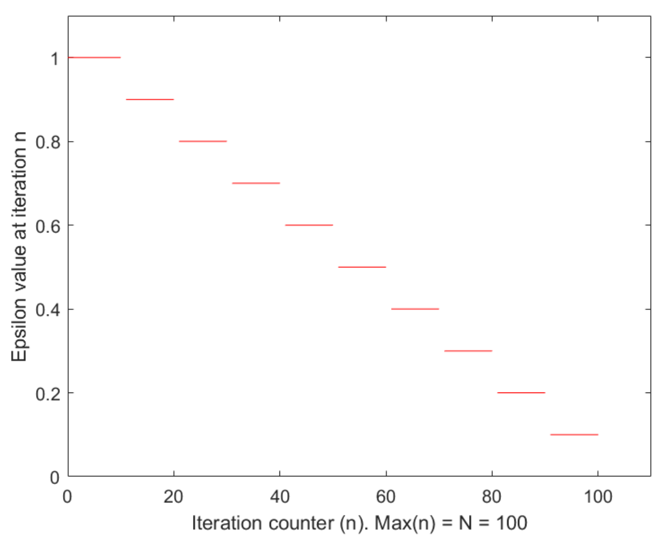


Figure 6.7: Illustration of the epsilon value

Convergence of ADP

Convergence is an important aspect in ADP as it gives insight into the algorithm's behaviour, particular its ability to obtain optimal solutions (Gosavi, 2009). It is not in this thesis objective to go in depth in the convergence of ADP, merely to present some aspects of it. The reader is advised to Tsitsiklis (1994) for a formal proof of convergence, and Gosavi (2009) and Powell (2007) for references to more literature.

In general, as $n \to \infty$, the Q-learning asymptotically converges to the optimal Q-values if the state and action space are discrete and finite, and under the following conditions:

1. $\alpha_{n-1} \geq 0, n = 1, 2, ...,$. The sum $\sum_{n=0}^{\infty} \alpha_n^2$ produces a finite value ($\leq \infty$), whereas the sum $\sum_{n=0}^{\infty} \alpha_n$ produces an infinite value ($= \infty$). α_{n-1} is referred to as the stepsize or learning rate.

2. All the state-action pairs are asymptotically visited infinitely often. This condition can be satisfied if, among other things, the agent has a non-zero probability of selecting any action in every encountered state.

While these might prove convergence in the limit, they provide no instructions for how to assure convergence in practice. Especially the assumption that the states must be visited infinity often are a big weakness Powell (2007), as the state and action space is many applications becomes very large. Often the modeller ends up using his subjective judgement to decide the adequate number of iteration before the algorithm converges, however, this must be done with caution. As seen in figure 6.8, the objective function for an ADP algorithm might seem to be flatting out (i.e. to be stabilising) which is an apparent evidence of convergence, but as the iteration counter increases the algorithm detects new opportunities which leads the objective function to new levels.

Selection of the Stepzise

As seen in the comments above regarding the convergence of ADP, the stepsize (or learning rate), α is an important property of the algorithm. Powell (2008, 184) states that two important issues regarding selection of stepsizes are (I) whether the stepsie ensures a certain convergence of the algorithm, and (II) whether the stepsize provides the fastes convergence. The first issue is mostly of theoretical importance.

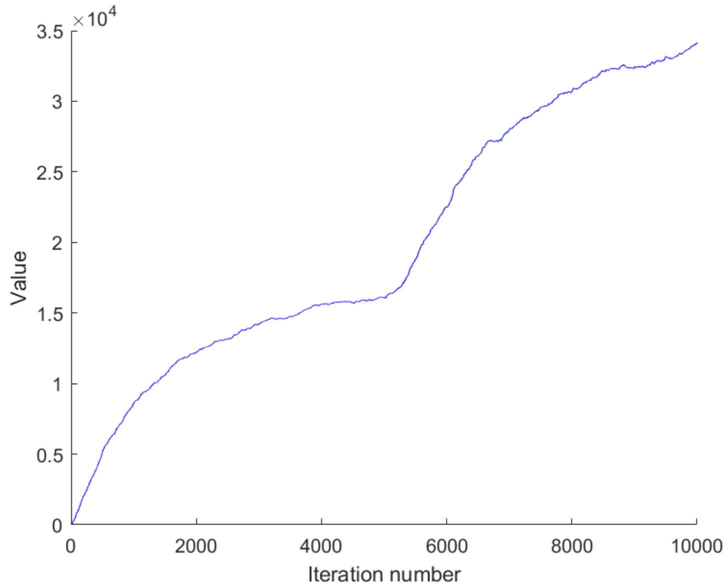


Figure 6.8: Illustration of apparent convergence

Powell (2007, 186-187) presents, among other, the constant stepsize, the harmoning stepzise sequence, and the stochastic stepsies as three classes of formulas useful to consider[11]. Below three forms of these formulas are presented. Note that α_{n-1} indicates that its value is computed using information available at iteration $n-1$.

The "one-over n" stepsize rule

$$\alpha_{n-1} = \frac{1}{n} \tag{6.13}$$

The "$1/n$" stepsize rule is one of the rules that satisfies the criteria of convergences mentioned in the section above. Despite working in theory, this rule tends to drop to zero to quickly resulting in *apparent convergence* while in reality being far from optimal (ref. figure 6.8). This is a problem with declining stepsizes in general.

Generalises Harmonic stepsize sequence

$$\alpha_{n-1} = \frac{a}{a+n-1} \tag{6.14}$$

[11]The literature on stepsize is wide, and the author encurages the reader to start in Powell (2007) for more on this.

a is a constant. Similarly as the "1/n" stepsize rule, this rule satisfies the condition for convergence. As it is dependent on one more parameters that the "1/n" rule, it can be tuned. For instance, increasing a slows the rate at which it drops to zero. In addition, one can experience with changing n to n^{β}, where β is a number between 1 and 0.

The Constant stepsize rule

$$\alpha_{n-1} = \begin{cases} 1 & if\, n = 1 \\ \bar{\alpha} & otherwise, \end{cases} \tag{6.15}$$

where $\bar{\alpha}$ is a constant stepsize choose. This rule is popular when many parameters are estimated, for which no single rules works. Other advantages is that it is requires no memory, and is easy to "tune" as it only depends on one variable. This thesis choose to apply the constant step size rule due to this its simplicity[12].

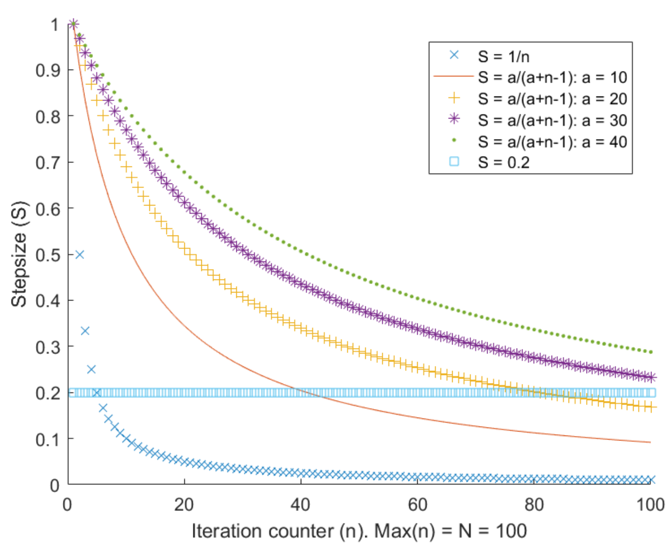


Figure 6.9: Illustration of the stepsizes for the various rules presented

[12]Generally, Powell (2007) recommend to initially start with a large step size, and as one get a sense of the number of iterations needed to get convergence reducing the stepsize to balance out the tradeoff between number of iterations and rate of convergence.

Part II - Research Contributions

Chapter 7

The Value-Aptitude-Design-Strategy (VADS) Framework

Bases on the knowledge gained from the literature review, the author proposes the Value-Aptitude-Design-Strategy (VADS) framework as a quasi-mathematical expression of the relationship between a stakeholder's aptitude, a design's configuration and the stakeholder's life cycle strategies for utilising the design, linking these three factors to the system's ability to deliver value (i.e. stay successfully) in specific context and need.

Value = Aptitude x (Design + Strategy)

In this framework, the word system not only refers to a physical system but also to the stakeholder's life cycle strategies for utilising it. Stakeholders refer to individuals, groups or organisations (e.g. operating managers, shipowners, classification societies, flag state, etc.), and the design refers to the physical system. Further, a specific design-strategy configuration is referred to as a *strategic system*. This notation is adapted from Miller and Lessard (2000), and is in this thesis defined as a set of distinct devices used to handle uncertainty. The notation design-strategy pair will also be used, a notation first[1] used by Schaffner (2014). Strategic system and design-strategy pairs will be used interchangeably.

As illustrated in table 7.1, the VADS framework expresses that both design and strategy (i.e. the

[1] By the authors knowledge

strategic system) are important aspects for enhancing stakeholder value. One cannot have design or strategy without having the other. However, one can be (at least in theory) successful if one has the optimal design for the current context and needs, while still having a sub-optimal strategy. In the same way, one can be (at least in theory) successful by utilising a suboptimal design with an optimal strategy for the current context and needs (therefore, the + operator). However, the shipowner must have the aptitude to align the design and strategy towards the operating context and needs (therefore, the x operator). Without aptitude, the stakeholder would not be able to utilise either the design or the strategy. For instance, one can have a highly flexible design, but without the ability to recognise the need to adapt, or without having the required resources (e.g. time, money, experience) to adapt, the value of this flexibility is low. This idea is illustrated in the table below. 0 and 1 represents the minimum and maximum ability the aptitude, design and strategy have to contribute to the system's total value delivery, respectively.

Table 7.1: Illustration of the dynamic relationship between Aptitude (A), Design (D) and Strategy (S) and their contribution to the system's ability to deliver value

Aptitude			Design		Strategy			Value		Degree of Success
0	X	(	0	+	0	)	=	0	⇒	Low
0	X	(	1	+	1	)	=	0	⇒	Low
1	X	(	0	+	1	)	=	1	⇒	Medium
1	X	(	1	+	0	)	=	1	⇒	Medium
1	X	(	1	+	1	)	=	2	⇒	High

As seen, the total value of the strategic system can be 0 (representing an unsuccessful system) if aptitude, design and strategy are not aligned, or it can be 2 (representing a highly successful system) if their dynamic relationship perfectly aligned. The author emphasises the importance of aligning the design and strategy with its aptitude, as this results in a magnifying effect and a high degree of success.

As illustrated in figure 7.1, the VADS framework extends the traditional system boundary in engineering (ref sec. 2.1), from solely focusing on the relationship between design and its surroundings, to add a new layer comprising the stakeholder's role in managing the system (i.e. aptitude and strategy).

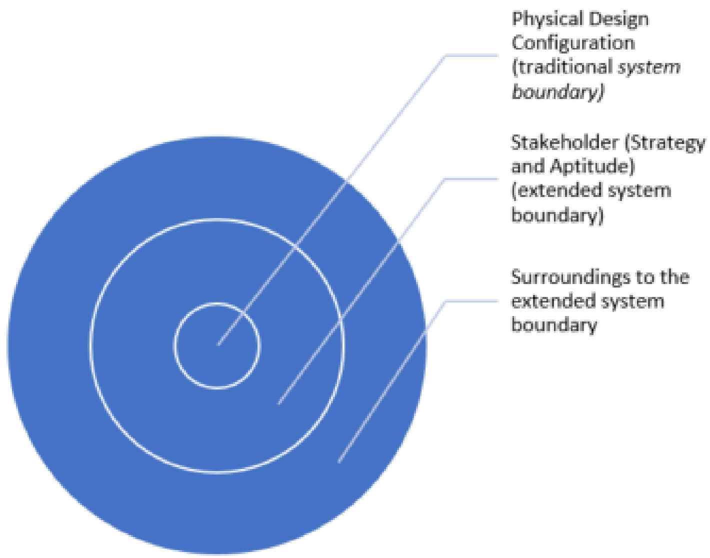


Figure 7.1: Illustration of the extended system boundary in the VADS framework

The idea of linking aptitude, design and strategy factors is supported by Mintzberg (1990) and Payne et al. (1996) that emphasises the need to align the product (design), the person (aptitude), and strategy. The idea is also related to the notation of a flexible system design concept proposes by Cardin et al. (2013), which comprises two components: (1) a strategy, and (2) an enabler in the design and management. The latter is equivalent to the design and aptitude in the VADS framework. In addition, a similar idea as the VADS is seen in literature on Operations strategy, especially in manufacturing/process industry, where Value, Capability, Asset and Process is linked (Mieghem and Allon, 2015).

Each of the four components in the VADS framework is further presented in the sections to come.

7.1 (V) Value

Oxford dictionaries[2] defines value to be *the worth of something compared to the price paid for it.* Ross (2006) links value to the *perceived benefit net of cost.* This benefit is not necessarily monetary. It theory, value can be any sort of desire the stakeholders has for the system (Hall, 1962).

[2]`https://en.oxforddictionaries.com/definition/value` [13.02.2017]

Examples are the traditional aspects *functionality, performance* and *quality*, and newer aspects as *Safer, Smarter*, and *Greener* (DNVGL[3]). Thus, value is a more comprehensive metric for evaluating systems than just profit Ross (2006); Saleh et al. (2007); Pierce (2010).

The concept of value is closely related to the concept of system success. Keeney (1992) emphasises that value is what stakeholders care about, and should therefore be the driving force behind every process. Therefore, the primary goal in conceptual ship design should be to identify value robust systems (Browning and Honour, 2008; Gaspar et al., 2016) that is, *systems able to deliver high value to key stakeholders over its entire life cycle* (McManus et al., 2007). Note that, while the literature is primarily focusing on architecting value robust physical systems, this thesis emphasises the need for identifying value robust strategic systems.

Recognising the broad aspect of value imposes a multidimensional evaluation criteria in the design phase, and is an important aspect enhancing complexity to the design environment. In general, one sees that commercial firms almost solely focus on profit, while non-commercial firms (like naval cases) have a wider view on value (Buland, 2017)[4]. The focus on the whole value spectrum imposes a shift in focus from minimising Life Cycle Cost (LCC) to maximising Life Cycle Value (LCV) (Pierce, 2010; Browning and Honour, 2008).

Stakeholders perceived value consists of articulated and unarticulated value (Ross, 2006; Ross and Rhodes, 2008b). Articulated value comprises the explicitly communicated values of the stakeholders, which defines the objectives, requirement and attributes of the system. The unarticulated value is what might give perceived value to the stakeholder, but are not explicitly communicated. The lack of explicit communication might be because the stakeholder "can't say" (e.g. forgot, don't know yet, intangible), "Don't say" (e.g. assumed to be known) or "Won't say" (e.g. it is a secret). The unarticulated values might become articulated, changing the perceived value of the system, such that decision makers must be aware of both the articulated and unar-

[3] `https://www.dnvgl.com/about/`

[4] The author is grateful to his classmate Marius Buland for all the discussions regarding value and utility throughout the course of writing this thesis. The reader is advised to Buland (2017) for more on these highly important topics.

ticulated values.

What stakeholders value, changes over time.The driver for change in value perception is (I) personal drift in stakeholders thinking of value (II) change in context affecting the system under consideration, and (III) shift in needs from unarticulated to articulated value (Ross, 2006). Ross (2006) states that personal drift in thinking is the most difficult to anticipate.McManus et al. (2007) states that the perceived success of a system is determined by the dynamic relationship between stakeholder's expectations (needs), the developed and operational environment of the system (context), and the form of the system (i.e. design). Due to the dynamic nature of value perception, a key challenge in conceptual ship design is to identify systems that can deliver high perceived value in the face of changes in stakeholder's value perception (Ross and Rhodes, 2008b).

In conceptual ship design, there is more than one stakeholder preference to consider. As different stakeholders have different preferences, the designer must perform some sort of aggregation. A common method for aggregation of stakeholders' preferences in engineering design is using multi-attribute utility theory (Keeney and Raiffa, 1993). In addition to Keeney and Raiffa (1993), the reader is advised to Arrow (1963), Scott and Antonsson (2000) and Buland (2017) for more on the aspect of utility theory.

7.2 (A) Aptitude

Stakeholder's aptitude refers to the shipowner's inherent ability and willingness to utilise the strategic system to best meet current and emerging contexts and needs. This is what in the end determine whether the strategic system excels. To do so, stakeholders must:

(I) Recognise the vulnerabilities and opportunities in the current, and emerging, context and needs.

(II) Be aware of the options inherent in its design configuration (i.e real *in* options) and set of strategies (i.e real *on* options) able to mitigate the vulnerabilities and exploit the opportunities.

(III) Have the ability to select the best course of action from those available in the strategic system.

(IV) Have the required resources needed, both tangible and intangible (e.g. time, money, staff, equipment, experience, competence), to efficiently utilise the strategic system.

Aptitude is critical both in relations to the success of the initial design configuration (i.e. ability to incorporating the right aspects and degree of changeability), but also the life cycle management of it (i.e. having the ability to monitor emerging context and needs, and implement corrective measures). Aptitude is closely related to the common obstacles of implementing change, stated by such as (I) ignorance (II) inattention (III) failure to plan (IV) stakeholders block, and (IV) external development (de Neufville and Scholtes, 2011).

The following table presents the relationship between a stakeholder's strategic system and their aptitude to ensure high stakeholder value. The word *tailored* indicates that the system either meets the current environmental context or stakeholders needs, or has incorporated the right changeability to adapt to it. As seen in table 7.1, stakeholders' value is high if they have the ability to utilise the strategic system which is tailored to the current context and needs. If the strategic system does not meet the current context and needs, but stakeholders aptitude is high, the system will still deliver some value. This can be the case when e.g. a vessel does not have incorporated the right modularity to easily alter its form and function to the current needs. It can still do so, but it comes at a higher cost (hence, it delivers medium value).

Table 7.2: Relationship between Strategic system and Stakeholders' Aptitude

		Strategic system	
		Strategic system is tailored to the current context and stakeholders' needs.	Strategic system is not tailored to the current context and stakeholders' needs.
Aptitude	Stakeholders' aptitude is high	High stakeholder value	Medium stakeholder value
	Stakeholders' aptitude is low	Low stakeholder value	Low stakeholder value

7.3 (D) Design

In the VADS framework, *design* represents the physical aspect of the strategic system (e.g. vessel). It is the design that performs the operations which result in stakeholder value. Further, it is the design's ability to perform those operations in a given context and to meet stakeholders' expectations (needs) that in the end determines the designs success (McManus et al., 2007). The design is related to the Physical performance dimension of system changeability proposed by Niese and Singer (2014), as it considers the ability of the design to change as a value-adding process.

The design configuration can, in two extremes, either be (I) perfectly fit for the current environmental context and stakeholders needs, or (II) not fit at all. In the first case, the design is able to deliver value and is therefore perceived as successful. However, as the design's fitness reduces so does its ability to deliver value. In the worst case, the design is unable to perform any operations under the current context and/or it is not able to meet stakeholders needs – it is perceived as unsuccessful. Related to the concept of changeability, some designs can have the ability to adapt to meet changes in context and needs incorporated. Thus, despite not being fit for the current context and needs, an adaptable vessel can be changed to again deliver stakeholder value (hence, be successful).

In the conceptual design phase, the designers are in the position to impact the design configuration. In this process, the designers must decide upon the five key questions which are presented below:

(I) **Is there a need for incorporating changeability?** The long life cycle, high complexity, and exogenous uncertainty which characterise ocean engineering systems requires methods that mitigate vulnerabilities, and exploits the opportunities, in order to stay successfully. Changeability is recognised as an active approach for managing this uncertainty.

(II) **What aspects (e.g. flexibility, robustness, adaptability, agility) of changeability should be incorporated?** Which of these that should be incorporated must be linked to best fit the vulnerabilities and opportunities that lie in the future, as well as the manager's aptitude to handle the changeability. Related questions are: What is the probability that the change options will be exercised? What design principles/mechanisms of change should enable the changeability? Are the solutions technically feasible?

(III) **What level of changeability is needed?** A design with a high level of changeability is designed to have a low threshold cost (e.g. time and money) associated with executing of future changes. However, this implies a higher initial building cost and a cost of carrying the change options. On the other side, incorporating low degree of changeability is seen as a more passive approach for management uncertainty, for which zero degree of changeability is equivalent to having a robust design.

(IV) **What is the value of incorporating changeability?**. The value of changeability is difficult to assess because it is latent (i.e. it does not provide any value when not executed). In fact, changeability might even reduce a system's potential performance e.g. by adding weight and size. However, the additional cost for implementing, and carrying changeability and the performance reduction is seen as the cost for the insurance for the future.

(V) **How should changeability be managed?** This is closely related to stakeholders aptitude and life cycle strategies, since it is these that in the end determine how the design is utilised in the current context and needs, and how it is adapted to meet emerging changes. This is a key question to consider in the proposed Design-Strategy Planning framework presented in the next chapter.

7.4 (S) Strategy

Specified to the VADS framework, strategy refers to a plan of actions stating how the design, and the organisation as a whole, should be used to best handle uncertainty. Such a strategy could for instance state which contracts to take, which market to operate in, and what design configuration to have in different scenarios. In general, strategy is closely related to the *process dimension* of system changeability discussed by Niese and Singer (2014). Table 7.3 presents various strategic decisions that can be taken at different levels in the organisation.

Table 7.3: Illustration of strategic decisions at different levels in the organisation (based on de Neufville (2004))

Decision level	Passive approach	Active approach	
		Real "in" options	Real "on" options
Strategic	Invest in a multifunctional vessel that can operate in a wide range of context and needs.	Build a OCV with a high level of changeability to enable a more cost- and time-effective change in form and function.	The option to sell or scrap the vessel when it is no longer found profitable, or the option to expand the fleet when market are rising.
Tactical	Invest in state-of the-art radar system which automatically signals if a lifting operation must be aborted.	The selection of a specific design configuration by reconfiguring a modular design.	The option to layup the vessel temporary. The selection of contract duration.
Operational	Implement operational procedures to guide an operation (i.e. linking resources and personnel).	Choose to use the large crane in an LWI operation, instead of a smaller one.	Option to delay operations until the weather is favourable.

Figure 7.2 illustrates how strategic decisions can impact the life cycle of an OCV vessel. The vessels life cycle starts when the shipowners decide to expand the fleet due to positive expectations of the future. The shipowner has several alternatives to expanding the fleet. Vessels can either be bought in the second-hand market or be built from scratch. Assuming the shipowner decides to build a new vessel, the design stage - the first phase in the vessel's life cycle, is initiated. Executing the real on options of initiating the project will cost. Going through the design and production phase, the shipowner has several opportunities to alter the course of the project. The project can be abandoned if the shipowner loses the positive expectations of market outcomes, or decide to rather buy in the second-hand market. And the project can be deferred to wait for more information. Also in the operation phase, the shipowner has a myriad of options to consider. Examples are to layup the vessel if it no longer is profitable, retrofitting it to take new opportunities, and to switch markets when other are found more favourable. The vessel is sold or scrapped when the shipowner finds it most profitable. The reader should note that

there are many of strategic decisions to be performed over the course of the vessel's life cycle. For more on these strategic decisions, see Lorange (2009), Axarloglou et al. (2013) and Shipping (2005).

