ENABLING SHIP CHANGEABILITY; *a* LIFECYCLE APPROACH *to the* MARITIME ENERGY TRANSITION

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Enabling ship changeability; a lifecycle approach to the maritime energy transition

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For Lotta

Preface

Dear reader,

This thesis and its contents have shaped the last years of my life and provided me direction for the future. It was not the path that I had imagined when I started, one I would have consciously chosen, or one I could have prepared for.

Along the way, there were many moments of uncertainty. Yet in each twist and turn, I learned that there is always a way forward, as long as you dare to adapt and are fortunate enough to have the right people around you to support you.

Through this journey, I have started to realize that dealing with uncertainty was never merely the subject of my thesis. It is something that has shaped me, that has always been present, but that I have only now started to appreciate. Becoming aware of its presence and gradually learning to embrace it has made me understand that uncertainty is not something to fear, but something that gives life its colour.

I hope that this work may offer you the same perspective.

Jesper Jan Zwaginga
Rotterdam, February 2026

Summary

The maritime energy transition, characterised by the shift toward alternative fuels to reduce emissions, presents the maritime industry with a complex and uncertain decision-making problem. It is complicated by multiple external factors, including the uncertain development of emission-reduction regulations, the performance of emission-reduction measures, and the availability of necessary infrastructural- and economic support. Further challenges arise from maritime industry-specific characteristics, such as the capital-intensive nature, long lifecycles, differences in operational requirements and the technical complexity of ships.

From the perspective of the vessel-level decision-maker, these interdependent and continuously evolving factors create deep uncertainty in emission-reduction decisions. For many, this resulted in a decision paralysis that is reflected in postponed fleet renewal investments, and the ageing of the global fleet. Consequently, the main research question this thesis addresses is: *How can decision-making in the maritime energy transition be supported to enable timely ship design- and retrofit decisions under deep uncertainty?*
To address the deep uncertainty in the maritime energy transition, this thesis explores how to enable the use of changeability as a strategic response. This shifts the perspective from reactive compliance to strategic preparation, increasing awareness of when, what, and how to adopt emission-reduction measures.

A literature review categorises decision-making challenges and proposes a theoretical framework that subdivides the decision space into a context space, object space, and value space, including the mappings between them. Within these spaces, two primary challenge categories are identified: complexity and uncertainty. Although conceptually distinct, their interaction can result in deep uncertainty, reinforcing decision paralysis. Building upon this foundation, the Framework for Exploration of Adaptive Robustness (FEAR) was developed to support vessel-level decision-makers. The framework structures the decision problem into three interconnected modules: What, How, and When, which are used to iteratively explore the integration of emission-reduction systems.

The What-module investigates alternative emission-reduction measures and the required modifications to the ship system architecture. System representations are constructed using models from a system library, and system architecture evolution is analysed using graph and set theory to compare alternatives qualitatively and quantitatively.

The How-module addresses the integration of system architectures and their changeability within the constraints of ship design. An automated ship layout methodology has been developed that explicitly incorporates system changeability considerations. This method quantifies the trade-offs between preparatory investments and adaptation costs, and identifies investments that reduce future retrofit expenditures.

The When-module evaluates emission-reduction pathways under uncertainty using adaptive robust optimisation. The optimisation is used to investigate which initial and retrofit selections of emission reduction measures remain robust under uncertain fuel costs and emission taxation, thereby providing insight into the value of changeability throughout the ship design lifecycle.

The modules are combined into the FEAR framework, which can be used to iteratively explore alternative system architectures and changeability during the concept design phase. As new technologies and information become available, the framework can be reapplied, enabling continuous evaluation of emission-reduction strategies and previously integrated change enablers. The practical use of the framework is investigated through a case study.

Incorporating change enablers during the initial design phase resulted in approximately 20-46% reduction in relative material and labour retrofit costs compared to a design without future preparation. This reduction is further influenced when accounting for lost revenue, retrofit timing, and additional yard costs. The results from the case study were discussed in an interview with expert designers, they agreed that it offers valuable tools to explore alternative emission-reduction measures and system- and ship-level preparations. The FEAR was found to be mainly beneficial to support decision argumentation. However, they also noted that the current form is not yet applicable in practice, as it requires a dedicated interface and further validation across multiple vessel types and system architectures.