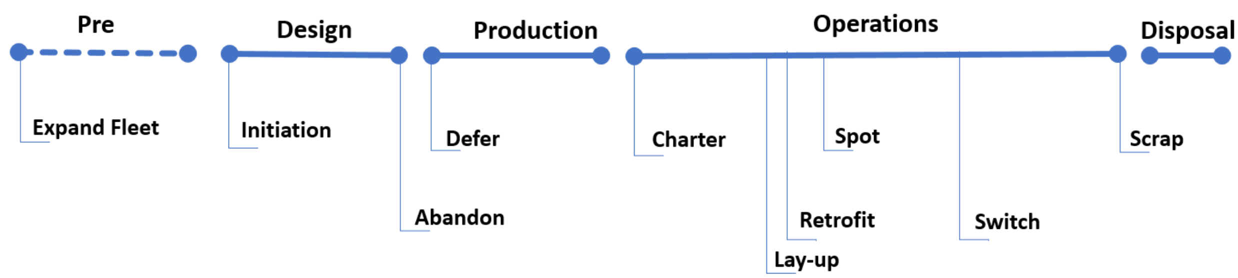


Figure 7.2: Illustration of strategic decisions impacting the vessel

Chapter 8

Design-Strategy Planning (DSP) for Uncertainty Management

This thesis proposes Design-Strategy Planning (DSP) as a systematic framework to support the active management of exogenous uncertainty throughout the entire life cycle of engineering systems. DSP is based on the fundamental idea of the Value-Aptitude-Design-Strategy framework, with the goal of developing value robust strategic systems with the means of handling uncertainty.

The DSP framework combines and extends the work on Scenario planning (e.g. Ringland (1998)), Dynamic Strategic Planning (DSP) (de Neufville, 2000), Adaptive Policymaking (AP) (Walker et al., 2001), Adaptive Airport Strategic Planning (AASP) (Kwakkel et al., 2010), the four-phase approach for developing flexible systems of de Neufville and Scholtes (2011), the taxonomy of systematic procedure for supporting the design of flexible engineering systems of Cardin (2014), the Accelerated Business Development Process (ABD) (Ulstein and Brett, 2012), and ideas from Physical Asset Management (e.g. Hastings (2015)). Note that the main ideas are from Kwakkel et al. (2010) and Cardin et al. (2013), whose frameworks are presented in appendix D.1 and D.2, respectively.

8.1 The Design-Strategy Planning Procedure

Figure 8.1 presents an overview of the framework. As seen, Design-Strategy Planning is an iterative four-step procedure, consisting of an (I) initialisation phase (II) development phase (III) implementation phase, and (IV) monitoring phase. These four steps are described in the sections to come. The objective is not to go in depth on all the aspects of this framework, but rather to highlight important aspects of it. Further, the framework is applied on the offshore case presented in the next chapter.

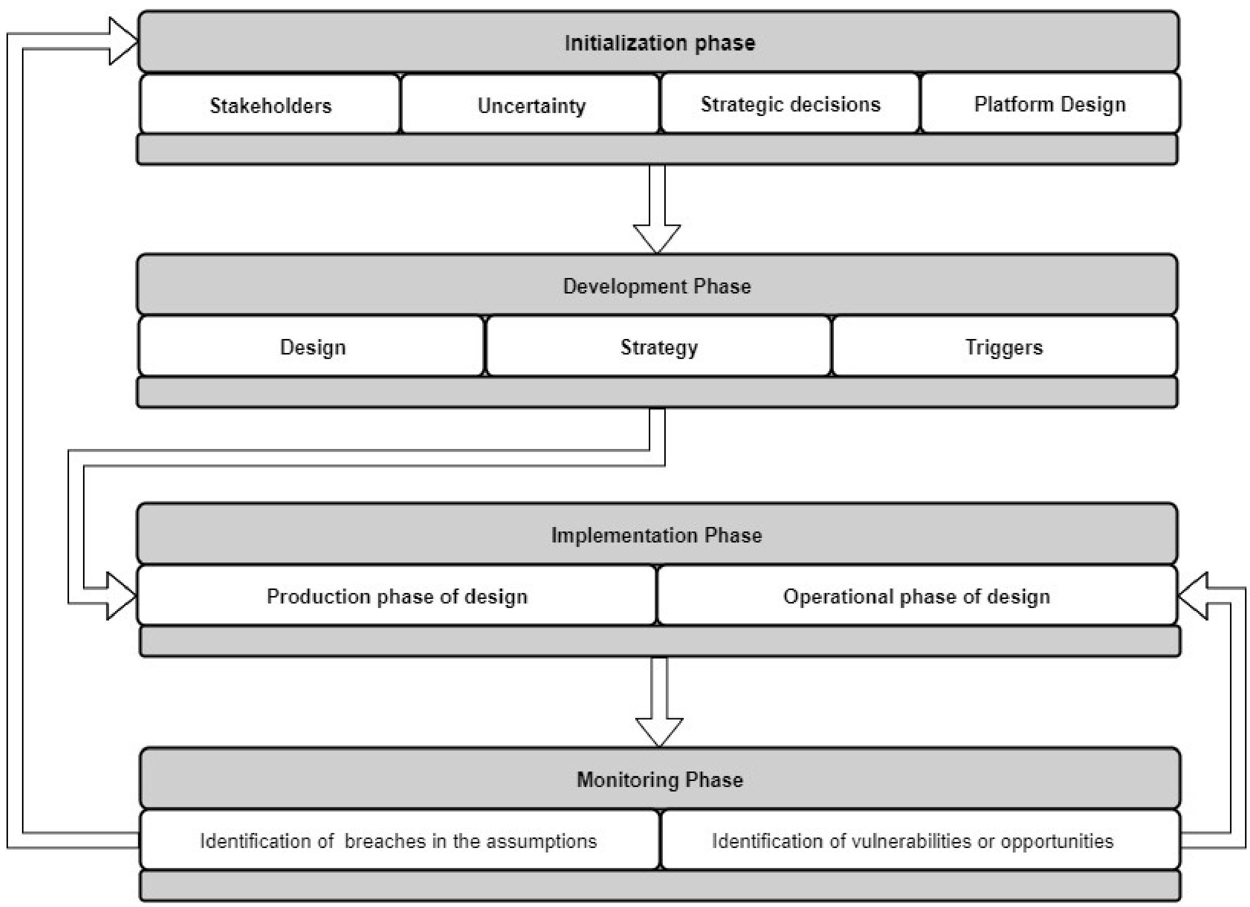


Figure 8.1: The Design-Strategy Planning (DSP) Framework

8.1.1 Phase I: Initialisation

Design-Strategy Planning starts off with the initialisation phase. The initialisation phase is an iterative, collaborative process between the designers and engineers, owners, operators and analysts. The goal is to end up with a complete picture on the commercial, operational and technical aspects of the problem.

Stakeholders

First, major stakeholders should be identified, and their objectives clarified. This is in line with the ideas of Keeney (1992), as the goal is to identify what stakeholders care about. Stakeholder analysis, business assessment, market analysis, competitive analyses and risk assessment can be used to support this process.

The objectives comprise stakeholders' business concept[1], requirements and expectations, and together they define criteria(s) for the system's life cycle success. Internal expectations can be economic, strategic, organisational and market-oriented. External expectations can be related to clients and stakeholders (e.g. reliability, flexibility, cost of service and quality) (Brett, 2017). Accurately stating requirements is essential, as the system cannot be better than the requirements it is to meet (Suh, 1990).

It is critical to understand stakeholders' ability, which can be established with a stakeholder analysis and SWOT analysis. Referring to section 7.2, some of the key questions to answer in such an analysis are: (I) are they able to recognise emerging vulnerabilities and opportunities? (II) Are they aware of strategic options to mitigate the vulnerabilities and exploit the opportunities? (III) Are they able to select the best course of action? (IV) Have they the required resources needed to efficiently execute the strategic options?

[1] http://www.businessdictionary.com/definition/business-concept.html

Uncertainty

Referring to chapter 3, uncertainty affects the life cycle success of vessels, as it might lead to unforeseen vulnerabilities and unforeseen opportunities. The objective of this process is to recognise, identify, model and quantify the major sources of uncertainty, as it is the major uncertainties that plays the most significant role in the life cycle success of the system. Both the likelihood and consequence should be assessed. As stated by Miller and Lessard (2000), assessing and understanding uncertainty is perhaps the most difficult process in uncertainty management.

Methods supporting this phase are, among others, bayesian theory, possibility theory, probability theory, statistical analysis, binomial lattice, decision trees, diffusion models, and scenario planning (de Weck et al., 2007; Cardin et al., 2013; Erikstad and Rehn, 2015; Strøm and Christensen, 2016).

Strategic Decisions

A key in the DSP framework is to identify the set of strategic decisions that allow stakeholders to mitigate vulnerabilities, and exploit opportunities inherent in the uncertainty. The first question to ask in this process is: *what if*? (Lorange, 2009; Gaspar et al., 2016). What if market continues to go up? What if markets start to fall? What if new regulations impose strict environmental protections? What if today's technology becomes obsolete? The second question to answer is: *what can we do about it*?. The answers to the latter question are both related to the real *on* options, such as the opportunity to lay up or sell the vessel if markets fall, and real *in* options, such as the opportunity to alter the physical system to meet changing operational contexts. The reader is advised to chapter 4 and chapter 5 for more examples of potential *in* and *on* options, respectively.

Some of these real options, typically the *in* options, must be implemented in the production phase, and/or be prepared in advance for it to be taken in the future. Others, typically the *on* options do not need to be prepared for at all. As later seen, this is a fundamental aspect of the *implementation phase* in the DSP process.

Platform Design

From the ideas of Cardin (2014), DSP should start from an existing set of platform designs. These platform designs serve as base designs that further will be enriched by adding adequate aspects and degree of changeability. Starting with pre-existing designs relaxes the computational burden compared to starting from scratch. The platform design is created using standard design approaches. The reader is advised to Martin and Ishii (2002), Kalligeros (2006), Erikstad (2009), Cardin (2014) and Rehn et al. (2017b) for more insight into platform designs.

8.1.2 Phase II: Development

The second step in the Design-Strategy Planning is the development phase, for which the objective is to develop the (I) strategic system and an (II) contingency plan. This phase is an iterative process in which the decision makers use quantitative and qualitative methods. The reader is further advised to Cardin et al. (2013) and Strøm and Christensen (2016) for an in-depth presentation of various quantitative methods that can be used to support the development phase.

Develop Strategic System Part I: Design

The development phase must decide upon which design configuration to select. First, the platform design must be selected. Secondly, as discussed in section 7.3, decision-makers must evaluate (I) if there is a need to incorporate changeability into to the platform design (II) what aspects of changeability that should be incorporated and (III) what level of changeability to incorporate (see figure 8.2). In general, the key in the process of selecting design configuration is to strike the balance between implementation and carrying cost against the reduced cost of executing the change option.

Develop Strategic System Part II: Strategy

Referring to chapter 7 life cycle strategy states how stakeholders are to best utilise the strategic system. It is based on selecting a set of the real options identified in the initialisation phase,

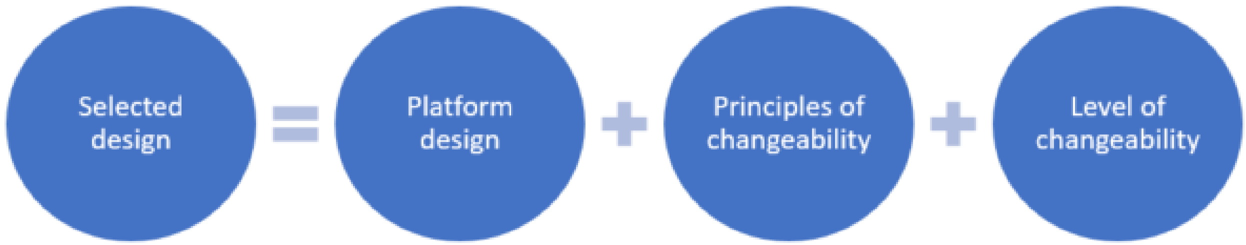


Figure 8.2: Illustration of the components of the selected design configuration

considering the ability stakeholders have to execute these options. The life cycle strategy should consider both the corporate, tactical and functional level in the organisation, and should have a long-term view rather than focusing on myopic, short-term benefits.

Develop Contingency Plan

The life cycle strategies, the real option incorporated in the physical system and trigger information are all a part of the contingency plan. The contingency plan states which options to execute as a result of various triggers. Triggers are critical information that should be monitored over the system's life cycle. This can either be information that (I) result in actions from the contingency plan to be implemented, or (II) result in a reassessment of the DSP process as the underlying assumptions for the development phase are changed.

8.1.3 Phase III & IV: Implementation and Monitoring

After the development phase, the plan is to be put into force. Some of the actions are immediately implemented in the *production phase* of design in which the selected platform design is built, incorporated with the selected principles and level of changeability. While the actions immediately implemented results in a *sunk costs*, the beauty of this process is that other actions are only committed if needed as a response to triggers identified in the monitoring phase.

After the vessel is launched, the monitoring phase monitors the surroundings of the strategic system looking for information triggering a response. If vulnerabilities or opportunities are located, the contingency plan states which mitigation or exploitation actions that should be implemented, respectively. Following the ideas of table 7.3 in section 7.4, these actions can be implemented on a strategic, tactical and operational level in the organisation. The idea is for the manager to constantly seek to best utilise the strategic system to meet the current market needs.

Further, if the monitoring phase locates major changes in context and needs breaching the underlying assumptions of the developed phase, the DSP process should be reassessed. Examples of such an instance could be if a shipowner has less free capital than expected in a down period of market.As a result, the shipowner would not have the same capital strength to execute alternations in the design configuration to meet new needs, as the remaining free capital is rather used to pay down debt. Other examples could be if the planned strategic options do not work as anticipated. Note that the DSP process would not start from the bare ground, as much of work already done in the implementation and developing phase can be reused.

8.2 A Markov Decision Processes Methodology to Support DSP

Figure 8.3 presents the proposed Markov decision processes methodology to support the Development phase in the Design-Strategy Planning framework. The MDP Methodology is based on a methodology proposed by Niese and Singer (2014) for assessing system changeability, which is presented in appendix D.3

As seen, all the knowledge gained from the initialisation phase in the DSP framework is used as input to the MDP methodology. The MDP methodology starts off using Markov decision process to model the decision problem. Using the notation of MDP presented in table 6.1, in section 6.2.1: The *time space* represents the times over the system's life cycle when decisions are made. The *system space* represents all possible states the system can encounter, consisting of both internal and external factors of the system. Remember that the *system* refers to the *strategic system*. The *decision space* consists of all decisions the stakeholders can make over the systems life cycle, these comprise decisions related to the design (i.e. real *in* options) and decisions related to managers strategies (i.e. real *on* options). The *contribution function* represents the contribution gained by making a particular decision in a given state, also often dependent on which state the system transits into. The contribution function is a representation of stakeholders objectives identified in the implementation phase of DSP. The *Stochastic variable* represents the exogenous uncertainty affecting the outcome of every decision made, and the *transition function* represents how the system evolves from system state to system state, which depends on the decision made and the exogenous uncertainty.

The Markov decision model is then solved using, for instance, approximated dynamic programming. The output from ADP is the decision matrix (DM) stating which decision stakeholders should make in each state to maximise the expected life cycle contribution of the system. The decision matrix is then used as input to the simulation model of the system's life cycle. From the life cycle simulation one get the expected life cycle contribution, and other insight using different metrics. Examples of metrics suitable to support this framework are the *temporal outdegree*, stating the systems changeability over time, and the *horizontal activity level*, stating the average number of system changes. The reader is advised to Niese and Singer (2014) for more insight into suitable support metrics.

The decision matrix, and the outputs from the life cycle simulation are then analysed to provide insight into the development phase in the Design-strategy planning framework. Examples of how this can be done is given in the illustrative case.

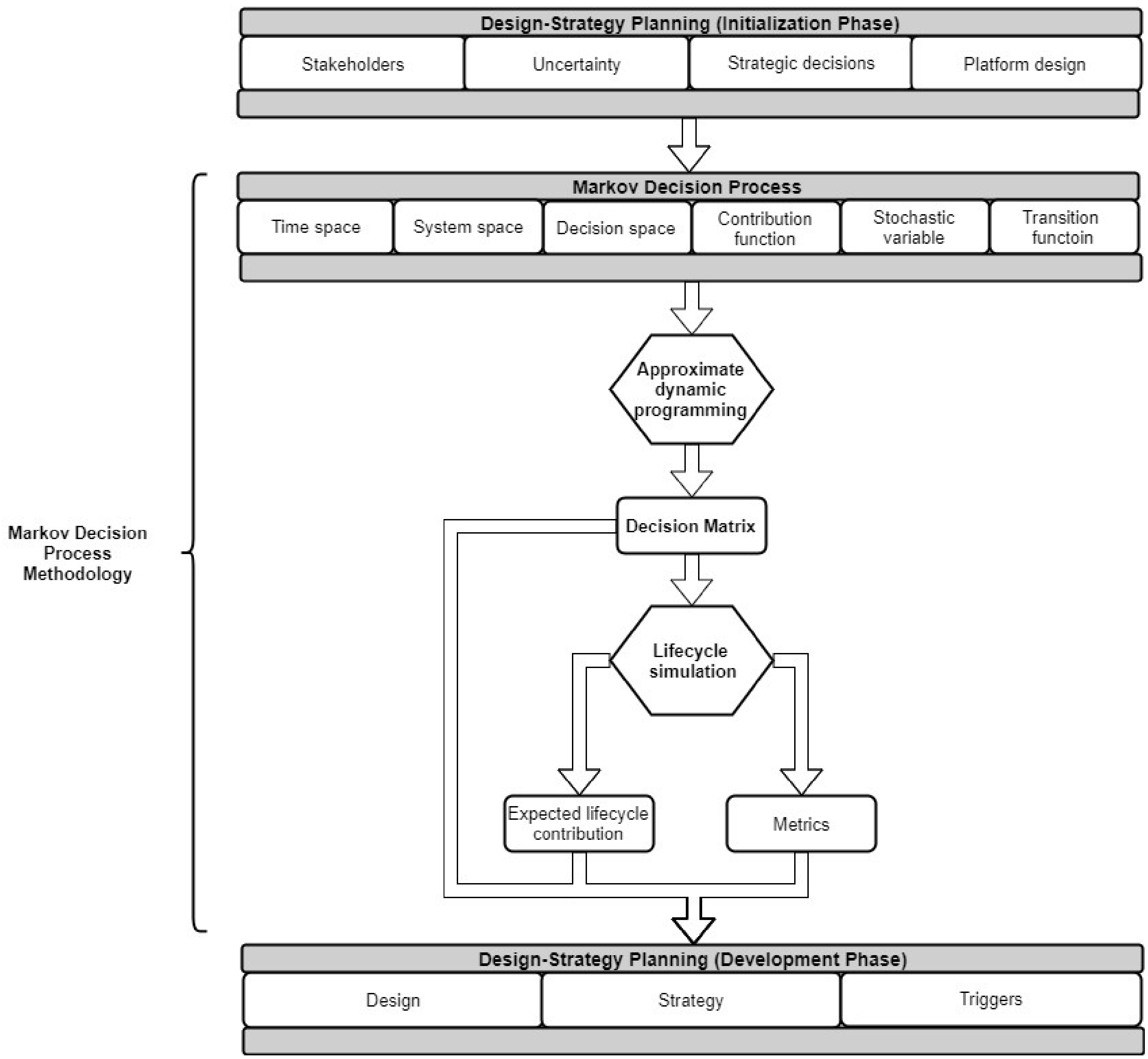


Figure 8.3: Proposed Markov Decision Process Methodology for supporting Design-Strategy Planning (based on Niese and Singer (2014)

Chapter 9

Illustrative Case

This chapter presents the application of Design-Strategy planning on an illustrative offshore case, in which a Markov decision processes methodology supports the development phase. The illustrative case is based on the work of Rehn et al. (2017a), Rehn et al. (2017b) and Pettersen et al. (2017).

9.1 Case Description

A shipowner has decided to invest in a new Offshore Construction Vessel to carry out a five year Offshore Decommission Support (ODS) contract in the North Sea. The shipowner has a long-term view of the investment, stating that his primary objective is to maximise the life cycle value of the investment. To do so, the shipowner takes use of the Design-Strategy Planning Framework to guide the process of developing a value robust strategic system.

9.2 DSP Phase I: Initialisation

The shipowner is assumed to have conducted the first phase in the DSP process (i.e. initialisation), for which the main points are briefly presented below.

Stakeholder(s): The shipowner serves as the only stakeholder to be considered. He has decided to enter the offshore construction segment, to undertake a five year offshore decommissioning contract. After the initial contract ends, the vessel will continue to operate in the North Sea. Stakeholders objective is to maximise life cycle value of the investment. This *value* is assumed to be solely monetary. With an experienced firm, with strong financials, in addition to high willingness to stay competitive in the dynamic north sea market, the stakeholder is assumed to have a high aptitude for handling uncertainty.

Uncertainty: A high degree of exogenous uncertainty affects the investment. The shipowner is particularly focused on the overall development of the economic state in the North Sea market, and the expected increase in operational requirements. The shipowner expected the offshore market to follow a 7-year cycle, and that operational requirements will steadily increase. There is in addition uncertainty related to whether the shipowner wins future contracts, and the day rates associated with various missions. The probability of winning a contract is dependent on supply-demand ration is the market, a factor correlated with the market state. The day rates are conditioned on the length of the contract, the mission, and the state of the market.

Strategic decision(s): There are strategic decisions to be made that are to be implemented in the design phase, and others that serve as part of the contingency plan that can be implemented in the operation phase. In relations to the design, the shipowner must choose a platform design, which principles and level of changeability to incorporate. In relations to the operations phase, the shipowner can decide which design configuration to have, which missions to take, and contract duration. He can also sell or layup the vessel if he finds it desirable.

Platform design: Two platform designs are considered (I and II). Both designs have a length of 120 metres, beam of 25 metres and a depth of 10 metres. The shipowner further can decide to equip the design with accommodation, main crane, light well intervention, remotely operated vehicles, cable laying equipment and moonpool. While base design I have accommodation capacity and main crane capacity of 250 persons and 400 tonnes, respectively, base design II has nothing more than an accommodation capacity of 400 persons. The rest of the topside equipment are seen as possible real *in* options to be executed during the life cycle if they are found profitable.

9.3 DSP Phase II: Development

This section presents how the Markov Decision Processes Methodology (ref. section 8.2) is used to support the development phase of DSP.