In conclusion, FEAR provides a theoretically substantiated, practical framework for structuring decision-making under deep uncertainty. By integrating considerations of existing alternatives, how they can be prepared for, and when they should be implemented, the framework enables proactive and adaptive decision-making in the maritime energy transition.

Samenvatting

De maritieme energietransitie, waarbij alternatieve brandstoffen worden gebruikt om emissies van de scheepvaart te reduceren, confronteert de maritieme sector met een complex en onzeker vraagstuk. Het wordt bemoeilijkt door uiteenlopende externe factoren, waaronder de onzekere ontwikkeling van regelgeving, de te gebruiken emissiereductie maatregelen, en de beschikbaarheid van noodzakelijke infrastructurele en economische ondersteuning, evenals sector-specifieke kenmerken zoals de kapitaalintensieve aard, lange levenscycli, verschillen in operationele vereisten en de technische complexiteit van schepen.

Vanuit het perspectief van de besluitvormer op scheepsniveau leiden deze onderling afhankelijke en dynamische factoren tot diepe onzekerheid in de besluitvorming rondom emissiereductie. Voor veel besluitvormers leidt dit tot verlamming, wat zich uit in het uitstellen van investeringen in vlootvernieuwing, en de toenemende leeftijd van de wereldwijde vloot. De centrale onderzoeksvraag van dit proefschrift luidt: *Hoe kan besluitvorming binnen de maritieme energietransitie worden ondersteund om tijdige ontwerp- en retrofitkeuzes onder diepe onzekerheid mogelijk te maken?*

Om besluitvorming onder deze diepe onzekerheid te ondersteunen, wordt in dit proefschrift onderzocht hoe veranderbaarheid kan worden ingezet als strategie. Hiermee verschuift het perspectief van reactie op externe factoren naar doelgerichte voorbereiding, waarbij expliciet aandacht wordt besteed aan de vragen wanneer, wat en hoe emissiereductie maatregelen kunnen worden geïmplementeerd.

Op basis van een literatuurstudie worden uitdagingen in besluitvorming gecategoriseerd en wordt een theoretisch kader ontwikkeld waarin het maken van beslissingen wordt onderverdeeld in een context ruimte, een object (keuze) ruimte en een waarderuimte, en de onderlinge mapping (relaties) tussen de ruimtes. Binnen elk van deze onderdelen kunnen twee hoofdcategorieën van uitdagingen voorkomen: complexiteit en onzekerheid. Hierbij definiëren we onzekerheid als een afwezigheid of onvolledigheid van informatie en complexiteit als een staat waar informatie moeilijk te structureren is door chaotische relaties of door een grote hoeveelheid. Hoewel deze conceptueel van elkaar verschillen, kan hun wisselwerking leiden tot diepe onzekerheid en daarmee besluitvorming verlammen. Voortbouwend op deze conceptuele basis wordt in dit proefschrift het Framework for Exploration of Adaptive Robustness (FEAR) ontwikkeld ter ondersteuning van besluitvorming op scheepsniveau. Dit raamwerk structureert het besluitvormingsvraagstuk in drie samenhangende modules: What, How en When. Deze modules worden iteratief toegepast om de integratie en voorbereiding van het schip op emissiereductie systemen systematisch te verkennen.

De What-module richt zich op het identificeren van alternatieve emissiereductie maatregelen en de daarvoor benodigde aanpassingen in de systeemarchitectuur van het schip. Hiervoor is een methode ontwikkeld waarmee systeem representaties worden opgebouwd met behulp van modellen uit een systeembibliotheek, waarna de methode de verschillen tussen systeemarchitectuur alternatieven zowel kwalitatief als kwantitatief vergelijkt.

De How-module richt zich op de integratie van deze systeemarchitecturen en hun veranderbaarheid, waarbij rekening wordt gehouden met de randvoorwaarden van het scheepsontwerp. Hiervoor is een twee-fase generatie methode voor scheepsindelingen ontwikkeld die expliciet systeemveranderbaarheid meeneemt. De methode maakt inzichtelijk hoe voorbereidings- en aanpassingskosten zich tot elkaar verhouden en welke investeringen toekomstige aanpassingskosten kunnen verminderen.