9.3.1 Modelling the System Space

The state space of the illustrative case is modelled as a finite, discrete and countable set of all possible states the strategic-system can encounter. Thus, system space consists of the state variables: *Design state*, *Strategy state*, *Mission state*, *Market state* and *Technical Requirement State*. In addition, due to varying market situation and changes in technical requirements, the problem is non-stationary such that the epochs (i.e. time) must be tracked. Therefore, the full state space description becomes:

System Space = (Design, Strategy, Mission, Market, Requirement, Epoch)

Design States

The design state represents the physical system under consideration (i.e. the vessel). It comprises both *fixed* design parameters representing the platform design, and *variable* design parameters representing the real *in* options that can be executed to alter the form and of the vessel (i.e. changeability). The design state parameters for the illustrative case are presented in table 9.1 and 9.3.

Table 9.1: Illustrative case (discretized) fixed design state variables

Design state variable	**Abbr.**	**Units**	**Value**
Length	L	[m]	120
Beam	B	[m]	25
Depth	D	[m]	10
Design for changeability level	DFC	[-]	[0 1 2]

As seen in table 9.1, in addition to specifying the main dimensions of the platform vessel also its design for changeability (DfC) level is stated. The DfC level affects the time and cost associated with performing a change, as increasing the DfC level reduced the time and cost of changing.

In contrast to DfC levels 1 and 2, DfC level 0 represents a *robust* vessel where no design effort has been put on preparing the vessel to physically adapt its form and/or function. Contrary, DfC level 1 can be obtained by e.g. strengthening the deck and DfC level 2 can be obtained by having a modular design (ref. table 4.2 in section 4.2). Note that DfC level 0 does not state that the vessel cannot change, it rather implies that it is expensive to change. Table 9.2 presents the reduction in the switching cost by different levels of changeability. As seen, for a vessel with DfC level 2, it is assumed that the switching cost has a 30% reduction compared to the vessel with DfC level 0. Further, table 9.2 also states the time uses on performing a switch.

Table 9.2: Changeability Cost and Time Matrix. ACC = accommodation, MC = main crane, LWI = light well intervention, ROV = remotely operated vehicles, PC = cable laying, MP = Moonpool

DFC level	ACC	MC	LWI	ROV	PC	MP	Switch time [days]
0	-	-	-	-	-	-	70
1	0.1	0.1	0.1	0.1	0.1	0.1	30
2	0.3	0.3	0.3	0.3	0.3	0.3	20

As seen in table 9.3, while none of the fixed design parameters are decision variables, most of the flexible design parameters are. The flexible design parameters that are not decision variables are dependent on the decision variables

Table 9.3: Illustrative case (discretised) flexible design state variables

Design state variable	Abbr.	Units	Values	Variable type
Accommodation	ACC	persons	[50,250,400]	**Decision Variables**
Main crane capacity	MC	tonnes	[0, 400,800]	
Light well intervention	LWI	tonnes	[0,300,600]	
Remotely operated vehicle	ROV	[-]	[No, Yes]	
Cable laying equipment	PC	[-]	[No, Yes]	
Moonpool	MP	[-]	[No, Yes]	
Deck Area	DA	[m]		**Not decision variables**
Weight	W	[tonnes]		
GM	gm	[m]		

Enumerating all combinations of the design variables gives 216 unique design configurations, some of which are not feasible. In the modelling procedure, the infeasible designs are excluded from the design space by imposing constraints based on knowledge of feasible design solutions. These constraints are: **Physical feasibility**, requiring only feasible design configurations and the available deck area to be greater or equal to 0. **Stability criterion**, requiring the metacentric height (GM) is greater or equal to 0.15 m. **Freeboard criterion**, requiring the freeboard (F) to be above 1.5 m. Imposing these constraints reduced the number of unique design state configurations for the initial system configurations to 12. Reducing the design space is crucial for reducing the course of dimensionality in the model.

Two initial OCV platform designs are considered in the case, each modelled with three levels of changeability. This results in six designs to analyse in total, all of which are presented in table 9.4. Platform design nr. I represent the high-spec version of the vessel. Platform design nr. II represents the low-spec version of the vessel.

Table 9.4: Spesifying the design configuration for the six vessels analysed

Platform design	Vessel ID	DfC level	ACC	MC	LWI	ROV	PC	MP
I	Vessel 1	0	250	400	0	No	No	No
I	Vessel 2	1	250	400	0	No	No	No
I	Vessel 3	2	250	400	0	No	No	No
II	Vessel 4	0	250	0	0	No	No	No
II	Vessel 5	1	250	0	0	No	No	No
II	Vessel 6	2	250	0	0	No	No	No

Strategy States

The Strategy state represents the shipowner's available strategic decisions . These decisions comprises whether to utilise the vessel in the (I) spot market, operating on one-year contracts, or in the (II) long-term market, operating on three-year contracts. The vessel owner can also after the initial contract is performed, sell the vessel if he finds that most profitable. Note that these three strategic alternatives represent real *on* options.

Mission States

As presented in table 9.5, the Mission state represents the set mission the shipowner can take after the initial contract ends. Note that *layup* is modelled as a mission state.

Table 9.5: Illustrative Case Mission States

Mission	**Abbr.**
Subsea Installation and Construction	OSC
Inspection Maintenance and Repair	IMR
Light Well Intervention	LWI
Field Decommission Support	ODS
Offshore accommodation	ACC
Offshore cable laying	OCL
Offshore platform supply	OPS
Offshore Aquaculture support	OAS
Layup	LU

It is assumed that all these nine missions are available in the market at any time. However, which mission the shipowner undertakes depends on several factors.

- First, there are technical requirements associated with each mission. To undertake a particular mission, the vessel must meet the mission operational requirements specific for each design parameter. These are dependent on the general *requirement state* in the market. Thus, an increase in the technical requirement imposes constraints on which contracts the vessel can undertake.

- Secondly, even if the vessel is able to take the mission, it competes for the contract on similar terms as all other players in the market. Thus, the probability for winning a contract is dependent on the supply-demand ratio of vessels, which is dependent on the state of the market. In a low market there are an over supply of vessels and the probability of winning a contract is reduced. As the market increases, the demand is high and the probability of winning a contract is higher. Details are in appendix F.2

- Finally, if the shipowner is both able to take several missions, and wins several contracts, he will always select the mission with the highest day rate. The day rate is assumed to be normal distributed with a mean and standard deviation dependent on the market state. The rate is also dependent on length of the contract taken, which is a strategic decision. A positive normal distributed drift is also included to represent the long-term trend of rising markets in the North Sea.

Market State and Technical Requirement State

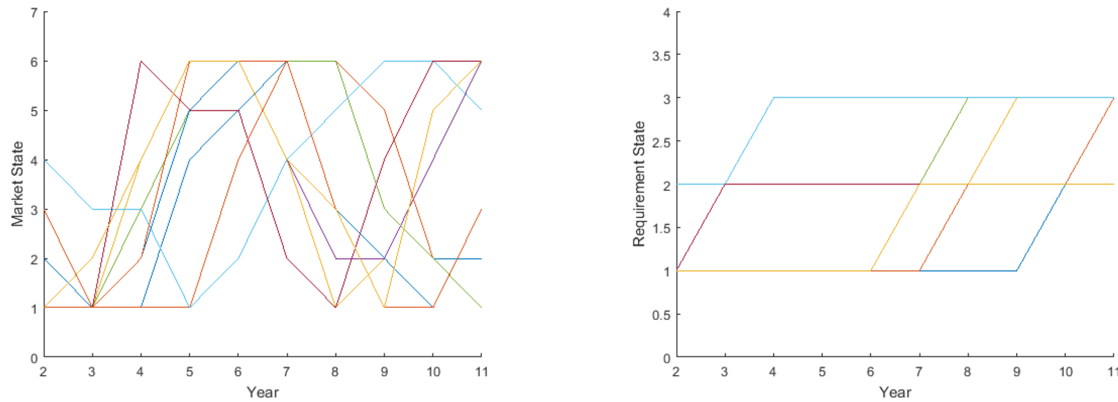
The market state and technical requirement state represents the two major sources of exogenous uncertainty in the illustrative case. While there is also exogenous uncertainty related to the day rates and the probability of winning contracts, these are dependent on state of the market and technical requirements.

Table 9.6: Discretisation of Exogenous Information (market and technical) in the Illustrative Case

Exogenous information	**Level**
Market State	[Low -, Low, Medium-low, Medium-high, High, High +]
Technical Requirement state	[Low, Medium, High]

Due to the cyclical nature of the offshore market, the market state is assumed to follow a sinus function with a seven-year period. Some stochastic is added in the period and as drift to make the market state exogenous. Figure 9.1a presents ten sample realisations of the market state. As seen, it is generally a low market state in years 2-4, and a high market state in 5-8. The market is expected to drift upward in the future.

The technical requirement state (TRS) is modelled as a Markov process with three levels: low, medium and high. It is assumed that the requirement state is low when the illustrative case begins. The probability of transition from low to low is 0.7, from low to medium is 0.3, from medium to medium is 0.9, from medium to high is 0.1, and from high to high is 0.1. Thus, if the requirement is increased it is assumed to never be reduced again. Therefore, the technical requirements are modelled with the belief that there will be stronger technical requirements in the future (figure 9.1b).



(a) Market State. 1-6 represents the six discretised market states presented in table 9.6

(b) Technical requirement state. 1-3 represents the three discretised states presented in table 9.6

Figure 9.1: 10 simulations of the market state and technical requirement state. Year 2 represents the first year after the initial 5 year contract ends.

9.3.2 Modelling Decisions

The decision states represent decisions the shipowner can do to alter the state of the system. Depending on the current state of the system, a decision can be made at the beginning of each year. The decision made influences which state the system will go into (figure 9.2). The manager can decide (i) the design configuration (ii) which strategies to follow (i.e short- or long-term contract, and sell) and (iii) which missions to take.

9.3.3 Transition Function

The transiting function, which determines which state the system transits into, is dependent on the current system state, decision made, and exogenous information revealed to the decision maker after the decision is made. The transition function contains one deterministic and one stochastic part. The probability of transitioning between design states and strategy states are deterministic, and fully dependent on the decision made (ref. section 9.3.2). The probability of transitioning between market states and technical requirement states are exogenous information to the decision maker (ref. section 9.3.1), and independent on the decision chosen. The concept behind the transition function is illustrated in figure 9.2.

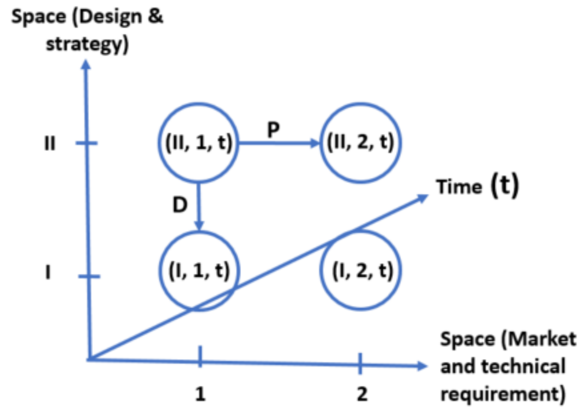


Figure 9.2: Illustration of the transition function in the illustrative case. P = probabilistic transition, D = deterministic transition

9.3.4 Model Flow

Figure 9.3 illustrates the model flow. The shipowner makes all his decisions one year prior to the current contract ending, which are immediately implemented the year after they are made. If the decision is to retrofit the vessel, this will result in a switching time reducing the number of days in operations. If the decision only is about which strategy and mission to take the vessel can immediately start operating. As previously noted, the time spent on switching is only dependent on the level of changeability incorporated into the model. This is further treated in the section to come.

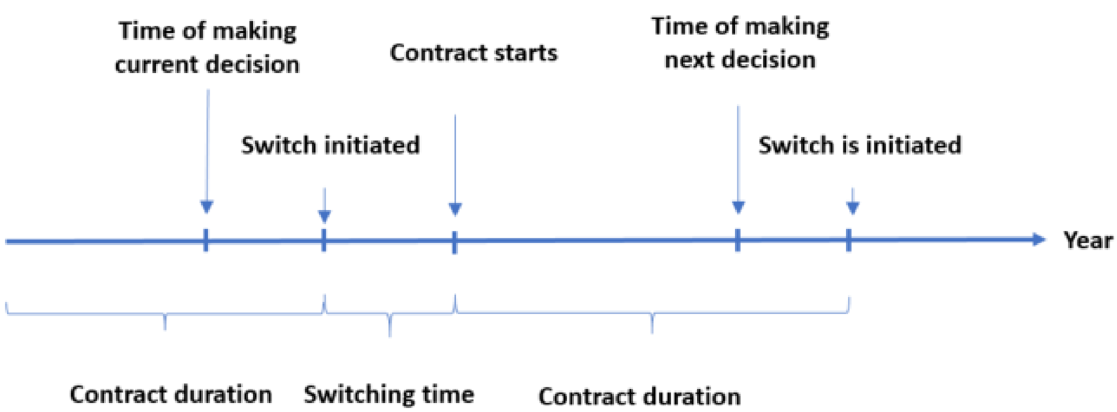


Figure 9.3: Illustration of the model flow.

9.3.5 Objective Function

Based on the knowledge gained from the initialisation phase, the objective should be to find the policy that maximises net present value (NPV) of the vessel, v, over its entire life cycle (t = $[0, 1, 2, ..., T]$). Only monetary value is considered, and assumed to be a factor of the revenues received from operations, subtracted the capital expenditures. The capital expenditure is assumed to only include building costs and switching costs. The following equation illustrates the NPV calculations for a specific vessel, v.

$$NPV_v = Buildingcost_v - \sum_{t \in T} \frac{Revenue_t - Switchingcost_{t,v}}{(1+r)^t} \tag{9.1}$$

In contrary to revenue, the two cost factors are assumed to be independent of time. Both cost and revenues are assumed to incur at the beginning of each time period. The building cost, in addition to the first year's revenue and switching costs are therefore not discounted. Note that a large discount rate, r, reduces the impact of future revenues and costs compared to the initial ones. In general, an NPV greater than zero indicates that the investment is profitable. The discount rate was set equal to the shipowners weighted average cost of capital (WACC) estimated to be 8%[1]. This basic cost structure disregards important expenditures related to operations, voyage and maintenance. This would have been important to include in order to value the vessel exactly.

Estimating building costs

The building cost is estimated using equation 9.2, in which $k^{buildingcost}$ is a scaling constant expressing the cost per lightweight of platform design, set equal to $8[k\$/MT]$[2]. Wls is the

[1] $r_{WACC} = \frac{E}{E+D} r_E + \frac{D}{E+D} r_D$, where D and E is the market value of the shipowner's debt and equity, respectively. Debt-equity ratio is assumed to be 60%. $r_E = 17.4\%$ and $r_D = 2.3\%$ is the equity cost of capital and debt costs of capital, respectively. The calculation is presented in appendix E. This estimated was based on the assumption that the risk of the investment is equivalent to the average market risk of the shipowner's investment, such that the investments cost of capital can be assessed based on the risk of shipowners firm. This assumption holds as the vessel investment is the same line of business as the rest of the shipowner's firm. The second major assumption is that the Dept-Equity ratio is constant which seldom hold as firm's increases their dept to gain advantage of tax shields. The final major assumption is that the market is *perfect*, stating that there are no corporate taxes, agency costs, financial distress. The WACC reflect the overall risk for debt and equity holders. See Berk and DeMarck (2014) for more on this.

[2] Obtained from Rehn et al. (2017b)

lightweight of the platform design without any topside equipment installed , $I(v)$ is the set of topside equipment installed, and $Cost^{DfC}$ is the additional cost to give the vessel a specific degree of changeability. The vessels lightweight is calculated using the scaling constant 0.23 $[kg/m^3]$[3] stating the lightweight of the platform design per length × breath × depth.

$$Buildingcost_v = k^{buildingcost} * wls + \sum_{i \in I(v)} Cost_i^{Install} + Cost^{DfC} \tag{9.2}$$

Estimating revenue

Function 9.3 expresses the revenue for a specific design configuration d_t, at time step t.

$$Revenue_t = (OpDays - time^{switch}_{d_{t-1},d_t}) * \max_{m_t \in M_{t,d_t}} (Rate(m_t)) * sf(s_t) \tag{9.3}$$

where $OpDays$ is the number of days in operation each year (assumed to be 300 days), $time^{switch}_{d_{t-1},d_t}$ is the switching time between vessel configuration d_{t-1} and d_t. d_{t-1} represents the previous design configuration, while d_t represents the current design configuration. If no switch occurred between $t-1$ and t, the switching time is zero. $Rate(m)$ is the day rate for operating contract m. The rate is assumed to be normal distributed with a mean and standard deviation that generally increases with the state of the market. $sf(s_t)$ represents the scaling factor which is dependent on the length of the contract taken (i.e. strategy chosen at time t (s_t). A long-term contract is assumed to have 20% lower rates than a short-term contract. Note that a vessel can only take a single contract per year.

If the vessel is sold, this is counted as revenue. The selling cost is dependent on the state of the market and the building cost. For instance, it the market state is *low (-)* it is assumed that the vessel will not be sold as any other are in need for a vessel when there are few contracts to take. If the market is *low*, the shipowner gets 10% of the building cost, and if the market is *high (+)* the shipowner get 70% of the building cost.

[3]Obtained from Rehn et al. (2017b)

Estimating Switching costs

Equation 9.4 expresses the cost of switching from the previous design configuration, d_{t-1}, to the current d_t, for the specific platform design under consideration v.

$$Switchincost_{t,v} = \sum_{r \in R(d_{t-1})} f_r^{DFC(v)} * Cost_r^{Remove} + \sum_{i \in I(d_t)} f_i^{DFC(v)} * Cost_i^{Install} \tag{9.4}$$

$Cost_r^{Remove}$ is the cost of removing topside equipment r, and $Cost_i^{Install}$ is the cost of purchasing and installing topside equipment i. These numbers are calculated based on the purchase price of the various topside equipment, and factors to account for installation and removal. The numbers are based on reference vessels[4]. $R(d_{t-1})$ and $I(d_t)$ represents the set of topside equipment that needs to be removed (R) from design configuration d_t and installed (I) on design configuration d_t for the design platform v to change from configuration d_1 to d_2. $f_{\cdot}^{DFC}$ is a factor that adjusts the installation cost and removal cost based on the cost of equipment i, and the platform vessels degree of changeability DFC (ref. table 9.2)

9.3.6 Results From the Development Phase

Following the MDP methodology presented in section 8.2: To solve the illustrative case, the Q-learning algorithm was first run for 5 000 000 iterations for each vessel alternative to obtain their life cycle policy. The policy indicated which action to make for each state-time configuration. Secondly, this policy was used as an input in a life cycle simulator to analyse the outcome of the policy. For each vessel alternative, 1000 life cycle simulations was performed. As the policy is a matrix with dimensions 648x10 for base design I and 1512x10 for base design II, the policy is too large to present in its whole. Therefore, an excerpt of the policy for vessel 2 is presented in table 9.7. Remember, vessel 2 represents platform design I with level of changeability 1 (ref. table 9.4).

The policy states which action to take for each state it encounters over its lifetime, represented in table 9.8. As seen, if vessel 2, in year 4, has design configuration 2, operating on a short-term contract in a medium-low (ML) market, with a high technical requirements (H) (i.e. it is in state

[4] I am thankful to Jose Jorge Garcia Agis for providing me with these numbers

nr. 63 of 648), the policy states that the shipowner should exercise action 34. From table 9.8, one sees that this action represents a change to design configuration 12, in addition to take short-term contracts. Retrofitting to design nr. 12 is a large operation, for which the accommodation is increased to 400 persons, and ROV and moonpool are installed. However, going back to table 9.7, one sees that if it rather is year 6, the shipowner should perform action 26, representing a change to design configuration 9, in addition to take long-term contracts. Retrofitting to design nr. 9 only includes increasing the accommodation capacity to 400 persons. Note that year 1 in the table represents the first year a decision must be made, i.e. year 4 in the vessel's life cycle. Thus, year 10 in the table represents year 14 in the vessel's life cycle. Remember, the decision is made one year prior to its execution.

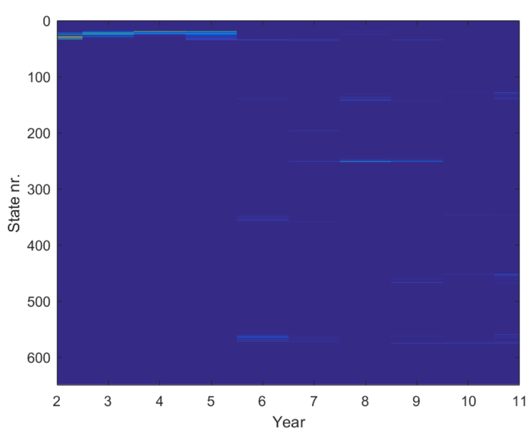
Table 9.7: Excerpt of the policy for vessel 2

State nr.	State Variables					Year									
	Design nr.	Strategy	Market	Requirement		1	2	3	4	5	6	7	8	9	10
60	2	Short	L	H	Action nr.	1	1	3	28	22	29	23	7	10	10
61	2	Short	ML	L		1	16	4	10	5	10	35	5	4	1
62	2	Short	ML	M		1	10	11	10	11	11	5	35	4	4
63	2	Short	ML	H		1	1	1	34	11	26	11	11	10	10
64	2	Short	MH	L		1	4	28	5	5	11	5	5	10	1

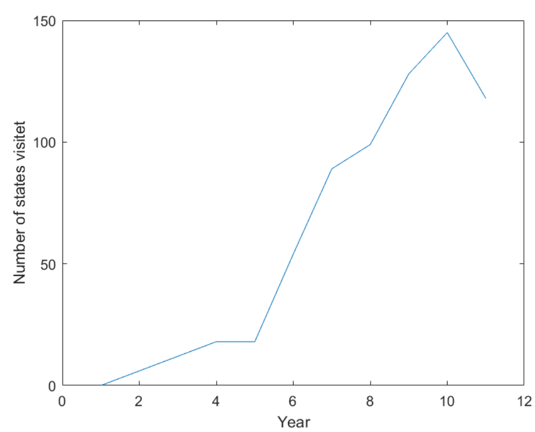
Table 9.8: Presentation of the actions in the policy for vessel 2, presented in table 9.7

Action nr.	Strategy	Design nr.	ACC [persons]	MC [tonnes]	LWI [tonnes]	ROV [-]	PC [-]	MP [-]
1	Short	1	250	400	0	No	No	No
3	Sell	1	250	400	0	No	No	No
4	Short	2	250	400	0	No	No	Yes
5	Long	2	250	400	0	No	No	Yes
7	Short	3	250	400	0	Yes	No	No
10	Short	4	250	400	0	Yes	No	Yes
11	Long	4	250	400	0	Yes	No	Yes
13	Short	5	250	400	300	Yes	No	No
16	Short	6	250	400	300	No	No	Yes
22	Short	8	250	400	300	Yes	No	Yes
23	Long	8	250	400	300	Yes	No	Yes
26	Long	9	400	400	0	No	No	No
28	Short	10	400	400	0	No	No	Yes
29	Long	10	400	400	0	No	No	Yes
33	Sell	11	400	400	0	Yes	No	No
34	Short	12	400	400	0	Yes	No	Yes
35	Long	12	400	400	0	Yes	No	Yes

Following the process presented in section 8.2, the policy obtained from the Q-learning algorithm is used in the life cycle simulation for further analysis. The state entry plot[5] presented in figure 9.4a indicates the likelihood for which vessel 2 is to enter a particular state thought its life cycle. The vessel has never encountered the states with the dark purple colour, the lighter the colour the more times the state has been visited. The figure is quite unreadable because of the vast number of different states the system can encounter, leading most of the figure to be dark purple. As also seen in figure 9.4b[6], most of the 648 possible states are impossible to encounter due to how the market and technological development is modelled, and how the policy is formed. From the figure, on see that the vessel's path from years 2 to 6 is to be expected with a high likelihood. However, after that there is great uncertainty related to how the dynamics will change. However, figure 9.4b not only states the number of alternations the vessel or the shipowner can take, which are deterministic, but also the number of alternations in forced by the state of the market and technology. Note that, in contrast to the tables above, these figures starts from year 2, representing the first year affected by the decisions after the initial contract ends (i.e year 5 in the vessel's life cycle). Thus, year 11 in the figures represents year 15 in the vessel's life cycle. This is how all figures and tables to come are structured.



(a) State entry plot



(b) Numbers of different states visited

Figure 9.4: The state entry plot and a plot over the number of different states visited per time step. Output from the lifecycle simulation (1000 iterations)

Figure 9.5 presents histograms of the life cycle contribution for each of the six designs, and table

[5]Niese and Singer (2014)

[6]Note that figure 9.4b to some extent is equivalent to the filtered outdegree (Ross (2006)), as it calculates the number of possible transitions the system can take in each time step

9.9 present the values for the mean, standard deviation, maximum and minimum. The contribution represents the present value measurement of a system costs and regards accumulated through time. As seen, base design I have in general the best overall performance. This indicate that installing additional crane capacity is beneficial over the system's life cycle. Further, one sees that base design I have a higher life cycle value that base design II. The best vessel over all is vessel 1, followed by vessels 2 and 3. The worst is vessel 4. In addition, one sees that life cycle value for vessels with changeability level 1 are higher than the ones with changeability level 2, however, the difference is negligible. It is striking that vessel 1, the robust solution of based design I, is the one with the highest expected life cycle value. This indicated that one has found a good design for the expected future state that is included in the model. However, also note that vessel 2 has a higher maximum value and a lower minimum value indicating a better configuration to mitigate the vulnerabilities and exploiting the opportunities. The *average number of switches*[7] represents the average number of simulated system changes performed during the vessel's lifetime. It indicates the amount of management direct involvement related to handling uncertainty, for which a higher number indicates more management involvement requires more resources to be committed[8]. This information indicates that there are now correlation between the average number of switches and the changeability level as the model is defined.

Table 9.9: Expected, standard deviation, maximum and minimum value of life cycle contributions [mill. USD] in the life cycle simulation (1000 iterations)

Base	**Vessel**	**Mean**	**Std**	**Max**	**Min**	**Average nr. of switches**
I	Vessel 1	32.4	14.2	90.4	-23.6	1.22
I	Vessel 2	24.5	16.8	93.3	-23.0	2.13
I	Vessel 3	23.0	19.4	82.1	-49.8	1.99
II	Vessel 4	7.5	19.3	85.7	- 66.2	1.79
II	Vessel 5	17.1	19.7	71.5	-44.8	1.73
II	Vessel 6	16.9	19.1	70.1	-60.5	1.89

[7]Referred to as the *horizontal activity level* by Niese and Singer (2014)

[8]This gives insight to the management dimension of changeability.

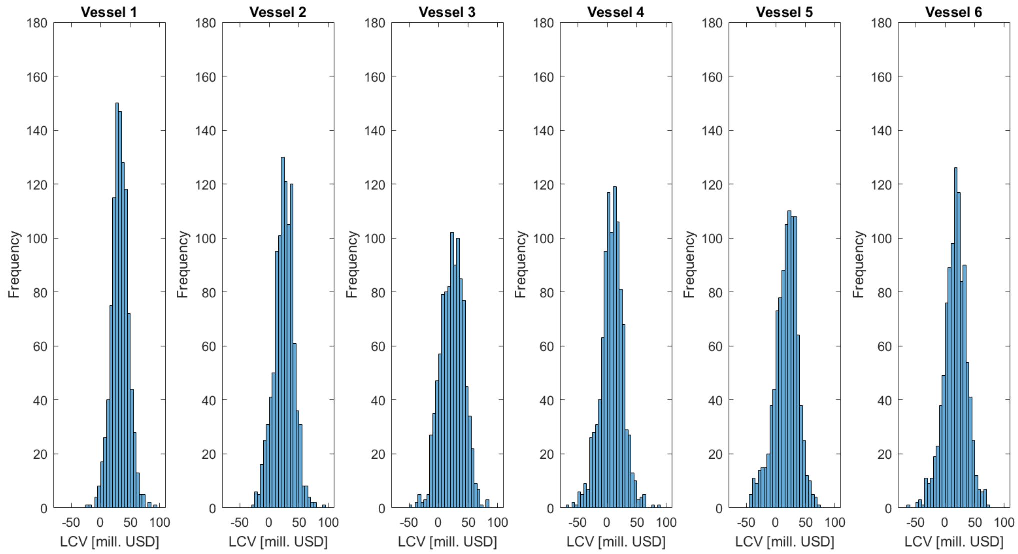
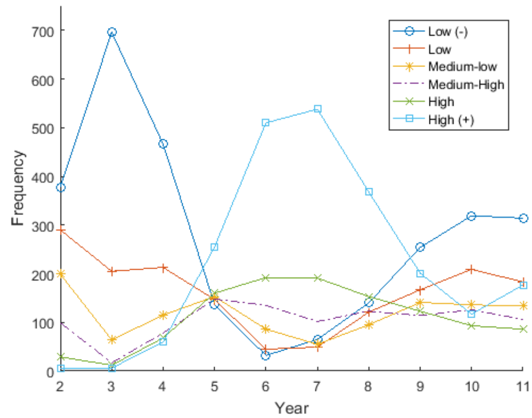
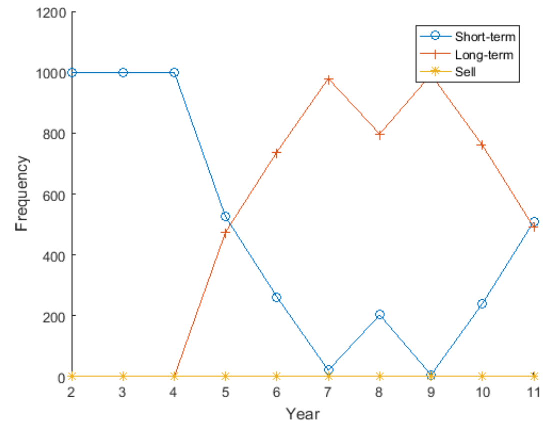


Figure 9.5: Histogram of the life cycle contribution for vessels 1-6 [mill. USD] in the life cycle simulation (1000 iterations)

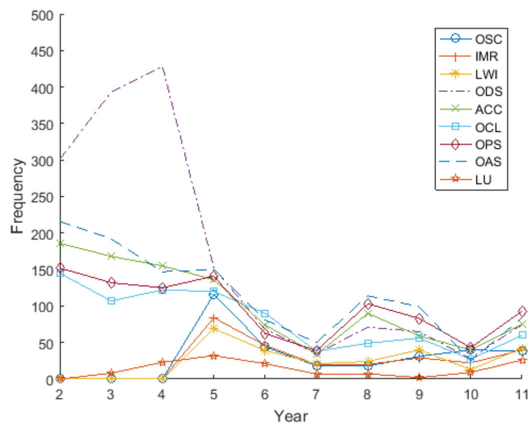
Figure 9.6 presents frequency of occurrences for (a) market state (b) strategy state, (c) mission state and (d) design state for vessel 2. Figure 9.6a presents the cyclical nature of the north sea offshore market, indicating that the shipowner expects a low market when the initial contract ends, and a high market in years 5-9 (i.e. years 8-12 in the vessel's life cycle).This will be the same for all vessels analysed. Figure 9.6b presents that the shipowner initially should take short-term contracts, and then take long-term contracts as the market increases. Most long-term contracts are taken in year 7 when the market usually is at its highest (high (+)), as this works as a hedge for the expected low markets in the end of the analysis. Note that the option to sell the vessel never is exercised. The life cycle strategies for vessels 1-6 are presented in appendix G, showing that the life cycle strategies are more or less similar for all designs. Figure 9.6c presents that the shipowner most often continues on a ODS contract after the initial five years ODS contract ends. Later, OPS, ACC and OAS - the tree missions with the least requirements - usually is taken. This might be because the technical requirements tend to increases in the end of the life cycle, making the more high-tech requiring missions harder to take. The expected increase in technical requirements is in line with figure 9.1b. Figure 9.6d presents which design that most often is switched to for each year. For the first three years after the initial contracts ends (years 2-4),



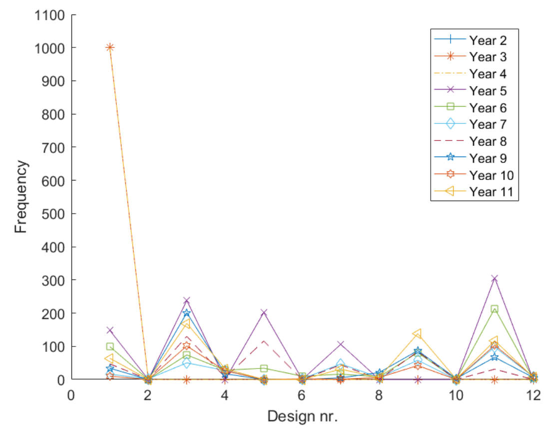
(a) Market State



(b) Strategy State



(c) Mission State

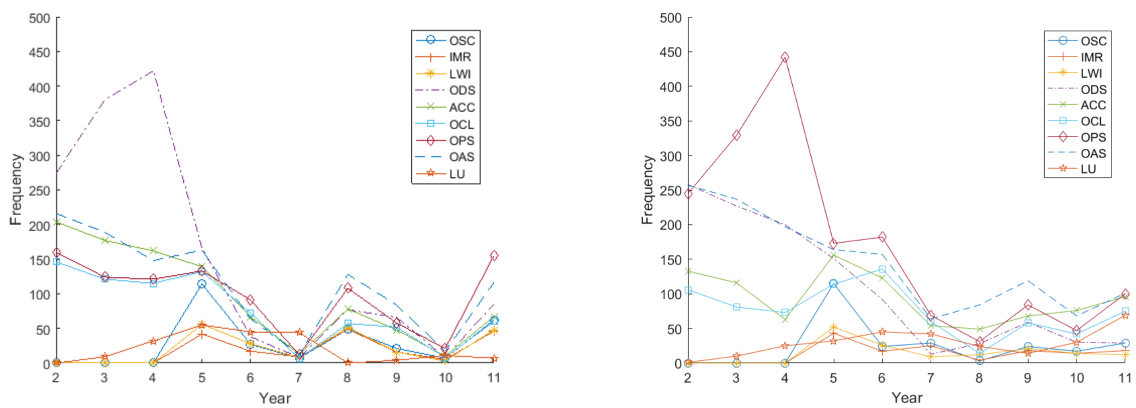


(d) Design State

Figure 9.6: Frequency of occurrences for market state, strategy state, mission state and design state for Vessel 2 in the lifecycle simulation (1000 iterations)

design nr. 1 is always kept. However, as the time passes by, the shipowner usually performs reconfiguration. In declining order, the shipowner most often reconfigured to design nr. 11, 3 and 9. The specifics of these vessel configurations are found in table 9.8. Both designs nr. 11 and 3 has installed ROV capability, but design nr. 11 also has an accommodation capacity of 400 persons, in contrast to the 250-person capacity of design nr. 3. Retrofitting to design nr. 9 only includes increasing accommodation capacity to 400 persons. This could indicate that it might be beneficial to have ROV capacity from the beginning, and that the shipowner also could consider increasing the initial accommodation capacity.

Figure 9.7[9] compares the mission selected for vessels 2 and 4. As known, both vessel 2 and vessel 4 have changeability level 1, however, while vessel 2 is from base design I, vessel 4 is from base design II. Comparing figure 9.7a and figure 9.7b, one sees that while vessel 2 mostly continues with ODS after the initial contract ends, vessel 4 often ends up with taking OPS and OAS contracts. This is probably because vessel 4 has less capabilities installed than vessel 2, and are therefore often forced to take contracts with less technical requirements. These contracts are often associated with a lower reward.



(a) Vessel 2 (b) Vessel 4

Figure 9.7: Frequency of mission selections for vessels 2 and 4

9.4 DSP Phase III & IV: Implementation and Monitoring

From the results presented in the previous section, the shipowner decided to build a vessel with an accommodation capacity of 250 persons, main crane capacity of 400 tonnes, in addition to installing a ROV.

Table 9.10: Summary of design configuration for the chosen vessel

L [m]	B [m]	D [m]	DfC [-]	ACC [persons]	MC [tonnes]	ROV [-]
120	25	10	1	250	400	Yes

Beside the ROV installed, the chosen vessel is similar as vessel alternative 2 presented earlier.

[9]The same figures for all vessel alternatives are presented in appendix G. These figures are the same for vessels with the same base design

However, as the results in the previous section indicated a desire to install ROV capacity over the vessels life cycle, the shipowner decided to install in right away. This increase the number of different missions the shipowner can compete for in the future, especially as the technical requirements are expected to increase. Even though the results section showed indicated a high value of increasing the accommodation capacity to 400 persons, the shipowner decided not to do so in the production phase. Instead, he decided to have the deck structure reinforced for later having the opportunity to add this capacity more cost and time efficient. This correspond to having changeability level 1 in the design. Even though incorporating changeability level 1 increases the building cost, it also reduce the cost and time needed if the accommodation capacity is later installed. Both installing addition ROV capacity and preparing for a further increasing in accommodation capacity represents an active managerial approach for hedging this investment for future uncertainty. The following table summarises the configuration of the chosen vessel.

As the life cycle policy differs for each vessel, the Markov decision process methodology was also run for the chosen vessel alternative. The policy then obtained represent the contingency plan the shipowner is to follow in order to maximise the investment's expected life cycle value. This policy was then used in the life cycle simulation to analyse how the chosen vessel would perform for the given policy.

Table 9.11: Example of one life cycle realisation for chosen vessel alternative

	Year	1	2	3	4	5	6	7	8	9	10
Uncertainty	Market	H	L	L (-)	L(-)	ML	H	H+	H+	H	ML
	Requirement	L	L	L	L	L	L	L	L	M	M
Decision	Decision made	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	No
	Design nr.	1	1	1	1	5	5	5	5	5	5
	Strategy	Short	Short	Short	Short		Long			Long	
	Mission	OAS	OAS	ACC	OAS	OPS	OPS	OPS	ODS	ODS	ODS
Contribution [mill. USD]		1,6	1,9	2,1	2,9	15,3	0,0	0,0	21.0	0,0	0,0

Figure 9.11 presents one lifecycle realisation for the chosen vessel by following the contingency plan (i.e. policy). This figure therefore illustrates how the shipowner would circulate in between the implementation phase and the monitoring phase in the Design-Strategy Planning frame-

work. Note that this table starts in year 1, which represents the first year the shipowner is to take an action (i.e. the 4th year in the vessels lifecycle). As seen in the figure, the shipowner experiences a cyclical market, and a slowly increase in technical requirements. To cope with this dynamic, the policy obtain from the Q-learning algorithm states that the shipowner should start off by keeping the initial design configuration (design nr. 1), before changing to design nr. 5 in year 5. This switch represents increasing the accommodation capacity from 250 persons to 400 persons. Luckily, the shipowner has already prepared for this retrofit by initially reinforcing the deck. This reduce the cost and time needed to perform the switch. Further, the policy states that the shipowner should take short-term contracts in the first four years, before taking long-term contracts for the reminder of the vessel's life cycle. Over its life cycle, the vessel operates a number of different missions, such as offshore aquaculture support (OAS), offshore accommodation (ACC), offshore platform supply (OPS), and offshore decommission support (ODS). In this particular life cycle realisation, the shipowner earned 44.8 [mill. USD]. Note that the contribution is 0 in years 6 and 7, and in years 9 and 10 because the contribution obtain in these years are accumulated to years 5 and 8, respectively.

Table 9.12: Expected, standard deviation, maximum and minimum value of life cycle contributions [mill. USD] in the life cycle simulation (1000 iterations)

Mean [mill. USD]	**Std [mill. USD]**	**Max [mill. USD]**	**Min [mill. USD]**
35.0	16.3	92.4	-18.2

As seen in table 9.12, the chosen vessel design had on average, for 1000 simulations, a life cycle contribution of 35.0 [mill. USD], with a standard deviation of 16.4 [mill. USD], a minimum value of -18.2 [mill. USD] and a maximum value of 92.4 [mill. USD]. Comparing this to the values for the first six vessels analyses presented in table 9.9, it seems like the chosen vessel is in fact a good alternative. It has the highest average life cycle contribution, the highest minimum value (which is good), and the second-best maximum value. It also has the second-best standard deviation (16.3 [mill. USD]), indicating reliable results of the mean value.

Part III - Discussion & Conclusion

Chapter 10

Discussion

10.1 Discussion of Research Contributions

The objective of this thesis was to contribute in developing frameworks and quantitative methods to support uncertainty management in conceptual design of engineering systems, with the focus on offshore vessels.

The thesis did so in four ways. First, by presenting a literature review over aspect related to the complexity and uncertainty affecting engineering systems. The review highlighted that uncertainty is as much related to opportunities as it is to vulnerabilities, and that an active management approach is necessary to mitigate the vulnerabilities and exploit the opportunities. Secondly, by proposing the Value-Aptitude-Design-Strategy (VADS) framework, stating that it is the dynamic relationship between aptitude, design and strategy that contributes to the strategic system's ability to deliver stakeholder value. We propose the term strategic system, comprising a specific design-strategy configuration, as a set of distinct devices used to handle uncertainty. Thirdly, by proposing the Design-Strategy Planning (DSP) framework, guiding the lifelong process of initiating, developing, implementing and monitoring strategic systems. DSP highlights the importance of dealing proactively with uncertainty for which stakeholders incorporate real (*in* and *on*) options. The real *in* options are related to designing for changeability, and the real *on* options are related to managerial strategies. Finally, by presenting and illustrating how a Markov Decision processes (MDP) methodology can be used to support the Design-Strategy planning framework. Together, the DSP-MDP framework represents a comprehensive toolkit for managing value robust strategic systems. The following figure presents how the different aspects of this thesis are interrelated.

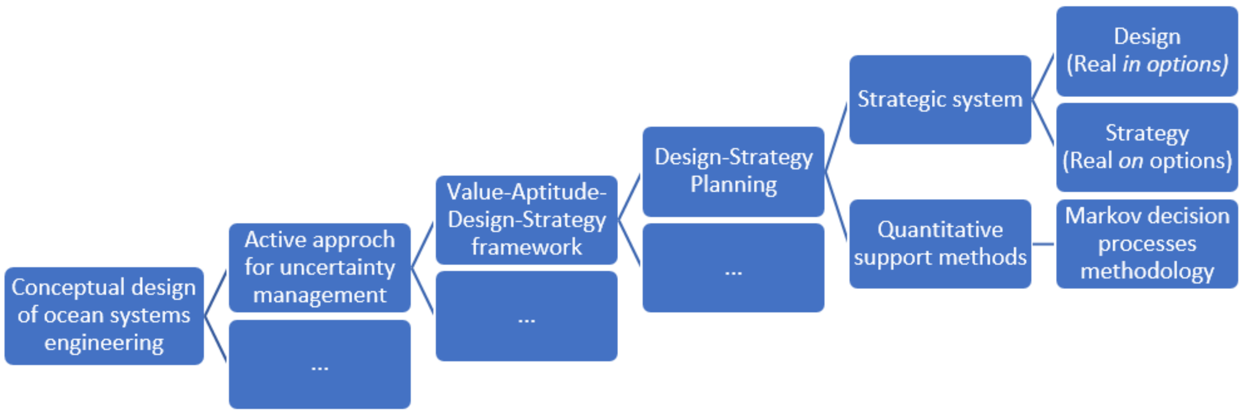


Figure 10.1: Scope of Thesis and Research Contributions

10.1.1 Discussion of the Literature Review

The literature review highlights uncertainty management as an inherently challenging task. Especially the combination of high system complexity, long lifetime, in addition to the rapidly changing commercial and operational environment makes engineering systems suffer under uncertainty. This is supported by the 135 offshore vessels currently in layup on the coast of Norway, as one can assume this is not solely due to the crack in the offshore market, but also an effect magnified of the inability of maritime decision makers to grasp and handle uncertainty. In line with the finding of Strøm and Christensen (2016), the author points out that too many decisions in the maritime industry seems to be based on intuition. As intuition is flawed, a statement especially true for the complex dynamic context of the maritime industry, the author points of the need to continuous developing frameworks supporting maritime decision makers.

Uncertainty management has almost solely focused on preventing the likelihood of technical failures, neglecting other aspects, such as the operational and commercial sources of uncertainty. This has led to robust vessel designs, often with multi-functional capacity, aiming at being reliable regardless of the outcome. This represents an asymmetric view of uncertainty, in which the focus is on the vulnerabilities while the opportunities are forgotten. It even seems like uncertainty often is ignored, as many maritime decision makers might think that uncertainty management is impossible after all. In line with McManus and Hastings (2005), the author states that to fully deal with uncertainty, managers should take an active approach, thereby incorporate measures to both mitigate the vulnerabilities and exploit the opportunities. While the engineering domain recognises incorporation of the lifecycle property changeability (i.e. flexibility, adaptability, robustness and agility) as means for handling uncertainty, the managerial domain recognises strategic flexibility. The proposed VADS and DSP frameworks aims at supporting uncertainty management, by combining the ideas from both the engineering and management literature.

10.1.2 Discussion of the Value-Aptitude-Design-Strategy Framework

The VADS framework extends the traditional system boundary in engineering, from solely focusing on the relationship between design and its surroundings, to include the managerial dimension comprising how stakeholders strategically utilise the design. Thus, while the literature is primarily focusing on architecting value robust physical systems, this thesis emphasises the need for identifying value robust strategic systems.