De When-module evalueert emissiereductiepaden onder onzekerheid met behulp van adaptieve robuuste optimalisatie. De module wordt gebruikt om te onderzoeken welke initiële en retrofitselecties van emissiereductiemaatregelen robuust blijven onder onzekere brandstofkosten en emissieheffingen, en biedt daarmee inzicht in de waarde van veranderbaarheid gedurende de levenscyclus van het scheepsontwerp.

Het FEAR is iteratief van aard en is met name toepasbaar tijdens de conceptontwerpfase, maar het kan opnieuw worden doorlopen wanneer nieuwe technologieën of aanvullende informatie beschikbaar komen. Hiermee wordt een continue evaluatie van emissiereductie strategieën binnen het schip en de waarde van eerdere veranderbaarheid-maatregelen mogelijk gemaakt. De praktische toepasbaarheid van het raamwerk is onderzocht aan de hand van een casestudy. Het integreren van veranderbaarheid-maatregelen in de initiële ontwerpfase resulteerde in een relatieve kostenbesparing tussen de 20-46% op materiaal- en arbeidskosten voor de aanpassing naar methanol, vergeleken met een ontwerp zonder voorbereiding op toekomstige aanpassingen. Deze kosten besparing word verder beinvloed wanneer er rekening wordt gehouden met gederfde inkomsten, het moment van retrofit en aanvullende werfkosten via de When-module. De resultaten van de casestudy zijn vervolgens doorgenomen met ervaren scheepsontwerpers. Zij onderschreven dat het raamwerk waardevolle hulpmiddelen biedt om alternatieve emissiereductie maatregelen en systeem- en scheepsniveauvoorbereidingen te verkennen. Wel gaven ze aan dat de huidige vorm nog niet direct toepasbaar is in de praktijk, onder meer vanwege het ontbreken van een gebruiksvriendelijke interface en de noodzaak tot verdere validatie voor verschillende scheepstypen en systeemarchitecturen.

Samenvattend ontwikkelt dit proefschrift met FEAR een theoretisch onderbouwd praktisch raamwerk voor het structureren van besluitvorming onder diepe onzekerheid. Door expliciet aandacht te besteden aan welke alternatieven beschikbaar zijn, hoe erop kan worden voorbereid en wanneer implementatie wenselijk is, faciliteert het raamwerk proactieve en adaptieve besluitvorming binnen de maritieme energietransitie.

Contents

Abbreviations

ABM Agent-Based Model.

ABP Assumption-Based Planning.

AC Associative Classification.

ADA Axiomatic Design Approach.

AHP Analytic Hierarchy Process.

ALP Approximate Linear Programming.

AMALGAM Adaptive Multi-Algorithm Genetically Adaptive Method.

ANN Artificial Neural Network.

ANOVA Analysis of Variance.

ANP Analytic Network Process.

APM Adaptation Planning Method.

ARAS Additive Ratio Assessment.

ARO Adaptive Robust Optimisation.

ATC Analytical Target Cascading.

BEA Break-Even Analysis.

BF Bayesian Framework.

BLISS Bilevel Integrated System Synthesis.

BSM Black–Scholes Model.

BYA Bayesian Inference.

CAP Capital Asset Pricing Model.

CAPEX Capital Expense.

CART Classification and Regression Trees.

CBA Cost–Benefit Analysis.

CC Chance Constraints.

CD Concurrent Design.

CLT Central Limit Theorem.

CM Collaboration Method.

COPRAS Complex Proportional Assessment.

CSO Concurrent Subspace Optimisation.

DA Decision Analysis.

DAP Dynamic Adaptive Planning.

DAPP Dynamic Adaptive Policy Pathways.

DCF Discounted Cash Flow.

DCM Discrete Choice Model.

DEA Data Envelopment Analysis.

DEM Discrete Event Modelling.

DEMATEL Decision Making Trial and Evaluation Laboratory.

DES Discrete Event Simulation.

DMM Domain Mapping Matrix.

DOE Design of Experiments.

DP Dynamic Programming.

DRO Distributionally Robust Optimisation.

DSE Design Space Exploration.

DSM Design Structure Matrix.

DST Dempster–Shafer Theory.

DT Digital Twin.

EA Evolutionary Algorithm.

EC Epsilon-Constraint Method.

EEA Epoch-Era Analysis.