Enhancing stakeholder *value* is the key objective in the VADS framework. This is in line with Keeney (1992), stating that value is what one care about and should therefore be the driving force behind every decision made. Unfortunately, decision makers have too narrow view on value. To fully grasp the value of an investment, decision makers must recognise its total utility in which both tangible and intangible values are considered. This also serves as a critic to this thesis, as the investment decision presented in the illustrative case was solely evaluated on monetary value. This was mainly because the author has little knowledge of utility theory, and the literature still does not provide clear procedures for how to measure utilities. Crucial factors that are especially difficulty to incorporate are social, personal, political that are hard to quantify. As the industry slowly realises that there is more than just monetary value to consider, such as safety and environmental issues, the author believes that more investments in the future will be evaluated based on a more comprehensive value perspective.

A key aspect of the VADS framework is the recognition of stakeholders' *aptitude*. Even though literature recognise the concept of changeability and lifecycle strategies for managing uncertainty, it often fails to recognise their dynamic interplay and stakeholders' ability to utilise it. As many decisions are one-of-a-kind, decision-maker lacks specific experience with taking them, thereby drastically affecting their ability to take solid decisions. Without the ability to recognise the emerging vulnerabilities and opportunities, without being aware of strategic options in the design and/or strategy, without the ability to select the best course of action, or having the necessary resources to do so, stakeholders fail to manage the system. If that is the case, even the most flexible system and best strategies fail to be successful. Further, if recognises, stakeholders' aptitude is often seen as a constraint for the decision problem. However, aptitude should rather be considered as a part of the solution to find. One of the basic questions to be answered is: what do my organisation need of money, experience, knowledge, etc. to best be prepared to handle the dynamic context and needs, and can it be obtained?

In the VADS framework, the *design* represents the physical aspect of the strategic system. Supported by literature, this thesis recognises designing for changeability as a valuable approach handling uncertainty by enabling the system to alter its form, function and/or operations. While a change in form and functions are direly related to alterations in the physical system (e.g. vessel), changes in the operations are related to the manager's operational strategies. Incorporating robustness serves as a passive approach for handling uncertainty, while flexibility, adaptability and agility are relating to the change in system form, serving as an active approach. So far, flexibility has been the main topic related to changeability in the literature. However, incorporating flexibility is not enough. To stay successful in rapidly changing context and needs, systems need the ability rapidly and cost efficiently change. Stakeholders should therefore to a larger extent focus on incorporating *agility*. Quick response in all levels of the organisation is essential to stay competitive in a highly dynamic business environment, in which slow movers are exposed to the entire downside of uncertainty, but is seldom able to take advantage of the upside. Thus, it is not only necessary to focus on the agility in the physical system, but also how effective the organisation can utilise it.

The VADS framework recognises the stakeholder's role of managing the design through its lifetime using strategies to alter its response to changing context and needs. It is an important dynamic interplay between design and strategy (i.e. the strategic system), as an active manager needs changeability to strategically meet changes in context and needs. Developing lifecycle strategies should be recognised as an ongoing process, in which managers constantly search for new ways to gain competitive advantage. Strategic plans should be incorporated in all levels of the organisation, and aligned towards the same objectives. It is essential to understand that having an active approach requires more management involvement. In contrast to a flexible design, a robust design is characterised by its ability to withstand changes in context and needs without a lot of managerial involvements. To reduce the need for managerial involvement, one can invest in a more adaptable design which changes itself. However, this comes with a high upfront cost and is often difficult to do in practice.

10.1.3 Discussion of Design-Strategy Planning

Throughout the project it became evident that the key for successful uncertainty management is not only the quantitative tools supporting the decision maker, but also the frameworks in which they are within. Based on this, the author decided to create the Design-Strategy Planning framework, building on the VADS principles.

In contrast to the traditional approaches for uncertainty management, this framework recognises that the future cannot accurately be foreseen. DSP highlights the importance of dealing proactively with this uncertainty by incorporating the idea of planned adaptation, for which stakeholders plans for mitigating future vulnerabilities and exploiting future opportunities by incorporating real (*in* and *on*) options. The real *in* options are related to designing for changeability, and the real *on* options are related to managerial strategies. Secondly, as these future changes in context and needs are uncertain, the contingency plan only commits some actions in the design phase, while others are prepared in the response to various trigger information. To do so, DSP incorporates a monitoring system to locate trigger situations which require response. The type of response is pre-defined in the contingency plan. The contingency plan must be adaptable to efficiently cope with the range of scenarios that might occur. This stands in contrast to the current practice, as the literature often only focuses on the value of the flexibility itself, disregarding the fact that the organisation must plan for the adaptation and have the ability to execute it.

Starting to recognise the managerial dimension might be a complicating process for engineers, as engineers traditionally only have considered the technical aspects. A key is therefore information sharing between the designers, engineers, owners, operators and analysts, with the goal of ending up with a complete picture on the commercial, operational and technical aspects of the problem. To do so, the owners must share their objectives, articulate what they value and their aptitude. The operators must share their technical and operational experience, the analysts must share their projections about the future, and the designers/engineers must share their knowledge about the physical system and what design solutions that are technically feasible and practical.

10.1.4 Discussion of the Markov Decision Processes Methodology

One of the key objectives of this thesis was to contribute in developing quantitative methods to support uncertainty management of engineering systems. The author therefore decided to propose Markov decision processes methodology, adapted from Niese and Singer (2014), to support the DSP framework.

A key benefit is that this methodology can capture the dynamic interaction between the changeable system designs and managerial strategies. With great flexibility, the framework includes both decisions related to the physical design (i.e. real *in* options) and stakeholder decisions (i.e. real *on* options), giving an extensive insight into the decision problem. This stands as major benefits with MDP as a quantitative tool for supporting DSP as it is able to capture the fact that managers use changeability to alter the system response to uncertainty.

Backward dynamic programming (BDP) is recognised as the standard form of solving MDP. Due to the number of disadvantages associated with this solution method, such as the course of dimensionality and the course of modelling, the author chose to use Q-learning, one of the basic methods of approximate dynamic programming, instead. In general, approximated dynamic Programming (ADP) stands as a powerful solution method able to cope with many of the drawback of BDP, thus more applicable real, complex problems. Particularly, the author is fond of the fact that one gets rid of the need to have probability transition functions, as Q-learning rather uses sample paths. Compared to BDP, a drawback with ADP is that it does not output the optimal policy, rather an approximation. It therefore must be used with caution. However, the author argues that the solutions always will be based on a set of weak assumptions and simplifications, such that the optimal policy is in reality just an approximation. Thus, if the ADP satisfactory approximated the real problem, it could in fact be more confident in the approximation.

Despite modelling flexibility, there is still a trade-off between the realism of the model and its complexity. The methodology turns out to be a black box, for which it is hard to interpret the results. As a policy is based on the knowledge of millions of lifecycle iterations, it is hard, if not impossible, to fully understand why certain decisions are chosen to be incorporated into the policy. Thus, trust in the generic model and the input parameters are of high importance to trust the output results. Unfortunately, due to the complexity associated with ocean engineering systems, it is difficult to make trustworthy models, capturing the relevant aspects of the system, providing stakeholders with results they believe in. Uncertainty related to the model validity could in fact make the decision harder to make.

In order to perform solid analysis, one needs extensive insight into the problem in addition to the fact that MDP requires experience to be applied. While this thesis has highlighted the drawbacks of forecasting, the MDP methodology still needs forecast data as input. As this input is highly uncertain, what is then the point of making a detailed policy? This is probably one of the greatest drawbacks of using MDP in the maritime industry. If MDP is used in other sectors, like in finance where stochastic processes to a larger extent is able to accurately predict the future MDP has great value, however, in the maritime industry this is not the case, and the application of the policy itself limited.

10.1.5 Discussion of the Illustrative Case

In relation to the illustrative case, there are a myriad of other aspects to discuss. One could for instance probably write an entire thesis solely focusing on the invalidity of the assumptions. However, the author chooses not to discuss the underlying assumptions as the objective was not to make the case as realistic as possible.

The purpose of the illustrative case was two-folded. First, it served as an illustration of the application of DSP and to make the ideas of the process more understandable, doing so by illustrating the initialisation, developing, implementing and monitoring phase. Secondly, it served as an illustration of the use of Markov decision processes. Thus, the author believes, and hopes, that the objective of the illustrative case is met.

However, one aspect should be highlighted: From the results, the policy generated and the overall trends in the strategic decisions seem to be valid. However, when it seems odd that the vessel 1, the robust alternative of platform designs I, was identified as the solution with the highest value as one could expect the more changeable options (e.g. vessels 2 and 3) to be more able to adapt to the dynamics in the model. Further, it is also odd that there are no logical patters indicating the value of incorporating different levels of changeability. One could expect the designs with changeability level 2 to be more valuable than the design with changeability level 1, and the design with changeability level 1 to be more valuable the robust design. However, this is not the case, and it is hard to understand why. This highlights one of the key difficulties with the ADP method. Its complexity, especially the temporal aspect and the tremendous number of iterations, makes it hard to understand the output of the model, and to find mistakes if there are any. This is probably also the case for more experiences analysts the author.

10.2 End Discussion

This thesis attempted to make a holistic quantitative model, capturing both the operational and functional domain of changeability. This extended previous work on this field, which mostly has considered once at the time. While real options analysis has centred around the strategic decision (i.e. operational domain), Epoch-Era analysis has focused on the physical domain of changeability (i.e. the functional domain). However, the author asks whether this actually solves the problem.

A challenge with many quantitative methods, such as Markov decision processes, is that they are inherently advances and found hard to apply for practitioners without in-depth knowledge of the method. It is essential to remember that a quantitative model always will remain as just a model of the real-world problem, and therefore just a simplification. One could believe that the higher the model fidelity the higher the model volatility, however, increasing model fidelity often leads to a higher need on assumptions. Thus, even though the model might end up with more detailed results, this is in fact not produce any more real insight. This is a fundamental aspect of quantitative analysis, that often is forgotten. Further, to end up with a conclusion recording the real problem one must interpret the model conclusions. This highlights the need for a human-model interaction. In line with the conclusion of Whitecotton et al. (1998), one needs a combined approach, for which the model objective information obtained from the model is combined with the decision maker(s) intuition and information outside the scope of the model to end up with a conclusion. Such a combined approach has the potential for being the most effective Simon (1987)

In relations to this, in order to get logical results one need reliable data. This is a key challenge with every quantitative tool attempting to model the real problem as realistic as possible, as there seldom are reliable data to obtain. For instance, how much does it cost to change accommodation from 100 people to 400 people, and how much time does it take? As this information is vital for the analysis, but cannot yet be obtained, on can never trust the model output. Further, while the literature, and the author himself, encourage more analysis to incorporate social, personal and political factors into the model, there are currently no procedures for doing so, especially when the analysis is for engineering systems operating over two decades. One could ask whether these analyses are after all useful. Because, as it is impossible capture all aspects of the problem, it is more likely than not, the future will be different than the model foresees.

However, most of the value of performing such analysis is not necessarily in the outputs itself, rather the process of identifying and modelling the problem. This process forces the decision makers to focus on what is their objectives are, what their major sources of uncertainty are, what their aptitude are, what their strategies are, etc. Thus, despite stating that it is too complex to model offshore cases with the adequate validity to base the decisions solely on it, it might still give insight useful to consider when making such investment decisions. However, rather than trying to create a holistic model that captures all the aspects of the real problem, one strategy should rather be to divide the problem into parts, thereafter solving them with adequate solution methods.

In general, a fundamental issue with analysis engineering systems is their long lifetime that stretches over decades. This make is difficult to evaluate the impact of early design decisions. The authors have not seen any relevant studies which have tracked the impact of such measures, making it difficult to claim the benefit of incorporating expensive measures for handling uncertainty in design. This stands as a key difficulty with designing for changeability, as while the implementation cost is high, the benefit is highly speculative and, at its best, has a long payback period.

The amount of information currently available for decision-makers might seem overwhelming, and new methodologies just enhance this overload. Not all this information is to the same degree relevant, and a key aspect of a decision-making process is the selection of which information to consider, to which degree each piece of selected information should weight, and how this is used to decide. Supported by Forrester (1977), the author states that the difference between a good manager and a bad manager lies in this point. Therefore, a key dilemma in developing new methodologies is that even though the results are valid and manager is aware of the results, he might choose not to consider it at all.

Chapter 11

Conclusion & Further Work

11.1 Conclusion

This thesis contributes to the research by developing frameworks and quantitative methods to support uncertainty management in engineering systems, focusing on offshore vessels. The proposed Value-Aptitude-Design-Strategy framework gives important insight into the dynamic interplay between stakeholder's aptitude, the design's configuration and stakeholder's strategy, and how these factors contribute to the strategic system's ability to deliver stakeholder value. While the literature is primarily focusing on architecting value robust physical systems, this thesis emphasises the need for identifying value robust strategic systems. The proposed Design-Strategy Planning (DSP) framework serves to support the process of developing, implementing and monitoring strategic systems, with the means of handling uncertainty. DSP is a lifelong process, which should be initiated in the conceptual design stage for engineering systems. Supported by the Markov decision processes methodology, DSP represents a comprehensive decision analysis framework.

While this thesis attempted to make a holistic quantitative model to handle uncertainty, that capture both the operational and functional domain of changeability, the author must ask whether this actually solves the problem. It seems that such as holistic model just ends up becoming too complex to make valid results. However, most of the value of performing such analysis is not necessarily in the outputs itself, rather the process of identifying and modelling the problem.

Because such a model forces the decision makers to focus on what their objectives are, what their major sources of uncertainty are, what their aptitude are, what their strategies are, etc. The author therefore highlights the need to continuous developing frameworks to support the inherent challenging task of handling uncertainty.

The knowledge from this thesis can be important in life cycle management of high-value, complex, engineering systems, with long lifetime, facing high degree of exogenous uncertainty. Hopefully the proposed Value-Aptitude-Design-Strategy framework, Design-Strategy Planning and the Markov decision process methodology will give valuable insight that enables maritime decision makers to better handle uncertainty.

11.2 Further Work

This thesis emphasises the importance of continuing developing frameworks and quantitative methods to support uncertainty management of engineering systems. To keep developing the proposed frameworks, further research should collaborate with industry partners, especially focusing on finding which questions to answer in every phase of Design-Strategy Planning . Examples of questions of interest are: How is the strategic planning process performed today? Which aspects of uncertainty are the most important to consider? What strategic decisions has previously the largest impact? In general, academia should to a large extent collaborate with the industry, as it is the industry that in the end can determine whether the proposed methods are applicable or not. Further, the proposed VADS and Design-Strategy Planning could be compared with other similar concepts, to determine their strengths and weaknesses for different problems and analytical situations. The author encourages researches to focus their effort on developing and improving one single planning approach, and building up a more detailed description on how the process should be followed.

DSP is a framework that can be supported by a wide range of different analytical tools. Inspired by the work of Cardin et al. (2013), future work could identify which decision-support tools that would be most applicable. The author especially encourages future research to (I) identify which sources of uncertainty that have the largest impact in different decision problems and what their probability are (II) how these bests are to be quantitative modeled. Further, there are still a lot to be done in the concept of utility theory. So, future researches are encouraged to better understand what stakeholders value, and how to build utility functions. Both in relations to the modelling of uncertainty and utility, the author states that future research should try to make simple models that are easy to implementation, preferably plug-and-play models. Too often research ends up presenting complicated formulas that are impossible to apply on real engineering problems.

The author did not compare the MDP methodology to other quantitative methods for analysing changeability, such as Epoch-Era analysis and Real option analysis. A possibility for future work can be to make a solid comparison on the strengths and weaknesses of each method for analysis changeability, to get a better understanding for which problems each method is most useful. Further, most of the work on changeability so far has been limited in valuing the impact on a single/few design-strategy configuration(s). The author encourages more research to dive into more complex, realistic problems in which there are a myriad of possible options, and not necessarily a well-defined alternative.

Two issues should be the focused on in relations to the Markov decision support methodology. First, the MDP community has not yet settled on a notational form. To further strengthen this field, the author encourages a collaborative effort to agree on one form. This would make it easier to communicate and spread knowledge, especially for practitioners new to this field. Secondly, most school books on MDP only concern infinite horizon problems. However, due to the non-stationary associated with the lifecycle of engineering systems, maritime practitioners should focus on developing methods that incorporates the aspect of time.

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Appendix A

Pre-project Report

Background

The primary objective in conceptual vessel design is to identify value robust solutions (Browning, 2005; Gaspar et al., 2016), that is, vessels able to deliver high value to key stakeholders over its entire lifecycle (Ross and Rhodes, 2008b). Unfortunately, due to the long lifetime, high system complexity (Gaspar et al., 2012) and exogenous uncertainties (Erikstad and Rehn, 2015; Agis et al., 2016) it is difficult, if not impossible, to identify which solutions that are in fact value robust, as the operating context, stakeholder's needs, and even the design changes over time (Ross and Rhodes, 2008b; McManus et al., 2007). Luckily, uncertainty can be managed and it is starting to be recognized as a key for developing vessels that are able to both mitigate the vulnerabilities and exploite the opportunities (McManus and Hastings, 2005). In this regard, Erikstad and Rehn (2015) state that there is still a need for quantitative methods to support uncertainty management in the maritime industry.

Primary Objective

The primary objective of this thesis is to investigate how exogenous uncertainty should be managed for ocean engineering systems, and developing frameworks and quantitative methods to support this process.

Scope of Work

The candidate should presumably cover the following main points:

- Present the concept of ocean engineering systems, and the complexity and uncertainty related to these systems. Focus on how uncertainty can be managed.
- Present '-ilities' as life cycle properties for architecting value robust systems. Focus on changeability.
- Present the topic of lifecycle strategies for handling uncertainty.
- Present the relationship between changeability and lifecycle strategies.
- Present and discuss Markov Decision Processes (MDP) as a quantitative method able to identify value robust solutions.
- Present a illustrative case from offshore vessel conceptual design, where scenario planning and different strategies of operations of offshore vessel is discussed and quantitatively assessed.
- Apply MDP on the presented case to identify value robust solutions.

Modus Operandi

Professor Bjørn Egil Asbjørnslett will be the supervisor at NTNU. The work shall follow the NTNU guidelines for Master thesis work. The workload shall correspond to 30 credits.

Bjørn Egil Asbjørnslett
Professor/ Main Supervisor

Appendix B

Implications for Naval Architecture Education

The objective of this note is to provide some of my thoughts on how the department of Marine technology (IMT) could draw knowledge from my work presented in my project and master's thesis.

The goal of my works has been on learning frameworks and quantitative methods to support decision making and uncertainty management related to ocean engineering systems (ES), focusing on the conceptual design phase. I strongly believe in this this topic because it is evident that too many decisions in the maritime industry still is based on gut-feeling (i.e. intuition). As intuition is flawed, every decision-maker should feel more secure about the decision if it were based on a more rational approach. I therefore recognize decision support and uncertainty management as an area in need-for-research, which should motivate the department to have a stronger focus on this key area. Especially TMR4115 – Design Methods – and TMR4135 – Special Vessel Design – are great courses to have a strong focus on this matter.

I will first point of that Markov decision processes (MDP) is a method beneficial to learn for students of naval architecture. As a modelling and solution technique for sequential decision problems, MDP can model and solve problems related to the life cycle of offshore vessels. In general, this gives comparable insight as from the well-known Net present value evaluation, Real options analysis, Monte Carlo simulation and linear optimization (both deterministic and stochastic). However, from my personal experience, MDP enables a more realistic model of the problem. This is especially the case when approximate dynamic programming (ADP) is uses as the solution approach, as this gets writ of the need for having transition probabilities. Further, the key strength is the the Markov decision methodology is able to both includes both decisions related to the physical design (i.e. real in options) and stakeholder decisions (i.e. real on options), giving an extensive insight into the decision problem. Before implementing MDP into classes, the department should encourage more students to investigate this promising fields of research, for instance starting with their project thesis. As the literature is extensive and there is little experience with MDP at NTNU, I encourage students to pair up to collaborate on such a project. The following book is the palace to start:

- Gosavi, a. (2009). Reinforcement Learning: A Tutorial Survey and Recent Advances. INFORMS Journal on Computing, 21(2), 178–192. `https://doi.org/10.1287/ijoc.1080.0305`

- Powell, W. B. (2007). Approximate Dynamic Programming - Solving the Curse of Dimensionality (First). Hoboken, NJ: Wiley.

As stated by the Law of the instrument (Abraham Maslow): *If the only tool one has is a hammer, then everything looks like a nail.* I therefore believe that any naval architect should have a toolkit consisting of many quantitative methods, as each of them have different strengths and weaknesses when applied on different problems. I therefore encourage students with interest in this fields to consider taking the following courses outside IMT:

- TIØ4126 – Optimization and Decision Support for Industrial Business Planning

- TIØ4130 – Optimization Methods with Applications

- TIØ4150 – Industrial Optimization and Decision Support

- TIØ4145 – Corporate Finance

- TIØ4285 – Production- and Network Economics

- TIØ4360 - Advanced Investment Analysis
- TMA2165 – Stochastic Processes
- TMA4285 – Time Series Models

Further, it is essential to understand that decision making is that this is an interdisciplinary field of research. While the major focus at the department still is on the technical aspects of engineering systems, one need to recognise the importance of the operational and commercial aspects on the life cycle success of these systems. To capture all these aspects, students' needs to gain insight from literature related to finance, phycology, strategy, management etc. I consider the following four books to be a suitable place to start:

- de Weck, O. L., Roos, D., & Magee, C. L. (2011). Engineering Systems - Meeting Human Needs in a Complex Technological World. Cambridge, MA: The MIT Press.
- Edwards, W., Miles, R. F., and Winterfeldt, D. V. (2007). Advances in decision analysis: from foundations to applications. Cambridge University Press
- Forrester, J. (1977). Industrial Dynamics. MIT Press, Cambridge. (Ninth). Cambridge, MA: MIT Press.
- Khatri, N. and Ng, H. (2010). The Role of Intuition in Strategic Decision Making. Human relations, 53(1):57–86.
- Lorange, P. (2009). Shipping Strategy - Innovating for Sucess (First). Cambridge, UK: Cambridge University Press.
- Phillips, D. T., Ravindran, A., and Solberg, J. J. (1987). Operations research: principles and practice. Wiley
- Skinner, D. C. (1999). Introduction to decision analysis: a practitioner's guide to improving decision quality. Probabilistic.
- Stopford, M. (2009). Maritime Economics (Third). New York, NY: Routledge.

Appendix C

Illustration of the System Hierarchy for Offshore Construction Vessels

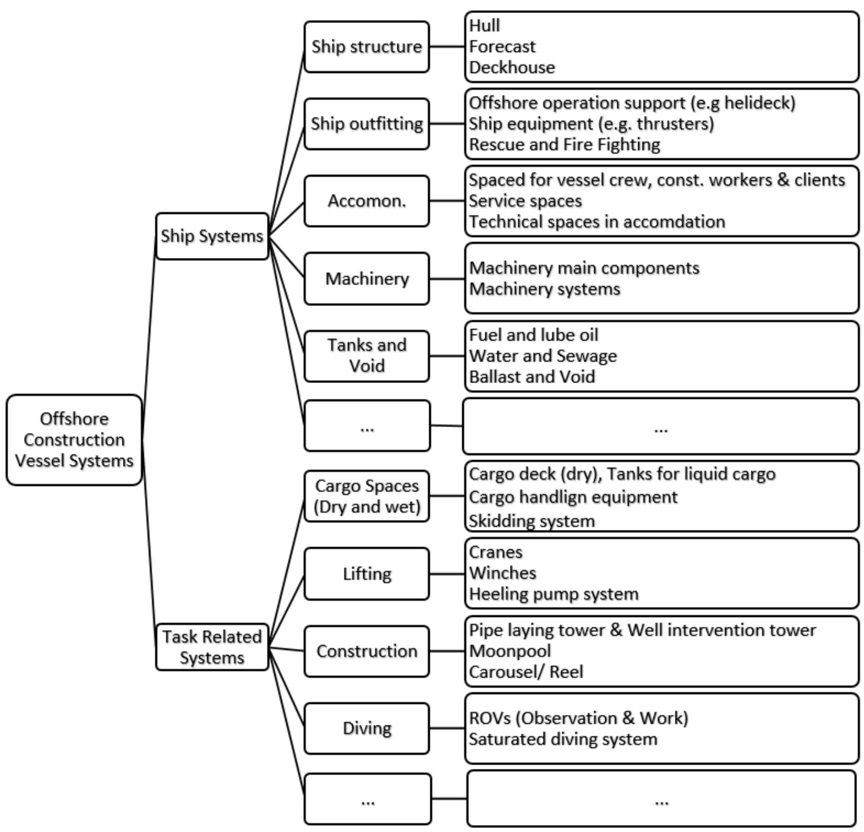


Figure C.1: Illustration of the System Hierarchy for Offshore Construction Vessels (based on (Levander, 2012; Ritchie, 2008; Pettersen, 2015)

Appendix D

Design-Strategy Planning

D.1 Adaptive Airport Strategic Planning

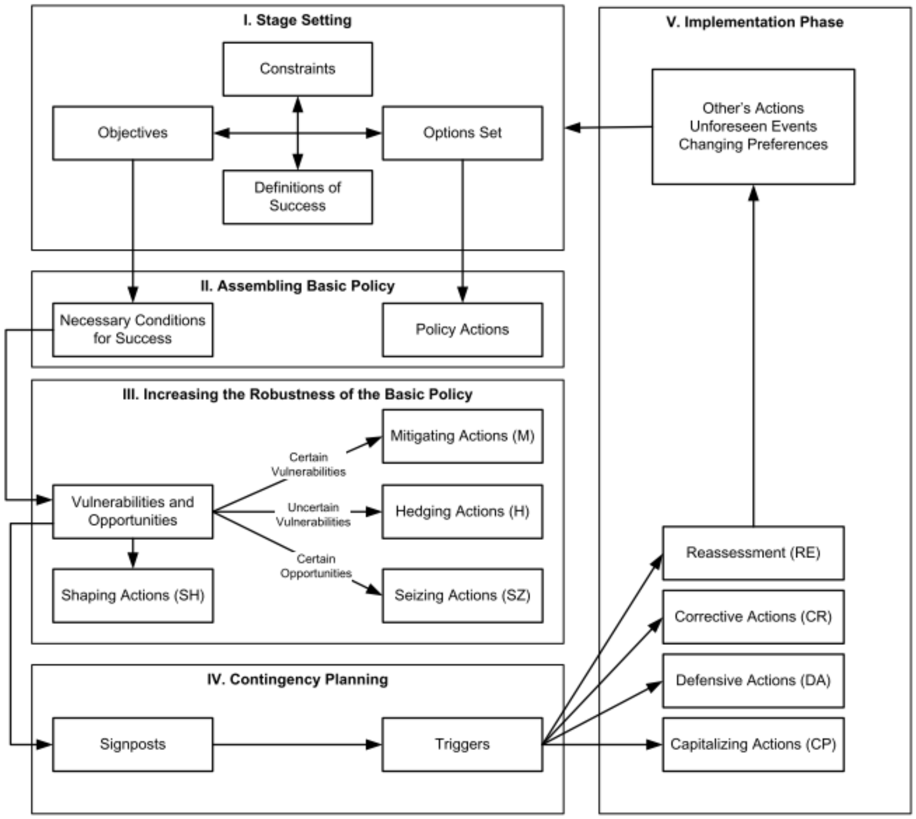


Figure D.1: Adaptive Airport Strategic Planning (Kwakkel et al., 2010)

D.2 Taxonomy for Supporting Design of Flexible Engineering Systems

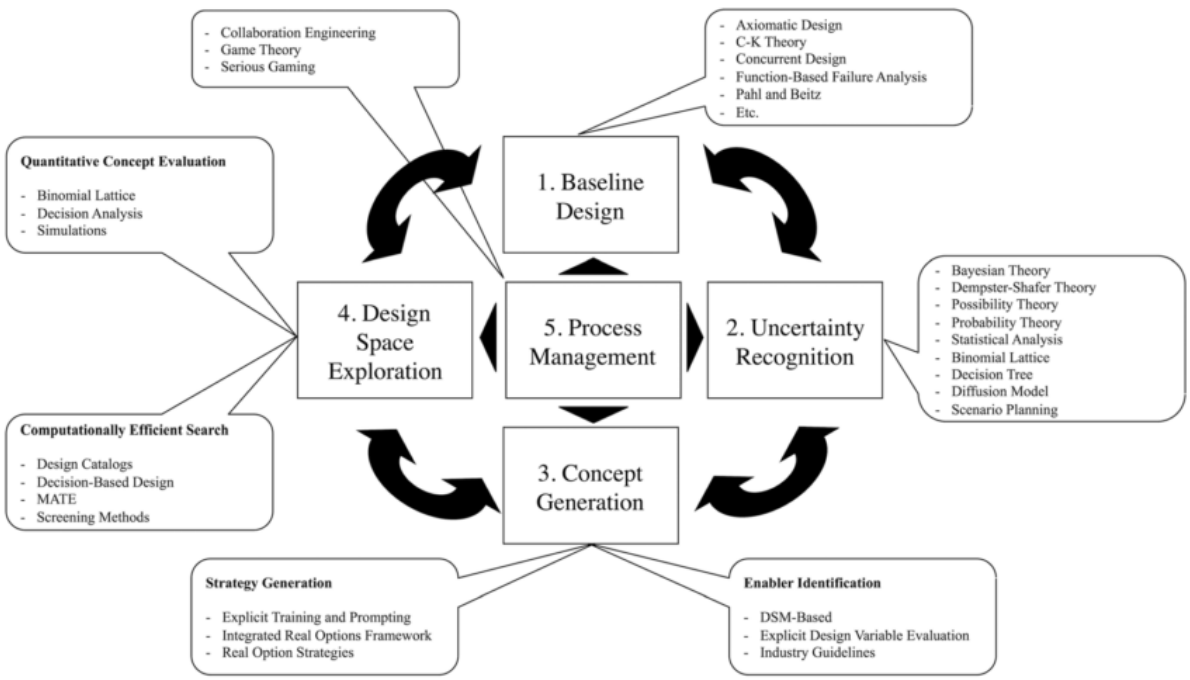


Figure D.2: Figure presenting the five-step taxonomy for designing flexible engineering systems (Cardin et al. (2013))

D.3 Markov Decision Process Methodology for Assessing System Changeability

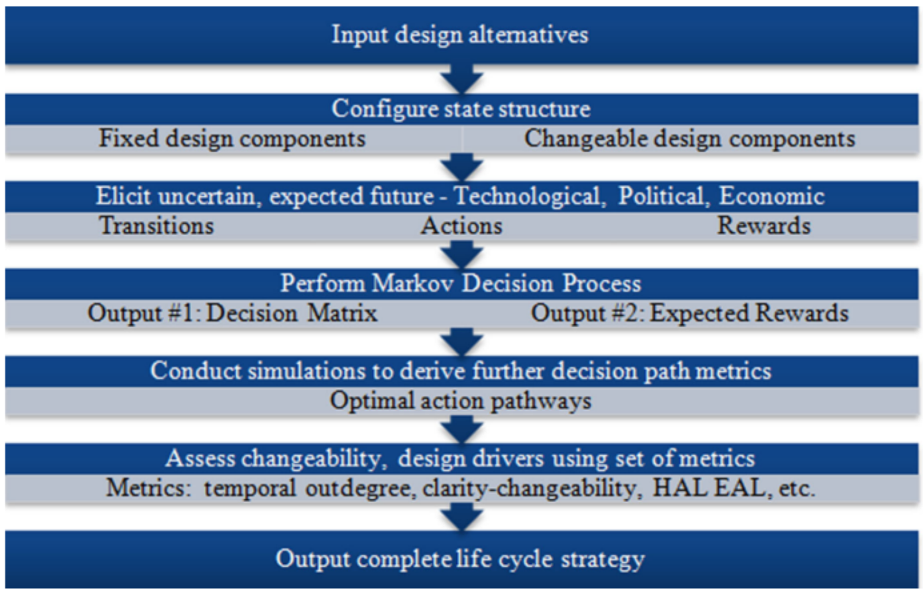


Figure D.3: Markov decision process methodology for assessing changeability (Niese and Singer, 2014)

Appendix E

Weighted Average Cost of Capital (WACC) Calculations

Year	Yearly average, 5 y gov. bond	OSEBX Yearly Return	Excess return
2015	0,99 %	5,3%	4 %
2014	1,82 %	3,4%	2 %
2013	1,93 %	21,9%	20 %
2012	1,59 %	14,7%	13 %
2011	2,56 %	-10,7%	-13 %
2010	2,83 %	18,0%	15 %
2009	3,33 %	70,4%	67 %
2008	4,43 %	-52,8%	-57 %
2007	4,77 %	13,7%	9 %
2006	3,90 %	33,6%	30 %
2005	3,27 %	41,0%	38 %
2004	3,61 %	37,2%	34 %
2003	4,58 %	47,0%	42 %
2002	6,36 %	-30,2%	-37 %
2001	6,31 %	-15,2%	-22 %
2000	6,38 %	12,3%	6 %
Average	3,7%	13,1%	9,4%
Risk free rate	0,94 %		
Expected market return	**10,38 %**		
Cost of capital			
Beta	Risk free rate	Expected market return	Equity Cost of capital
1,74	0,94 %	10,38 %	17,4%
Cost of Debt			
	NIBOR 6M(10.12.2016)	Risk Premium	Debt Cost of Capital
	1,29 %	1,00 %	2,29 %
Market/Company Inputs		**WACC**	**8%**
Corporate tax	-		
Debt	-		
Equity	-		
Debt Ratio	60 %		
Equity Ratio	40 %		

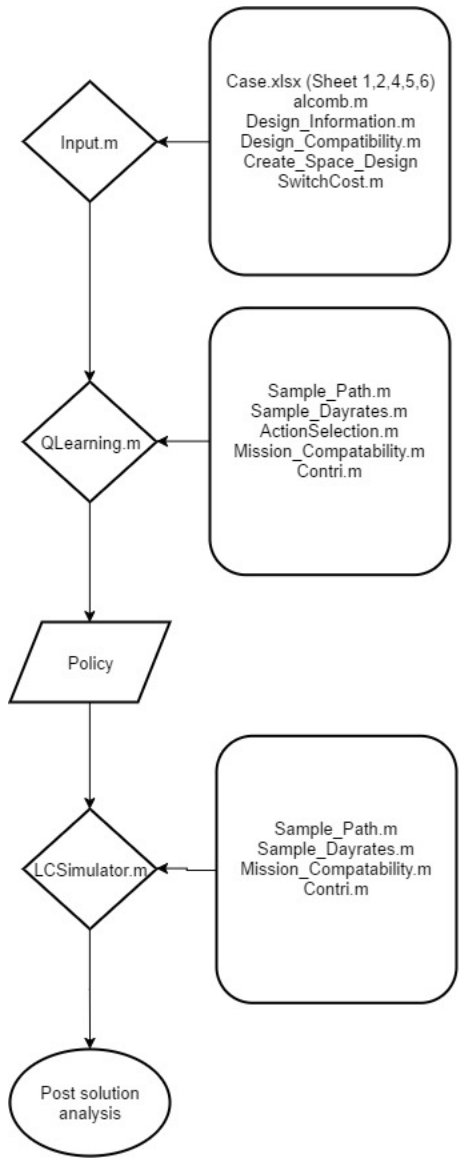
Figure E.1: Weighted Average Cost of Capital (WACC) Calculations (Strøm and Christensen, 2016)

Appendix F

Matlab codes

F.1 Flowchart of Matlab Codes

The following figure presents the flowchart of the matlab codes and excel sheets used to form the Markov decision process methodology. All the codes and sheets are provided in the appendix, each containing a brief description of its use.



F.2 Matlab - Input.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This scrip contains and generates input data to the Q-learning Algorithm
% (QLearning.m) and to Life Cycle Simulator (LCSimulator.m). Most of the
% date is obtained from the excel file "Case.xlsx". The script calls upon
% the functions: "allcomb.m", "Fix_Information." and "Design_Compatibility."
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Obtain Variable Design State Parameters
N_Var_Design = 6;   % Number of variable design state parameters
N_ACC = 3; % Number of variable Accommodation (ACC) parameters
N_MC = 3; % Number of variable Main Crane Capacity (MC) parameters
N_LWI = 3; % Number of variable Light Well Intervention (LWI) parameters
N_ROV = 2; % Number of variable Remotely Operated Vehicles (ROV) parameters
N_PC = 2; % Number of variable Cabel laying equipment (PC) parameters
N_MP = 2; % Number of variable Moonpool (MP) parameters

%% Create Variable Design State Sets
Set_ACC = 1:N_ACC;    % Set ACC
Set_MC = 1:N_MC;      % Set MC
Set_LWI = 1:N_LWI;    % Set LWI
Set_ROV = 1:N_ROV;    % Set ROV
Set_PC = 1:N_PC;      % Set PC
Set_MP = 1:N_MP;      % Set MP

%% Fixed Design State Parameters
N_Fix_Design = 4;   % Number of fixed design state parameters
Length = 120;       % [m]
Beam = 25;          % [m]
Depth = 10;         % [m]
DfC = [0 1 2]; % Degree of Changeability (DfC) [-]

%% Specify Starting State for Design
Start_Design = [2 2 1 1 1 1]; % Representing base design (I)
%Start_Design = [2 1 1 1 1 1]; % Representing base design (II)
```

```
%% General information
Lifetime = 10; % Length [Years] of lifetime  considered
N_Design = length(DfC); % Number of vessels analysed
time_short = 1; % Length [Years] of short-term contract
time_long = 3; % Length [Years] of long-term contract
N_Space_Market = 6; % Number of possible market states to encounter
N_Space_Mission = 9; % Number of possible missions states to take
N_Strategy = 3; % Number of possible strategies
OpDays = 300; % Days in operation per year
SDays = [70 30 20]; % Days to perform switch based on DfC level
disc = 0.08; % Select Dissocunt Rate (r)
gamma = (1/(1+disc)); % Discount factor
% Probability of wining a contract
probwin = [0 0.2 0.8; 0 0.3 0.7; 0 0.4 0.6; 0 0.5 0.5; 0 0.6 0.4; 0 0.7 0.3];

%% Physical Design State Requirements
N_Requirement = 3; % Number of levels for technical requirements
F_min = 1.5;       % Freeboard criteria [m]
GM_min = 0.15;     % GM criteria [m]
DA_min = 0;        % Deck area critaria [m^2]

%% Switching costs [mill. USD]
Switch_CM = cell(N_Var_Design,1);
Switch_CM{1} = xlsread('Case.xlsx',4,'D5:F7'); % ACC
Switch_CM{2} = xlsread('Case.xlsx',4,'D10:F12'); % MC
Switch_CM{3} = xlsread('Case.xlsx',4,'D15:F17'); % LWI
Switch_CM{4} = xlsread('Case.xlsx',4,'D20:E21'); % ROV
Switch_CM{5} = xlsread('Case.xlsx',4,'D24:E25'); % PC
Switch_CM{6} = xlsread('Case.xlsx',4,'D28:E29'); % MP

%% Mission Requirements to each variable design parameter:
% (ACC, MC, LWI, ROV, PC, MP)
Requirement_Matrix = cell(N_Space_Mission,1);
Requirement_Matrix{1} = xlsread('Case.xlsx',2,'D5:I7'); % OSC
Requirement_Matrix{2} = xlsread('Case.xlsx',2,'D8:I10'); % IMR
```

```
Requirement_Matrix{3} = xlsread('Case.xlsx',2,'D11:I13'); % LWI
Requirement_Matrix{4} = xlsread('Case.xlsx',2,'D14:I16'); % ODS
Requirement_Matrix{5} = xlsread('Case.xlsx',2,'D17:I19'); % ACC
Requirement_Matrix{6} = xlsread('Case.xlsx',2,'D20:I22'); % OCL
Requirement_Matrix{7} = xlsread('Case.xlsx',2,'D23:I25'); % OPS
Requirement_Matrix{8} = xlsread('Case.xlsx',2,'D26:I28'); % OAS
Requirement_Matrix{9} = xlsread('Case.xlsx',2,'D29:I31'); % LU

%% Transition matrix for techncial requirements
TM_Requirement = xlsread('Case.xlsx',7,'B2:D4');

%% Changeability Cost Matrix.
Change_CM = xlsread('Case.xlsx',8,'B3:G5');

%% Dayrates for each mission for each market state
Dayrates_Data = cell(1,N_Space_Market);
Dayrates_Data{1,1} = xlsread('Case.xlsx',5,'D10:E18'); % Low (-)
Dayrates_Data{1,2} = xlsread('Case.xlsx',5,'F10:G18'); % Low
Dayrates_Data{1,3} = xlsread('Case.xlsx',5,'H10:I18'); % Medium-low
Dayrates_Data{1,4} = xlsread('Case.xlsx',5,'J10:K18'); % Medium-high
Dayrates_Data{1,5} = xlsread('Case.xlsx',5,'L10:M18'); % High
Dayrates_Data{1,6} = xlsread('Case.xlsx',5,'N10:O18'); % High (+)

% Difference between dayrates for short-term and long-term contracts
ScalingFactor = xlsread('Case.xlsx',5,'D5:F5');

%% Create entire (full) design space by enumerating all possible ...
% ... combinations of the variable design state parameters. Some of ...
% ... these designs are not fesiable.
% NB: [Space_Design_Var_full] = [ACC level, MC level, LWI level, ...
% ... PC level, MP level]
[Space_Design_Var_full] = allcomb(Set_ACC,Set_MC, Set_LWI,Set_ROV, Set_PC,Set_MP);
N_Space_Design_Var_full = length(Space_Design_Var_full);

%% Obtain information regarding all designs in "Space_Design_Var_full."
% NB: [Space_Design_Fix_full] = [Deck Area, Freeboard,Deadweight, GM]
```

```
[Space_Design_Fix_full, Lightweight] = Design_Information(Space_Design_Var_full,
    N_Space_Design_Var_full, N_Var_Design, Length, Beam,Depth, F_min);

%% Obtain compitability matrix
V = [N_ACC, N_MC, N_LWI, N_ROV, N_PC, N_MP];
Design_Compatability_Matrix = cell(N_Var_Design);
counter = 4;
for ii = 1: N_Var_Design
    for jj = 1:V(ii)
        Design_Compatability_Matrix{ii}(jj,:,1) = xlsread('Case.xlsx',1, strcat('C',
    num2str(counter),':E',num2str(counter)));
        Design_Compatability_Matrix{ii}(jj,:,2) = xlsread('Case.xlsx',1, strcat('F',
    num2str(counter),':H',num2str(counter)));
        Design_Compatability_Matrix{ii}(jj,:,3) = xlsread('Case.xlsx',1, strcat('I',
    num2str(counter),':K',num2str(counter)));
        Design_Compatability_Matrix{ii}(jj,:,4) = xlsread('Case.xlsx',1, strcat('L',
    num2str(counter),':N',num2str(counter)));
        Design_Compatability_Matrix{ii}(jj,:,5) = xlsread('Case.xlsx',1, strcat('O',
    num2str(counter),':Q',num2str(counter)));
        Design_Compatability_Matrix{ii}(jj,:,6) = xlsread('Case.xlsx',1, strcat('R',
    num2str(counter),':T',num2str(counter)));
        counter = counter + 1;
    end
end
%% Create the total fesiable Design Space by deleating unfesiable designs ...
% ... in [Space_Design_Var_full] based in Design State Requirements ...
% ... (i.e. required deck area, GM and freeboard).
% NB: [Space_Design] = [ACC level, MC level, LWI level, ...
% ... PC level, MP level]
[Space_Design_New] = Design_Compatibility(Design_Compatability_Matrix,
    Space_Design_Var_full,Space_Design_Fix_full, N_Var_Design, F_min, GM_min, DA_min);
N_Space_Design_New = length(Space_Design_New);

%% Create the actual design space to analyse
% It is assumed that one never will reduce the level of equipment on a
% vessel. Thus, only designs with equal or more equipment capability that
```

```
% the initial design (Start_Design) is analysed

[Space_Design] = Create_Space_Design(Space_Design_New,N_Space_Design_New,N_Var_Design,
    Start_Design);
N_Space_Design = length(Space_Design);

%% Initialize starting state (i.e. base design)
state_idx_start = find(Space_Design(:,1) == Start_Design(1) & Space_Design(:,2) ==
    Start_Design(2) & Space_Design(:,3) == Start_Design(3) & Space_Design(:,4) ==
    Start_Design(4) & Space_Design(:,5) == Start_Design(5) & Space_Design(:,6) ==
    Start_Design(6));

%% Creating Sets of Desigs, Missions, Markets, Strategy and Requirements
Set_Design = 1:N_Space_Design; % Set of Design States
Set_Mission = 1:N_Space_Mission; % Set of Mission states
Set_Market = 1:N_Space_Market; % Set of Market states
Set_Strategy = 1:N_Strategy; % Sef of Strategy states
Set_Requirement = 1:N_Requirement; % Set of Requirement states

%% Create State Space by enumerating all combinations of ...
% ... design states, strategy states, market states and requirement states.
% NB: [Space_State] = [Design nr., Strategy nr., Market nr., ...
% ... Requirement nr.]
[Space_State] = allcomb(Set_Design, Set_Strategy, Set_Market, Set_Requirement);
N_Space_State = length(Space_State); % Number of possible states

%% Create Action Space by enumerating all ...
% ... combinations of design states and strategy states.
% NB: [Space_Action] = (Design nr., Strategy nr.)
Space_Action = allcomb(Set_Design, Set_Strategy);
N_Space_Action = length(Space_Action);

%% Generate Switchign costs
[switch_cost] = SwitchCost(Switch_CM,N_Space_Design, N_Var_Design, Space_Design,Change_CM
    ,N_Design);

```