ELECTRE Elimination et Choix Traduisant la Realite.

EM Environmental Measures.

EMA Exploratory Modelling and Analysis.

ENV Environmental Management Systems.

EPD Environmental Product Declaration.

ESM Engineering System Matrix.

EST Energy Saving Technology.

ET Event Trees.

EU European Union.

EV Expected Value.

FA Factorial Sampling.

FAST Fourier Amplitude Sensitivity Test.

FD Flow Diagram.

FEAR Framework for Exploration of Adaptive Robustness.

FI Fuzzy Integral.

FMEA Failure Mode and Effect Analysis.

FO Forecasting.

FPF Fuzzy Pareto Front.

FS Fuzzy Sets.

FTA Fault Tree Analysis.

GA Genetic Algorithm.

GAME Game Theory.

GBB Geometric Brownian Bridge.

GBM Geometric Brownian Motion.

GDE3 Generalised Differential Evolution 3.

GHG greenhouse gas.

GNT Grey Number Theory.

GP Gaussian Process.

GRA Grey Relational Analysis.

GT Gross Tonnage.

GWP Global Warming Potential.

IBEA Indicator-Based Evolutionary Algorithm.

IG Info-Gap Method.

IL Inductive Learning.

IM Interval Model.

IMO International Maritime Organisation.

ISP Ill-structured problem.

JD Jump Diffusion.

KBE Knowledge-Based Engineering.

KER Kernel Methods.

KMC k-Means Clustering.

KNN k-Nearest Neighbours.

KRIG Kriging.

LCA Life Cycle Assessment.

LCC Life Cycle Costing.

LCM Life Cycle Management.

LCV Life Cycle Value.

LHS Latin Hypercube Sampling.

LNG Liquid Natural Gas.

MAC Marginal Abatement Cost.

MAE Multi-Attribute Expense.

MARS Multivariate Adaptive Regression Splines.

MATE Multi-Attribute Tradespace Exploration.

MAU Multi-Attribute Utility.

MBSE Model-Based Systems Engineering.

MC Markov Chain.

MCA Multi-Criteria Analysis.

MCS Monte Carlo Sampling.

MDO Maritime Diesel Oil.

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MDP Markov Decision Process.

MFM Multi-Fidelity Model.

MH Metaheuristics.

MII Mutual Information Index.

MILP Mixed Integer Linear Programming.

MINLP Mixed-Integer Nonlinear Programming.

ML Machine Learning.

MMSM Meta/Surrogate Modelling.

MOEA Many-Objective Evolutionary Algorithm.

MOGA Multi-Objective Genetic Algorithm.

MOO Multi-Objective Optimisation.

MOORA Multi-Objective Optimisation on the Basis of Ratio Analysis.

MORDM Multiple Objective Robust Decision Making.

MPC Model Predictive Control.

MPS Mode Pursuing Sampling.

MSSP Multi-Stage Stochastic Programming.

MTGS Mahalanobis–Taguchi Gram–Schmidt System.

NAV Normalised Attribute Values.

NPV Net Present Value.

OE Open Exploration.

OMOPSO Multi-Objective Particle Swarm Optimisation.

OPEX Operational Expense.

OPT Optimisation.

OR Operations Research.

PAES Pareto Archived Evolution Strategy.

PBD Point-Based Design.

Pbox Probability Box Model.

PCA Principal Component Analysis.

PCE Polynomial Chaos Expansion.

PD Probabilistic Design.

PF Pareto Front.

PID Proportional–Integral–Derivative Controller.

PM Probability Model.

PN Petri Net.

POMDP Partially Observable Markov Decision Process.

PP Product Platforms.

PPE Power Propulsion and Energy.

PRIM Patient Rule Induction Method.

PROMETHEE Preference Ranking Organisation Method for Enrichment Evaluations.

PSO Particle Swarm Optimisation.

QFD Quality Function Deployment.

RBD Reliability Block Diagram.

RBF Radial Basis Function.

RCAR Regularised Class Association Rules Algorithm.

RD Robust Design.

RDiM Robustness Discrepancy Model.

RDM Robust Decision Making.

RF Random Forest.

RL Reinforcement Learning.

RM Robustness Measures.

RO Robust Optimisation.

ROA Real Options Analysis.

RR Ridge Regression.

RS Rough Sets.

RSC Responsive System Comparison.

RSM Response Surface Method.

RT Risk Theory.

SA Sensitivity Analysis.

SAW Simple Additive Weighting.

SBD Set-Based Design.

SC Spectral Clustering.

SCA Scenario Analysis.

SD Scenario Discovery.

SDY System Dynamics.

SE Systems Engineering.

SENT Shannon Entropy Technique.

SFOC Specific Fuel Oil Consumption.

SIM Simulation.

SP Stochastic Programming.

SPEA Strength Pareto Evolutionary Algorithm.

SVM Support Vector Machine.

TCO Total Cost of Ownership.

TDN Time-Expanded Decision Network.

TFO Technology Foresight.

TRM Technology Roadmap.

UQ Uncertainty Quantification.

VIKOR Multi-Criteria Optimisation and Compromise Solution.

WASPAS Weighted Aggregated Sum Product Assessment.

WSP Well-structured problem.

1
Introduction

1.1 The maritime energy transition and the Choices Today

The maritime energy transition, characterised by the shift toward alternative fuels to reduce emissions, is accelerating. It is driven by urgent climate goals and increasingly stringent emission regulations [198, 322]. This has resulted in a surge in research and development efforts on emission reduction measures [24, 468]. Nevertheless, in data from June 2025, the percentage of vessels that are alternative fuel-capable is 2%, while only 0.8% are alternative fuel-ready [356]. Worse still, of the alternative fuel capable ships, 60% are Liquid Natural Gas (LNG) capable, which, despite reducing other harmful emissions (SO_x,NO_x and PM), can increase greenhouse gas (GHG) emissions due to methane slip [326]. Luckily, as described in the same 2025 data, a 14.5% GHG reduction has been realised with respect to 2008 through operational speed reduction (21% for bulkers and 27% for container vessels, with a 20-30% reduction resulting in an estimated CO_2 reduction of 48.8-65.7% [423]), in combination with 10% of the fleet (number of vessels) using Energy Saving Technology (EST) [94]. The EST most commonly applied are the reduction of hull resistance through measures like bow enhancement or air lubrication (48% of EST), or by improving propeller efficiency using measures like propeller ducts and pre-swirl stators (45% of EST) [94].

Unfortunately, despite these efforts, the ageing fleet (the average age of the fleet is currently 18 years and has increased by around 21% with respect to 2013) in combination with the fleet growth in number (there are 42% more vessels than 2008) has resulted in GHG per GT increasing, from 80.5% in 2021 to 85.5% in 2025 [94].

Fortunately, in addition to the currently used EST and alternative fuels, there are various additional options to reduce emissions. For example, eight years ago, studies already reported that emissions per gross tonnage could be reduced by more than 75% [58] or by 80% compared to conventional fuels [26] by combining multiple available reduction measures. Moreover, a range of other promising emission-reduction measures, including alternative fuels, carbon capture and EST, have been, and continue to be developed. However, the selection and implementation of emission reduction strategies can vary across ship types

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[161, 162], are influenced by legislative actions [412], and depend on whether measures are applied to newbuilds or existing vessels [374]. Furthermore, the actual emission reduction and associated costs of alternative fuels are highly dependent on policies, feedstocks, infrastructure and production pathways [200]. Consequently, to address these uncertainties and achieve the emission reduction targets set for 2050, the literature suggests that a combination of alternative fuels, carbon capture technologies and ESTs, rather than a single reduction measure, will remain necessary [433].

Due to these developments, the maritime industry now stands at a pivotal crossroads. Emissions from newbuild and existing vessels need to be reduced as quickly as possible [433] to keep global warming under 1.5 $^{\circ}$C. To achieve this, CO_2 emissions need to be reduced by 48% from 2019 levels by 2030 [343]. However, even though combining existing measures already offers significant reductions in emissions, the majority of decision-makers still have to decide how to act, with approximately 90% of vessels still lacking EST and 98% lacking alternative fuel capability [94]. As evidenced by the rapid ageing of the fleet, most are waiting to see how regulation, technology, economy, and infrastructure develop. This delay in action not only worsens the GHG footprint over the lifecycle of a ship but can also lock vessels into suboptimal or obsolete technologies, especially as ships age and struggle to recoup the costs of later retrofits. Consequently, this thesis aims to support stakeholders who are involved in design, build and retrofit decisions of a vessel:

How to make robust investments and emission reduction decisions today, despite uncertainty about what technologies, regulations, economic or infrastructure conditions will dominate tomorrow?