```
%% Building Cost Estimation
FaktorCost = 8;
BuildCost = Lightweight*FaktorCost+switch_cost{1}(1,state_idx_start)*100/1000000;
SellingCost = [0*BuildCost, 0.1*BuildCost, 0.3*BuildCost, 0.5*BuildCost, 0.6*BuildCost
    ,0.7*BuildCost];
```

F.3 Matlab - allcomb.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function returns all combinations of elements in an vector
% Retrived from: https://se.mathworks.com/matlabcentral/fileexchange/...
% ... 10064-allcomb-varargin-
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [A] = allcomb(varargin)

% ALLCOMB - All combinations
%    B = ALLCOMB(A1,A2,A3,...,AN) returns all combinations of the elements
%    in the arrays A1, A2, ..., and AN. B is P-by-N matrix is which P is the product
%    of the number of elements of the N inputs. This functionality is also
%    known as the Cartesian Product. The arguments can be numerical and/or
%    characters, or they can be cell arrays.
%
%    Examples:
%       allcomb([1 3 5],[-3 8],[0 1]) % numerical input:
%       % -> [ 1  -3   0
%       %      1  -3   1
%       %      1   8   0
%       %        ...
%       %      5  -3   1
%       %      5   8   1 ] ; % a 12-by-3 array
%
%       allcomb('abc','XY') % character arrays
%       % -> [ aX ; aY ; bX ; bY ; cX ; cY] % a 6-by-2 character array
%
%       allcomb('xy',[65 66]) % a combination
%       % -> ['xA' ; 'xB' ; 'yA' ; 'yB'] % a 4-by-2 character array
%
%       allcomb({'hello','Bye'},{'Joe', 10:12},{99999 []}) % all cell arrays
%       % -> {  'hello'  'Joe'        [99999]
%       %       'hello'  'Joe'             []
%       %       'hello'  [1x3 double] [99999]
```

```
%       %       'hello'  [1x3 double]       []
%       %       'Bye'    'Joe'          [99999]
%       %       'Bye'    'Joe'              []
%       %       'Bye'    [1x3 double] [99999]
%       %       'Bye'    [1x3 double]       [] } ; % a 8-by-3 cell array
%
%   ALLCOMB(..., 'matlab') causes the first column to change fastest which
%   is consistent with matlab indexing. Example:
%     allcomb(1:2,3:4,5:6,'matlab')
%     % -> [ 1 3 5 ; 1 4 5 ; 1 3 6 ; ... ; 2 4 6 ]
%
%   If one of the arguments is empty, ALLCOMB returns a 0-by-N empty array.
%
%   See also NCHOOSEK, PERMS, NDGRID
%        and NCHOOSE, COMBN, KTHCOMBN (Matlab Central FEX)

% Tested in Matlab R2015a
% version 4.1 (feb 2016)
% (c) Jos van der Geest
% email: samelinoa@gmail.com

% History
% 1.1 (feb 2006), removed minor bug when entering empty cell arrays;
%     added option to let the first input run fastest (suggestion by JD)
% 1.2 (jan 2010), using ii as an index on the left-hand for the multiple
%     output by NDGRID. Thanks to Jan Simon, for showing this little trick
% 2.0 (dec 2010). Bruno Luong convinced me that an empty input should
% return an empty output.
% 2.1 (feb 2011). A cell as input argument caused the check on the last
%      argument (specifying the order) to crash.
% 2.2 (jan 2012). removed a superfluous line of code (ischar(..))
% 3.0 (may 2012) removed check for doubles so character arrays are accepted
% 4.0 (feb 2014) added support for cell arrays
% 4.1 (feb 2016) fixed error for cell array input with last argument being
%     'matlab'. Thanks to Richard for pointing this out.

```

```
narginchk(1,Inf) ;

NC = nargin ;

% check if we should flip the order
if ischar(varargin{end}) && (strcmpi(varargin{end},'matlab') || strcmpi(varargin{end},'
    john')),
    % based on a suggestion by JD on the FEX
    NC = NC-1 ;
    ii = 1:NC ; % now first argument will change fastest
else
    % default: enter arguments backwards, so last one (AN) is changing fastest
    ii = NC:-1:1 ;
end

args = varargin(1:NC) ;
% check for empty inputs
if any(cellfun('isempty',args)),
    warning('ALLCOMB:EmptyInput','One of more empty inputs result in an empty output.') ;
    A = zeros(0,NC) ;
elseif NC > 1
    isCellInput = cellfun(@iscell,args) ;
    if any(isCellInput)
        if ~all(isCellInput)
            error('ALLCOMB:InvalidCellInput', ...
                'For cell input, all arguments should be cell arrays.') ;
        end
        % for cell input, we use to indices to get all combinations
        ix = cellfun(@(c) 1:numel(c), args,'un',0) ;

        % flip using ii if last column is changing fastest
        [ix{ii}] = ndgrid(ix{ii}) ;

        A = cell(numel(ix{1}),NC) ; % pre-allocate the output
        for k=1:NC,
            % combine
```

```
            A(:,k) = reshape(args{k}(ix{k}),[],1) ;
        end
    else
        % non-cell input, assuming all numerical values or strings
        % flip using ii if last column is changing fastest
        [A{ii}] = ndgrid(args{ii}) ;
        % concatenate
        A = reshape(cat(NC+1,A{:}),[],NC) ;
    end
elseif NC==1,
    A = args{1}(:) ; % nothing to combine

else % NC==0, there was only the 'matlab' flag argument
    A = zeros(0,0) ; % nothing
end
```

F.4 Matlab - Design_Information.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function calculates avaiable deck area, freeboard, deadweight and GM
% for a design.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [Space_Design_Fix_full, Lightweight] = Design_Information(Space_Design_Var_full,
    N_Space_Design_Var_full, N_Var_Design, Length, Beam,Depth, F_min)

Space_Design_Fix_full = zeros(N_Space_Design_Var_full,1); %[Deck Area, Freeboard,
    Deadweigth, GM]

%%% Initialize data
% Deck area [m2] requirement for each topside equipment
DeckArea_Eq(1,:) = xlsread('Case.xlsx',6,'B4:D4'); % ACC
DeckArea_Eq(2,:) = xlsread('Case.xlsx',6,'B5:D5'); % MC
DeckArea_Eq(3,:) = xlsread('Case.xlsx',6,'B6:D6'); % LWI
DeckArea_Eq(4,:) = xlsread('Case.xlsx',6,'B7:D7'); % ROV
DeckArea_Eq(5,:) = xlsread('Case.xlsx',6,'B8:D8'); % PC
DeckArea_Eq(6,:) = xlsread('Case.xlsx',6,'B9:D9'); % MP

% Weight [tonn] for each design parameter
Weigth_Eq(1,:) = xlsread('Case.xlsx',6,'B13:D13'); % ACC
Weigth_Eq(2,:) = xlsread('Case.xlsx',6,'B14:D14'); % MC
Weigth_Eq(3,:) = xlsread('Case.xlsx',6,'B15:D15'); % LWI
Weigth_Eq(4,:) = xlsread('Case.xlsx',6,'B16:D16'); % ROV
Weigth_Eq(5,:) = xlsread('Case.xlsx',6,'B17:D17'); % PC
Weigth_Eq(6,:) = xlsread('Case.xlsx',6,'B18:D18'); % MP

% Center of gravity [m] for each design parameter
CoG_Eq(1,:) = xlsread('Case.xlsx',6,'B22:D22'); % ACC
CoG_Eq(2,:) = xlsread('Case.xlsx',6,'B23:D23'); % MC
CoG_Eq(3,:) = xlsread('Case.xlsx',6,'B24:D24'); % LWI
CoG_Eq(4,:) = xlsread('Case.xlsx',6,'B25:D25'); % ROV
CoG_Eq(5,:) = xlsread('Case.xlsx',6,'B26:D26'); % PC
```

```
CoG_Eq(6,:) = xlsread('Case.xlsx',6,'B27:D27'); % MP

% Scaling factors [-]
Deck_Area_koefficient = xlsread('Case.xlsx',6,'C30');
Lightweighth_Koefficient = xlsread('Case.xlsx',6,'C31');

% Various constands
rho_water = xlsread('Case.xlsx',6,'C32');   % Sea water density [tonn/m3]
Cb = xlsread('Case.xlsx',6,'C33');   % Block Coefficient [-]

%%% Estimating Avaiable Deck [m2] for each design configuration
% Estimate the avaiable Deck area for a vessel without any topside ...
% equipment installed:
Space_Design_Fix_full(:,1) = Deck_Area_koefficient*Length*Beam;

% Subtract the required deck area for each equipment installed
for ss = 1: N_Space_Design_Var_full
    for vv = 1: N_Var_Design
        Space_Design_Fix_full(ss,1) = Space_Design_Fix_full(ss,1) - ...
            DeckArea_Eq(vv,Space_Design_Var_full(ss,vv));
    end
end

%%% Estimating lightship weight [tonnes] for each design configuration
% Estimate the  ligtship  weigth of the vessel without any topside ...
% equipment installed
Weighth_Design(1:N_Space_Design_Var_full,1) = ...
    Lightweighth_Koefficient*Length*Beam*Depth;

Lightweight = Weighth_Design;

% Add the weight for each equipment installed
for ss = 1: N_Space_Design_Var_full
    for vv = 1: N_Var_Design
        Weighth_Design(ss,1) = Weighth_Design(ss,1) + ...
            Weigth_Eq(vv,Space_Design_Var_full(ss,vv));
```

```
    end
end

%%% Estimating the Volume displacement for each vessel configuration
Volume_Displacement(:,1) = Weighth_Design(:,1)./rho_water;

%%% Estimating the draught for each vessel configuration
T(:,1) = Volume_Displacement(:,1)./(Cb.*Length.*Beam);

%%% Estimating the freeboard for each vessel configuration
Space_Design_Fix_full(:,2) = Depth - T(:,1);

%%% Estimating Deadweight for each design configuration
Space_Design_Fix_full(:,3) = rho_water.*Cb.*(Length.*Beam).*...
    (Depth-F_min) - Weighth_Design(:,1);

%%% Estimating GM for each design configuration
KB(:,1) =  T(:,1)/2;
BM(:,1) = (Beam^2)./(12.*T(:,1));
sum_Weight_CoG(1:N_Space_Design_Var_full,1) =  (Lightweighth_Koefficient*Length*Beam*Depth)*(Depth/2);
for ss = 1: N_Space_Design_Var_full
    for vv = 1: N_Var_Design
        sum_Weight_CoG(ss,1) = sum_Weight_CoG(ss,1) + CoG_Eq(vv,Space_Design_Var_full(ss,vv))*Weigth_Eq(vv,Space_Design_Var_full(ss,vv));
    end
    KG(ss,:) = sum_Weight_CoG(ss,1)/Weighth_Design(ss,1);
end

Space_Design_Fix_full(:,4) = KB(:,1) + BM(:,1) - KG(:,1);
end
```

F.5 Matlab - Design_Compatibility.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function enumerates the entire fesiable design space (Space_Design)
% by imposing restriction (Deck Area > 0 [m2], GM >= 0.15 [m] and Freeboard
% > 1.5 [m])on the design space enumerated by all combinations of the
% design space variables (Space_Design_Var_full)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [Space_Design] = Design_Compatibility(Design_Compatability_Matrix,
    Space_Design_Var_full,Space_Design_Fix_full, N_Var_Design, F_min, GM_min, DA_min)

N_Space_Design_Var_full = length(Space_Design_Var_full);

% Find infesiable Design configurations in Space_Design_Var_full
Comp(1:N_Space_Design_Var_full,1) = 1; % Initialize all to be fesiable
for ss = 1:N_Space_Design_Var_full
    System_Vector_current = Space_Design_Var_full(ss,:);
    for cc = 1:N_Var_Design
        for ccc = 1:N_Var_Design
            if Design_Compatability_Matrix{cc}(System_Vector_current(cc),
    System_Vector_current(ccc),ccc) == 2 || Space_Design_Fix_full(ss,1) < DA_min ||
    Space_Design_Fix_full(ss,2) <= F_min || Space_Design_Fix_full(ss,4) < GM_min
                Comp(ss) = 2; % Design ss is infesiable
            end
        end
    end
end

Space_Design = []; % Create matrix to contain fesiable designs
sss = 1; % counter
for ss = 1:N_Space_Design_Var_full
    System_Vector_current = Space_Design_Var_full(ss,:);
    if Comp(ss) == 1
        Space_Design(sss,:) = System_Vector_current;
        sss = sss + 1;
```

```
        end
end
end
```

F.6 Matlab - Create_Space_Design.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function creates the actual design space to be analysed.
% It is assumes that one never will reduce the level of equipment on a
% vessel. Thus, only designs with equal or more equipment capability that
% the initial design (Start_Design) is analysed
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [Space_Design] = Create_Space_Design(Space_Design_New,N_Space_Design_New,
    N_Var_Design,Start_Design)

for nn = 1:N_Space_Design_New
    for vv = 1:N_Var_Design
        if Space_Design_New(nn,vv) < Start_Design(1,vv)
            Delete(nn) = 1; % Design nn does not hold the assumption
            break
        else
            Delete(nn) = 0; % Design nn holds the assumption
        end
    end
end

A = find(Delete == 0); % Find those vessel numbers that holds the assumption
[~, N_A] = size(A); % Find the number of vessel that holds the assumption

% Create design space to analyse (i.e. Space_Design)
counter = 1; % Counter
Space_Design = zeros(N_A,N_Var_Design);
for aa = 1:N_A
Space_Design(counter,:) = Space_Design_New(A(aa),:);
counter = counter + 1;
end
```

F.7 Matlab - SwitchCost.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function calculates the cost of switching from one design (ss)
% configuration to another (sss) for each design analysed (ii).
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [switch_cost] = SwitchCost(Switch_CM,N_Space_Design, N_Var_Design, Space_Design, Change_CM, N_Design)

% Create matrix for analysis
S_cost = cell(N_Design,1);
for ii = 1:N_Design
    S_cost{ii,1} = zeros(N_Space_Design);
end

% Calculate switching cost for each design ii, switching between design
% configuration ss to sss.
for ii = 1:N_Design
    for ss = 1:N_Space_Design
        SystemVector_curr = Space_Design(ss,:);
        for sss = 1:N_Space_Design
            SystemVector_next = Space_Design(sss,:);
            for sv = 1:N_Var_Design
                S_cost{ii}(ss,sss) = S_cost{ii}(ss,sss) + Change_CM(ii,sv).*Switch_CM{sv}(SystemVector_curr(sv),SystemVector_next(sv));
            end
        end
    end
end

% Prepear output
switch_cost = S_cost;
end
```

F.8 Matlab - QLearning.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Q-Learning Algorithm. The script follows the generic Q-learning algorith
% presented in the thesis. The output of this algorithm is the Policy
% indicating which action to take for each state-time combination.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% Max number of interations (Step. 0b in generic algorithm)
N_Interations_Q = 500000;

% Initialize Matrixs for Further analysis
Q_SumSum = cell(N_Design,1); % Sum of Q-Matrix

 con_total_Q = cell(N_Design,1); % Life-cycle contribution
 for nn = 1:N_Design
   for ii = 1:N_Interations_Q
    con_total_Q{nn}(ii,1) = 0;
   end
end

for ii = 1:N_Design % Spesify which design(s) to analyse

    % Initialize Q-Matrix (Step. 0a in generic algorithm)
    Q = cell(1,Lifetime + 2);
     for tt = 1:Lifetime + 2
         Q{1,tt} = zeros(N_Space_State,N_Space_Action);
     end

     % Calculate Switching time
     SwitchDays = SDays(ii);

    iter = 1; % Set interation counter (Step 0c. in generic algorithm)

while iter  <= N_Interations_Q

```

```
% Output information
fprintf('Design nr. %d, Interation nr. %d\n',ii, iter);

% Initialie Starting State (Step 0d. in generic algorithm)
state_idx_action = state_idx_start;

% Sample market state and requirement state for the given interation (Step. 1 in generic algorithm)
[Sample_Market, Sample_Requirement] = Sample_Path(Lifetime, TM_Requirement);

% Sample dayrates for the given interation (Step. 1 cont. in generic algorithm)
[Sample_DayRates] = Sample_Dayrates(Sample_Market, Lifetime,N_Strategy, N_Space_Mission,ScalingFactor,Dayrates_Data);

% Select Learnign Rate
if iter == 1
    alpha = 1;
else
    alpha = 0.7;
end

% Simulate the vessel's lifetime (Step 2 in generic algorithm)
tt_current = 2; % 2 represents year 5, 3 represents year 6, etc.
while tt_current < Lifetime + 2

    %%% Select action (Step 2a. in generic algorithm)
    tt_action = tt_current - 1; % Time when action is taken
    [action_idx, tt_next] = ActionSelection(tt_action,Q, iter, N_Interations_Q, tt_current, Lifetime, time_long, time_short, state_idx_action, Space_Action, N_Space_Action);

    %%% Simulate outcome of action (Step 2b. in generic algorithm)
    % I.e. find current state (stochastic parameter)
    state_idx_current = find(Space_State(:,1) == Space_Action(action_idx,1) & Space_State(:,2) == Space_Action(action_idx,2) & Space_State(:,3) == Sample_Market(tt_current) & Space_State(:,4) == Sample_Requirement(tt_current));
```

```

    % Obtain information of previous and current states
    design_previous = Space_State(state_idx_action,1);
    design_current = Space_State(state_idx_current,1);
    strategy_current = Space_State(state_idx_current,2);
    market_current = Space_State(state_idx_current,3);
    requirement_current = Space_State(state_idx_current,4);

    % Estimate immediate Contribution (Step. 2c).
    [Comp] = Mission_Compatability(N_Space_Mission,N_Var_Design,Space_Design,
Requirement_Matrix,requirement_current,design_current);
    [contribution,rew,miss] = Contri(probwin, SellingCost, market_current,OpDays,
SwitchDays,ii, Comp, N_Space_Mission, Sample_DayRates, strategy_current, tt_current,
switch_cost, design_previous, design_current, disc);
    con_total_Q{ii}(iter,1) = con_total_Q{ii}(iter,1) + contribution;

    % Q learning
    Q{1,tt_action}(state_idx_action,action_idx) = (1-alpha)*Q{1,tt_action}(
state_idx_action,action_idx) + alpha*(contribution + gamma*max(Q{1,tt_current}(
state_idx_current,:)));

    % Prepeare next step
    state_idx_action = state_idx_current;

    % Change time step
    tt_current = tt_current + tt_next;

end % while tt < Lifetime

    % Update information
    for tt = 2:Lifetime + 2
        Q_SumSum{ii}(iter,tt) = sum(sum(Q{1,tt}));
    end

    % Update interation counter (Step 3. in generic algorithm)
    iter = iter + 1;
```

```
end
    % Store information
    if ii == 1
        Q_Design_1 = Q; % Changeability level 0
    elseif ii == 2
        Q_Design_2 = Q; % Changeability level 1
    else % ii == 3
        Q_Design_3 = Q; % Changeability level 2
    end
end

% Extract Policy and Value Function (Step 4. in generic algrithm),
% in addition to design and strategy for further analysis
Policy = cell(N_Design,1);
Value_function = cell(N_Design,1);
Design = cell(N_Design,1);
Strategy = cell(N_Design,1);

for ii = 1:N_Design
    if ii == 1
        Q_post = Q_Design_1;
    elseif ii == 2
        Q_post = Q_Design_2;
    else % ii == 3
        Q_post = Q_Design_3;
    end
    for tt_act = 1:Lifetime
        for ss = 1:N_Space_State
            [Value_function{ii}(tt_act,ss), Policy{ii}(ss,tt_act)] = max(Q_post{1,tt_act
    }(ss,:));
            Design{ii}(ss,tt_act+1) = Space_Action(Policy{ii}(ss,tt_act), 1);
            Strategy{ii}(ss,tt_act+1) = Space_Action(Policy{ii}(ss,tt_act), 2);
        end
    end
end
```

F.9 Matlab - Sample_Path.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function samples one life cycle path for the market state
% (Sample_market)and one for the technical requirement state
% (Sample_Requirement).
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [Sample_Market, Sample_Requirement] = Sample_Path(Lifetime, P_Requirement)

    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %%% Sample Market State
    Sample_Market = zeros(1,Lifetime + 2); % Create Vector for MarketSample

    % Obtain paramters for the market simulation (modeled as a sinus
    % function)
    A = 1; % Amplitude of sinus function
    P = normrnd(7,1); % Period of sinus function
    B = (2*pi)/P;
    Shift = -pi ; % Phase shift in sinus function
    C = -(Shift)*B;
    D = 10; % Vertical shift in sinus function

    % Simulate market state (continous function)
    t = 0:Lifetime+2;
    drift = 0;
    for x = 1:(Lifetime + 2)
        MarketRate_Base(1,x) = A*sin(B*t(x)+C) + normrnd(D,0.2) + drift;
        drift = drift +  0.01 + normrnd(0, 0.005*D); % drift in market state
    end

    % Discretizise the continous market function into 6 levels
    for tt = 1:(Lifetime + 2)
        if MarketRate_Base(1,tt) <= D - (2*A/3)
            Sample_Market(1,tt) = 1; % Market state: low (-)
        elseif MarketRate_Base(1,tt) <= D - (A/3)
```

```
                Sample_Market(1,tt) = 2; % Market state: low
            elseif MarketRate_Base(1,tt) <= D
                Sample_Market(1,tt) = 3; % Market state: medium-low
             elseif MarketRate_Base(1,tt) <= D + (A/3)
                Sample_Market(1,tt) = 4; % Market state: medium-high
             elseif  MarketRate_Base(1,tt) <= D + (2*A/3)
                Sample_Market(1,tt) = 5; % Market state: high
             else %MarketRate_Base(1,tt) <= D + A
                Sample_Market(1,tt) = 6; % Market state: high (+)
             end
        end

        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        %%% Sample Requirement State
        Sample_Requirement = zeros(1,Lifetime + 2); % Create Vector for Technical Requirements
        Sample_Requirement(1) = 1; % Know the market state when the vessels first operates

        for tt = 2:Lifetime + 2
               if Sample_Requirement(tt-1) == 1 && tt > 9
                Sample_Requirement(tt) = 2; % Medium technical requirements
               else
                r = rand; % Pick a random number in [0,1]
                Sample_Requirement(tt) = sum(r >= cumsum([0,P_Requirement(Sample_Requirement(tt-1),1),P_Requirement(Sample_Requirement(tt-1),2),P_Requirement(Sample_Requirement(tt-1),3)])); % Find next market state
               end
        end
end
```

F.10 Matlab - Sample_Dayrates.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function samples the day rates for one realisation of a vessels life
% cycle
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [Sample_DayRates] = Sample_Dayrates(Sample_Market, Lifetime,N_Strategy,
    N_Space_Mission,ScalingFactor,Dayrates_Data)

    % Collect simulation of market state
    Market_state = Sample_Market;