1.1.1 Main challenge categories that surround vessel-level emission reduction decision-making

For stakeholders who are involved in design, build and retrofit decisions of a vessel, the decision to reduce emissions is complicated by several political, financial, and technological challenges. Figure 1.1 summarises the main challenge categories that surround vessel-level emission-reduction decisions in the maritime energy transition. As illustrated in Figure 1.1, vessel-level emission reduction decisions are impacted by multiple external factors. Political targets stimulate emission reductions, while the characteristics that are specific to the maritime industry and the available emission-reduction options constrain which pathways are feasible. At the same time, economic and infrastructural support is crucial to apply emission reduction in practice. Each of these domains occurs at different levels of detail with its own distinct challenges. From the perspective of a vessel-level decision-maker, the interconnections and ongoing development at these levels further complicate emission-reduction decisions. As such, the maritime energy transition is not a set of isolated challenges, but a complex web of interactions and uncertain developments, with the ship caught in the middle. Consequently, this thesis approaches the maritime energy transition as a decision-making problem hierarchically decomposed into interconnected levels [68], each with its own decisions and challenges that affect vessel decisions. The challenges are discussed below.

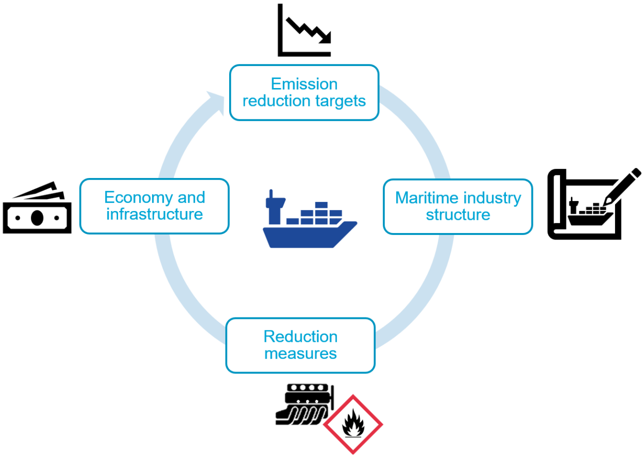

Figure 1.1: Challenge categories influencing vessel-level emission reduction decision-making. The vessel is surrounded by four domains: emission reduction targets, maritime industry structure, emission reduction options and economy and infrastructure, highlighting the multiple dimensions of decision-making.

1.1.2 Emission reduction targets

Although the necessity of reducing GHG emissions is widely acknowledged, emission reduction targets play a crucial role in stimulating action, particularly given the global character of the maritime industry. However the emission reduction targets and regulation have been changing in the last decade. In 2018, the International Maritime Organisation (IMO) adopted an initial strategy aiming to reduce carbon intensity by 40% by 2030 and by 70% by 2050, while also targeting a 50% reduction in total GHG emissions by 2050 relative to 2008 levels. In 2023, the IMO revised this strategy, strengthening its ambition by targeting a reduction of at least 20% in total GHG emissions by 2030, 70% by 2040, and achieving net-zero emissions by 2050 [197].

Furthermore, the IMO recently proposed a progressively tightening annual reduction requirement based on a ship's GHG Fuel Intensity (GFI), alongside financial incentives intended to support early adopters of low-emission technologies [198].

To enforce such targets, global institutions such as the United Nations and the IMO depend on local governments and global cooperation. However, under President Trump, the United States withdrew from the United Nations' Paris Agreement and from discussions on emissions reduction at the IMO, instead prioritising economic gains over climate policy [152]. This even resulted in the vote to enforce GFI measures being delayed by one year. Meanwhile, other institutions like the European Union (EU) set stricter targets, proposing a general GHG reduction of 55% by 2030 and 90% by 2050 with respect to 1990 [97, 98]. Additionally, in 2025, the FuelEU regulations further tightened maritime CO_2 emissions reduction targets by 31% by 2040 and 80% by 2050 relative to 2020 levels [322].

These ongoing developments, along with differences in reference times and local enforcement of regulations, create uncertainty about what to comply with and when. Furthermore, the fragmentation of regulation not only threatens the ability to limit global warming, but it also distorts competition between regions, hindering long-term planning and investment in low-emission technologies [152]. Furthermore, the existence of multiple interdependent stakeholders with conflicting perspectives and preferences [342], contributes to the complex structure of the maritime industry [59].

1.1.3 Maritime industry specific characteristics

There are several characteristics specific to the maritime industry that complicate emission reduction decision-making.

First, the maritime industry consists of a large number of ship types, with widely differing capabilities and energy requirements. For example, Clarksons recognises 180 different ship types [94], ranging from bulk carriers and tugs to heavy-lift crane vessels and naval ships, examples of which are shown in Figure 1.2.

The diversity in ship types, sizes, and operational profiles results in emission reduction

(a) Trailing suction hopper dredger Vox Alexia (front) and offshore installation vessel Boreas (back) [313]

(b) Naval frigate HNLMS Tromp (left) and Multi-function support ship HNLMS Karel Doorman (right) [288]

Figure 1.2: Variety of ship types due to differing operational requirements.

measures affecting vessels in different ways [162]. Consequently, the appropriate energy transition pathway is highly dependent on ship type [237, 277].

Second, ships are capital-intensive assets and typically remain in service for 30 years or more, while emission reduction regulations and technologies evolve at a much faster pace. This dynamic also affects existing vessels that were built without consideration of future emission reduction requirements. Furthermore, due to their long lifecycles, vessels constructed today will need to comply with emission regulations and compete with more technologically advanced ships by 2050. Therefore, building a ship solely for the economic conditions prevailing at the time of ordering, as was common practice in the past [341], is no longer sufficient. In addition, to retrofit existing vessels and equip newbuilds with novel emission reduction technologies at uncertain points in the future requires substantial shipyard capacity [407], which further increases built and retrofit times.

Third, ship design projects are typically characterised as being large and complex, with a high cost of error, while facing physical, social, economic, political, legal and, as is the case for maritime emission reduction, environmental constraints [347]. Depending on the type of ship, the design process can be more complex due to an increase in difficult-to-structure information, while establishing relationships between choices and objectives becomes challenging [290]. Consequently, the ship design process is often described as a complex, wicked, or ill-structured problem [15, 333], as it is a problem that can only be understood in retrospect, making performance estimation difficult [168]. Furthermore, incorporating more innovative efforts in a design is found to increase complexity [68], which makes the innovation necessary for the energy transition a driver of a more complex design process. Another aspect of design is a clear division between specification and operational phases, as a design functions independently of its designer [347]. Consequently, operational uncertainties regarding future emission reduction options must be included during design decision-making. In early-stage ship design, the design freedom and uncertainty regarding the impact of early decisions on later stages are both high. This design uncertainty gradually decreases until the ship has been built, while decisions are already made, making changes costly [275]. More importantly, external uncertainties regarding regulations, the ship's operation, and its systems persist throughout its lifetime, while the most influential decisions have already been made. Consequently, in the context of the maritime energy transition, complexity, uncertainty, and including additional financial and environmental objectives present significant challenges in ship design decision-making [5, 132, 438] that are preferably dealt with when design freedom is still high.

1.1.4 Impact of uncertainties regarding emission reduction measures

To reduce emissions, there has been a surge in research and development concerning emission reduction measures [24, 468]. However, the emission reduction potential and associated costs of these measures remain uncertain and depend on feedstocks, infrastructure, and production pathways [200, 338]. Therefore, this section investigates how differences and uncertainties regarding emission reduction measures affect maritime emission reduction decision-making.

A ship can be understood as a complex system of integrated subsystems [14, 132]. Because of this, the selection, interconnection, and integration of individual components within a vessel influence the overall project complexity. In particular, for novel emission-reduction measures, estimating their impacts on vessel performance, operational capabilities, and economic outcomes is challenging due to the strong interdependencies between subsystems. As shown in Figure 1.3, various alternative fuels and EST, as well as economic and operational measures, can be implemented individually or in combination to reduce emissions.