    SampleDayRates = cell(1,N_Strategy);

    for kk = 1:N_Strategy
        for mm = 1:N_Space_Mission
            drift = 0;
            for tt = 2: Lifetime + 2
                drift = drift + normrnd(0.05,0.05);
                % for short and long-term strategy, kk)
                SF = ScalingFactor(kk);
                % mean of normal distribution
                Mean = Dayrates_Data{1,Market_state(tt)}(mm,1);
                % standard deviation of normal distribution
                Std = Dayrates_Data{1,Market_state(tt)}(mm,2);
                % dayrate sample
                SampleDayRates{1,kk}(mm,tt) = drift*ScalingFactor(kk)*normrnd(Mean,Std);
            end
        end
    end

    Sample_DayRates = SampleDayRates; % Output

end
```

F.11 Matlab - ActionSelection.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function selects which action to take. This conserns both which
% design configuration and strategy to take.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [action_idx, tt_next] = ActionSelection(TT_action,QMatrix, ITER, N_ITERATIONS_Q, TT_current, LIFETIME, TIME_long, TIME_short,STATE_idx_action, SPACE_Action, NN_Space_Action)

    % Select epsilon statin the probabillity of exploration.
    % Epsilon = 1 -> always pick randon action. Epsilon = 0 -> always pick
    % best option.

    if ITER <= 0.1*N_ITERATIONS_Q
        epsilon = 1;
    elseif ITER <= 0.2*N_ITERATIONS_Q
        epsilon = 0.9;
    elseif ITER <= 0.3*N_ITERATIONS_Q
        epsilon = 0.8;
    elseif ITER <= 0.4*N_ITERATIONS_Q
        epsilon = 0.7;
    elseif ITER <= 0.5*N_ITERATIONS_Q
        epsilon = 0.6;
    elseif ITER <= 0.6*N_ITERATIONS_Q
        epsilon = 0.5;
    elseif ITER <= 0.7*N_ITERATIONS_Q
        epsilon = 0.4;
    elseif ITER <= 0.8*N_ITERATIONS_Q
        epsilon = 0.3;
    elseif ITER <= 0.9*N_ITERATIONS_Q
        epsilon = 0.2;
    else %iter <= 1*N_Interations_Q
        epsilon = 0.1;
    end
```

```

    % Select action
    r = rand; % Pick a random number in [0,1]
    x = sum(r >= cumsum([0,1-epsilon,epsilon])); %[ 0, prob(Exploit), prob(Explore)
    if x == 1 % Model shall exploit if r lies in the intervall [0; 1-epsilon]
        if TT_current <= (LIFETIME +2 - TIME_long) % All actions can be taken
            [~,action_idx] = max(QMatrix{1,TT_action}(STATE_idx_action,[1:1:NN_Space_Action]));% Find the action that maximized Q
        else % Can only select short-term contract or sell
            x = [1:3:NN_Space_Action]; % Sjort-term actions
            y = [3:3:NN_Space_Action]; % Scraping actions
            H = [x;y];
            H = H(:);
            [~,pos_H] = max(QMatrix{1,TT_action}(STATE_idx_action,H));% Find the action that maximized Q
            action_idx = H(pos_H);
        end
    else % Model shall explore if r lies in the intevall [1- epsilon, epsilon]
        if TT_current <= (LIFETIME +2 - TIME_long)
            action_idx = randsample(NN_Space_Action,1);
        else % Can only select short-term contract or sell
            action_idx = randsample(find(SPACE_Action(:,2) == 1 | SPACE_Action(:,2) == 3),1);
        end
    end

    % Time to next selection epoch
    if SPACE_Action(action_idx,2) == 1 % Short-term contract
        tt_next = TIME_short;
    elseif SPACE_Action(action_idx,2) == 2 % Long-term contract
        tt_next = TIME_long;
    else % scrap/sell
        tt_next = inf; % The interation will end
    end
end % Function
```

F.12 Matlab - Mission_Compatability.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function creates a compatability matrix, consisting of 1 and -inf
% representign wether or not the vessel is able to undertake a particular
% mission
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [Comp] = Mission_Compatability(N_Space_Mission,N_Var_Design,Space_System,Requirement_Matrix,market_requirement,system_current)

NotValid = [];
for mi = 1:N_Space_Mission
    for vs = 1:N_Var_Design
        if Space_System(system_current,vs) < Requirement_Matrix{mi}(market_requirement,vs)
            NotValid(mi) = 1; % Do not hold requirement
            break
        else
            NotValid(mi) = 0; % Do hold requirement
        end
    end

    if NotValid == 1  % Design do not hold requirements
        Comp(mi) = -inf; % Not compatible
    else % Design holds requirements
        Comp(mi) = 1; % Compatible
    end
end
```

F.13 Matlab - Contri.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This function calculates the contribution [mill. USD] of taking a
% particular action. The contribution is based on the mission selected
% (depending of the vessels technical capabilities), the lengt of the
% contract (i.e. strategy), and the state of the market
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


function [contribution,con_reward,mission_current] = Contri(probwin,SellingCost,
    market_current,OpDays, SwitchDays,ii, Comp,  NN_Space_Mission, Sample_DayRates,
    strategy_current, tt_current, switch_cost, design_previous, design_current,disc)

if strategy_current == 3 % Sell
    con_reward = SellingCost(market_current); % Reward
    con_switch = 0; % Switching costs
    mission_current = 0; % Mission taken
    % Estimate contribution
    contribution = (con_reward - con_switch)*(1/(1+disc)^(tt_current-0));

else

    % Find out if the contracts are won or lost
    win = zeros(1,NN_Space_Mission);
    for mm = 1:(NN_Space_Mission - 1)
        r = rand; % Pick a random number in [0,1]
        p = sum(r >= cumsum(probwin(market_current,:)));
        if p == 1
            win(1,mm) = 1; % Contract is won
        else
            win(1,mm) = 0; % Contract is lost
        end
    end
    win(1,9) = 1; % Lay-up is always an option

```

```
% Calculate the reward for each mission
Days = OpDays - SwitchDays;
Reward = [];
for mm = 1:NN_Space_Mission
    if strategy_current == 1 % Short-term contract
        % If design is not compitable with mission (mm) and the Dayrate is negatice
        if Comp(mm) == -Inf && Sample_DayRates{1,strategy_current}(mm,tt_current) < 0
            Reward(mm) = -(win(1,mm)*Comp(mm)*Days*Sample_DayRates{1,strategy_current}(mm,tt_current));
        else % dayrate is positive
            Reward(mm) = win(1,mm)*Comp(mm)*Days*Sample_DayRates{1,strategy_current}(mm,tt_current);
        end
    else % Long-term contract
        % If design is not compitable with mission (mm) and the Dayrate is negatice
        if Comp(mm) == -Inf && Sample_DayRates{1,strategy_current}(mm,tt_current) < 0
            Reward(mm) = -(win(1,mm)*Comp(mm)*Days*Sample_DayRates{1,strategy_current}(mm,tt_current)+Comp(mm)*OpDays*Sample_DayRates{1,strategy_current}(mm,tt_current)*(1/(1+disc)^1)+Comp(mm)*OpDays*Sample_DayRates{1,strategy_current}(mm,tt_current)*(1/(1+disc)^2));
        else
            Reward(mm) = win(1,mm)*Comp(mm)*Days*Sample_DayRates{1,strategy_current}(mm,tt_current)+Comp(mm)*OpDays*Sample_DayRates{1,strategy_current}(mm,tt_current)*(1/(1+disc)^1)+Comp(mm)*OpDays*Sample_DayRates{1,strategy_current}(mm,tt_current)*(1/(1+disc)^2);
        end
    end
end

% Find and take the avaiable mission with highest reward
[con_reward, mission_current] = max(Reward);

% Fint the contribution of being in that particular statee (Step 2. c)
con_switch = switch_cost{ii}(design_previous, design_current); % Switching cost

% If the last time-step is reached, the sunset value is calculated
```

```
    if  (tt_current == 11 && strategy_current == 1) || (tt_current == 8 &&
    strategy_current == 2)
        SellC = SellingCost(market_current);
    else
        SellC = 0;
    end

    contribution = (con_reward - con_switch + SellC)*(1/(1+disc)^(tt_current-0));
end
end
```

F.14 Matlab -LCSimulator.m

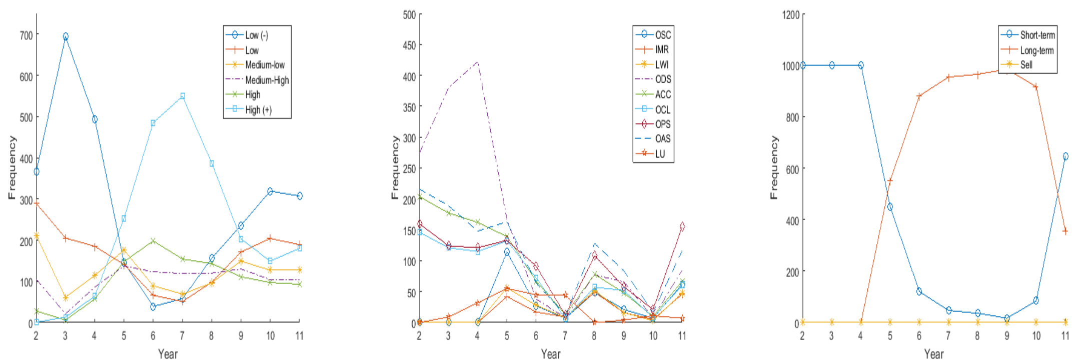
```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Life Cycle Simulator
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% Max number of interations
N_Interations_sim = 1000;

% Life-cycle contribution
 con_total_sim = cell(N_Design,1);
 for nn = 1:N_Design
    for ii = 1:N_Interations_sim
     con_total_sim{nn}(ii,1) = 0;
    end
 end

% Prepear matrixes for simulation
action = cell(N_Design,1);
design = cell(N_Design,1);
strategy = cell(N_Design,1);
market = cell(N_Design,1);
requirement = cell(N_Design,1);
comp_tracker = cell(N_Interations_sim,1);
con = cell(N_Design,1);
mission = cell(N_Design,1);

for ii = 1:N_Design % Specify which design(s) to analyse
    iter = 1;

    while iter <= N_Interations_sim

         % Initialie Starting State
         state_design = state_idx_start;
         state_strategy = 2;

```

```
    % Output information
     fprintf('Design nr. %d, Interation nr. %d\n',ii, iter);

     % Sample market and requirement for the given interation (Step. 1)
     [Sample_Market_sim, Sample_Requirement_sim] = Sample_Path(Lifetime,TM_Requirement);

     % Sample dayrates for the given interation (Step. 1 cont.)
     [Sample_DayRates_sim] = Sample_Dayrates(Sample_Market_sim, Lifetime,N_Strategy,N_Space_Mission,ScalingFactor,Dayrates_Data);

     % Track information
     market{ii}(iter,:) = Sample_Market_sim; % Market State
     requirement{ii}(iter,:) = Sample_Requirement_sim; % Technical Requirement State

     % Simulate the vessel's lifetime (Step 2 in generic algorithm)
     tt_current = 2; % 2 represents year 5, 3 represents year 6, etc
     while tt_current < Lifetime + 2

         tt_action = tt_current - 1; % Time when action is taken
         state_idx = find(Space_State(:,1) == state_design & Space_State(:,2) == state_strategy & Space_State(:,3) == Sample_Market_sim(tt_action) & Space_State(:,4) == Sample_Requirement_sim(tt_action));

         % Take action based on Policy
             if Policy{ii}(state_idx,tt_action)== 0
                 action{ii}(iter,tt_action) = randsample([1:N_Space_Action],1);
             else
                 action{ii}(iter,tt_action) = Policy{ii}(state_idx,tt_action);
             end

             design{ii}(iter,tt_current) = Space_Action(action{ii}(iter,tt_action),1);
             strategy{ii}(iter,tt_current) = Space_Action(action{ii}(iter,tt_action),2);

         % Calculate Switching time
```

```
            SwitchDays = SDays(ii);

            % Estimate immediate Contribution
            [Comp] = Mission_Compatability(N_Space_Mission,N_Var_Design,Space_Design,
    Requirement_Matrix,requirement{ii}(iter,tt_current),design{ii}(iter,tt_current));
            comp_tracker{iter}(tt_current,:) = Comp;
            [contribution,rew,miss] = Contri(probwin,SellingCost, Sample_Market_sim(
    tt_action),OpDays, SwitchDays,ii, Comp, N_Space_Mission, Sample_DayRates_sim,
    strategy{ii}(iter,tt_current), tt_current, switch_cost, state_design, design{ii}(iter
    ,tt_current), disc);
            con{ii}(iter,tt_current) = contribution;
            con_total_sim{ii}(iter,1) = con_total_sim{ii}(iter,1) + contribution;
            mission{ii}(iter,tt_current) = miss;

            % Update information
            state_design = design{ii}(iter,tt_current);

            % Update time
            if strategy{ii}(iter,tt_current) == 1 % Short-term contract
                tt_current = tt_current + time_short;
            elseif strategy{ii}(iter,tt_current) == 2 % Long-term contract
                tt_current = tt_current + time_long;
            else % Vessel is sold
                tt_current = inf;
            end
        end

        % Update interation counter
        iter = iter + 1;
    end
end
```

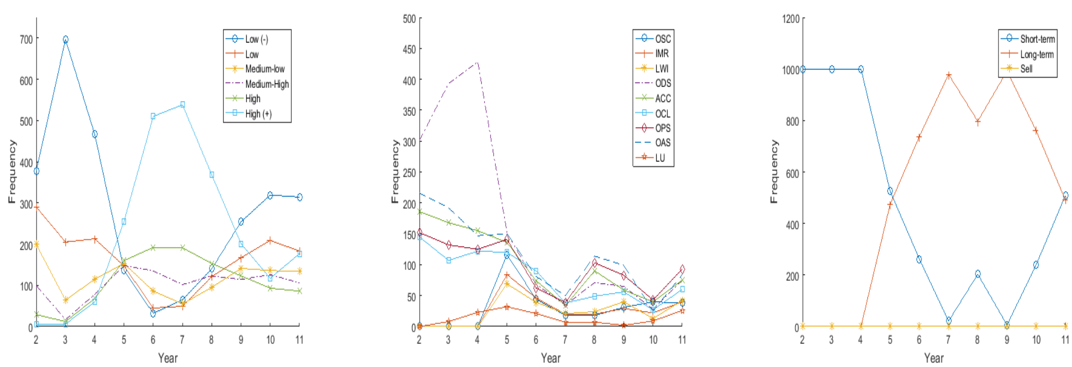
Appendix G

Results From the Illustrative Case



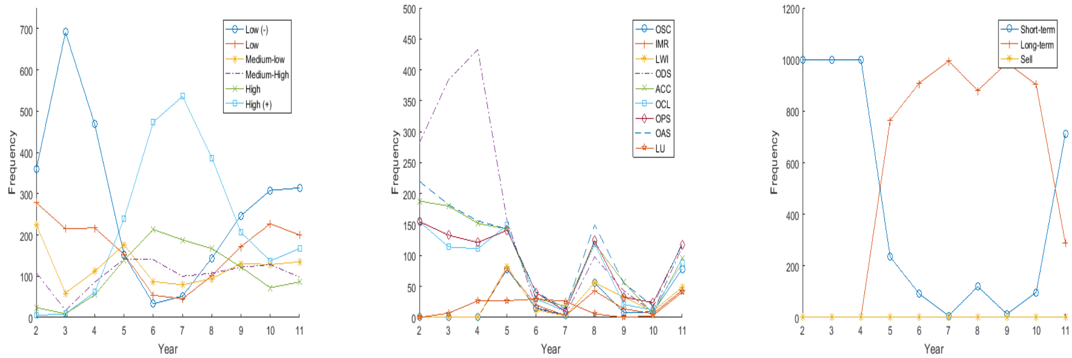
(a) Market state (b) Mission state (c) strategy state

Figure G.1: Market state, mission state and strategy state for vessel alternative 1



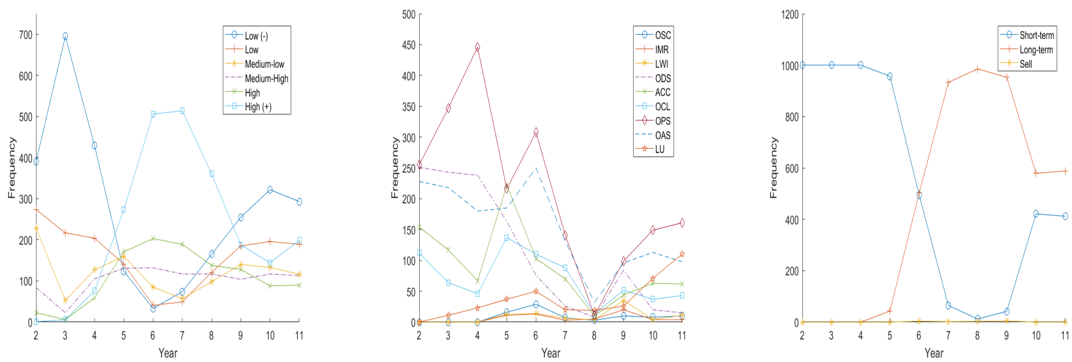
(a) Market state (b) Mission state (c) Strategy state

Figure G.2: i Market state, mission state and strategy state for vessel alternative 2



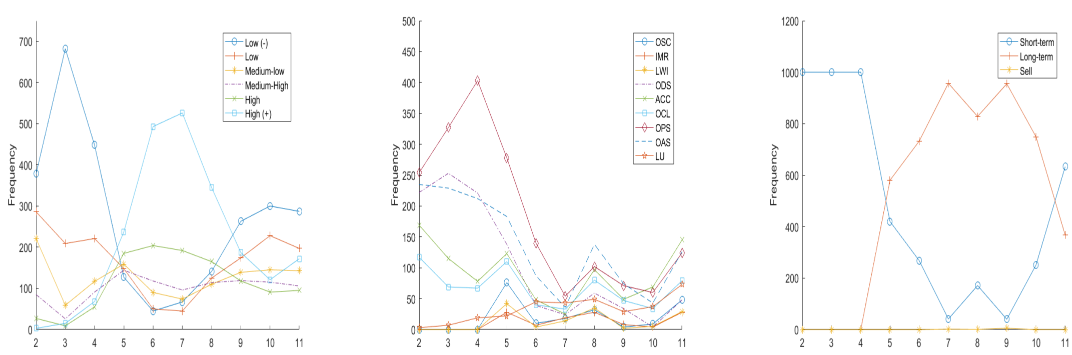
(a) Market state (b) Mission state (c) Strategy state

Figure G.3: Market state, mission state and strategy state for vessel alternative 3



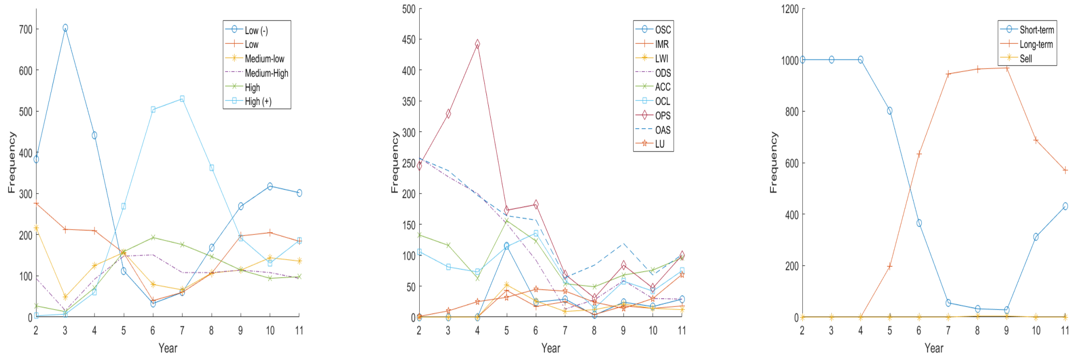
(a) Market state (b) Mission state (c) Strategy state

Figure G.4: Market state, mission state and strategy state for vessel alternative 4



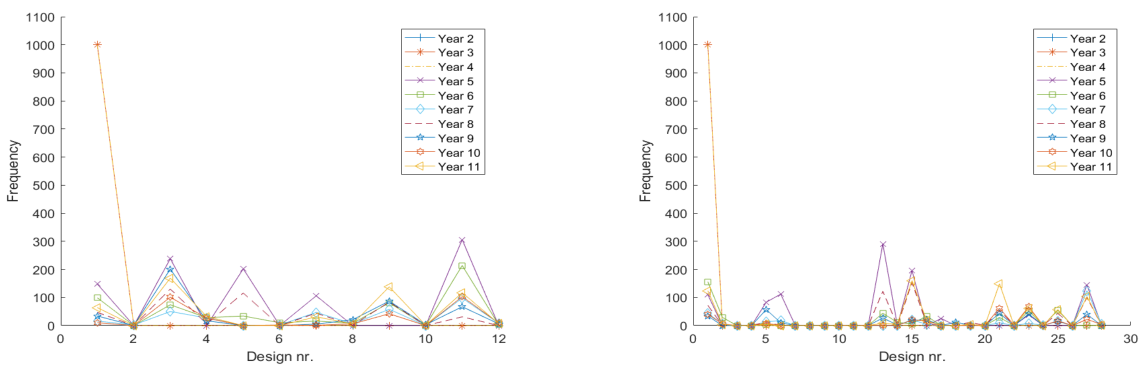
(a) Market state (b) Mission state (c) Strategy state

Figure G.5: Market state, mission state and strategy state for vessel alternative 5



(a) Market state (b) Mission state (c) Strategy state

Figure G.6: Market state, mission state and strategy state for vessel alternative 6



(a) Vessel 2 (b) Vessel 4

Figure G.7: Design alterations over the vessels lifecycle - vessel 2 and 4.

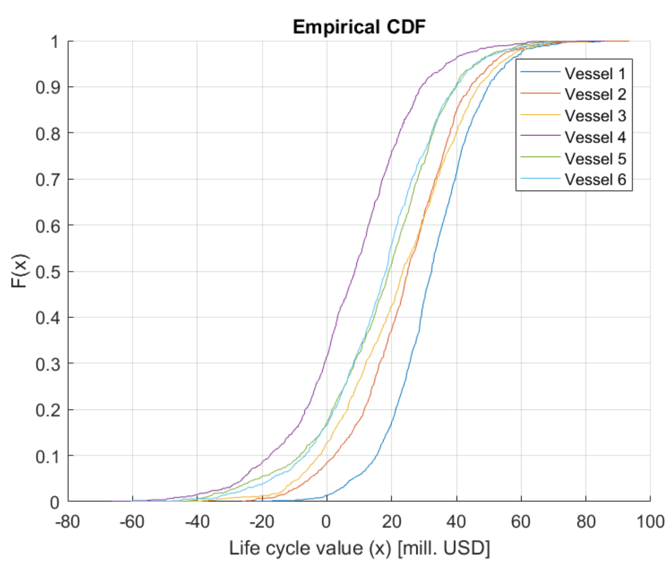


Figure G.8: Empirical CDF DfC 0 1 2.