Multiple emission reduction measures target specific elements of the onboard energy infrastructure. For example, energy-saving technologies such as hull optimisation or propeller design improvements typically enhance propulsive efficiency, while hybrid-electric powertrains aim to improve power utilisation. In addition, research into alternative energy carriers with reduced carbon footprints is expanding, encompassing fuels such as methanol, LNG, hydrogen carriers, biofuels, and e-fuels [24, 205, 468, 481]. These energy carriers store hydrogen using physical methods (compression or liquefaction), material-based liquid carriers (LOHCs), or solid-state storage (hydrides) [357].

Furthermore, beyond conventional combustion technologies, alternative energy conversion systems such as advanced nuclear reactors and fuel cells are being explored for commercial maritime applications. However, as many of these measures remain under development, operational experience is limited [26, 165]. Consequently, uncertainties

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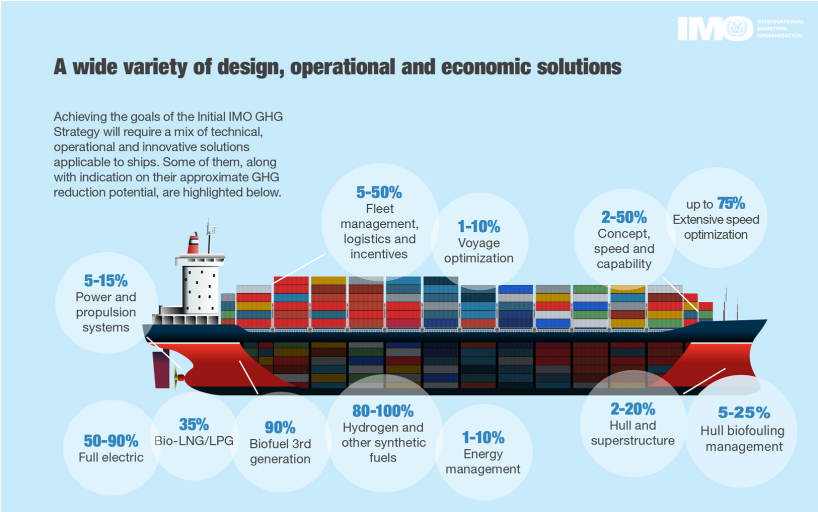

Figure 1.3: Figure accessed from [202], produced by IMO to reflect different operational, economic and design solutions including emission reduction potential estimates.

persist regarding their actual emission reduction potential and possible adverse side effects. Ongoing technological development also introduces uncertainties related to installation, operation, maintenance, and safety [358, 445, 460].

In addition, production and operational costs can vary significantly due to external factors, creating further uncertainty regarding the availability and practical applicability of these technologies [49, 170, 230]. As a result, many measures expected to deliver substantial emission reductions are still immature and would require radical technological shifts for widespread implementation [205], thereby complicating decision-making during ship design and operation.

1.1.5 Impact of economic and infrastructure support

While reduction targets are mostly driven by societal and environmental imperatives [184, 188, 390, 459], the successful implementation of emission reduction measures also depends on overcoming financial and logistical barriers. These barriers increase uncertainty in the maritime industry about which energy transition pathway to follow.

Regarding economic support, the energy transition is highly dependent on the substantial investments required for the commercial viability of emission reduction measures, as well as on issues such as sunk costs, missing economic incentives, and conflicting stakeholders' interests [184, 390]. For example, the costs and success of alternative fuels depend strongly on the production chain and operational aspects such as global availability [49, 170, 230]. From an infrastructure perspective, the local price and availability of alternative fuels depend heavily on demand and developments in other (local) industrial sectors, increasing uncertainty about which fuel to use and when.

Furthermore, maritime revenue, such as freight rates, is closely linked to the global economy and typically experiences cyclical fluctuations in response to shocks in fuel prices, shipping demand and supply, and their residual effects [207, 414]. Maritime investment and business decisions frequently lag behind this cycle due to long-term contracts and the long build times of ships, which increases the impact of shocks on income uncertainty and volatility [225]. If maritime emission reduction decisions lag behind in a similar manner, individual stakeholders risk increasing their dependence on external actors and competitors. Consequently, to effectively manage and implement the changes required to achieve the maritime energy transition, maritime companies must become more adaptive to change [415].

Due to the capital-intensive nature of ships, financiers play a critical role in supporting newbuild and retrofit projects with capital to enable emission reductions [146, 410]. Several barriers to decarbonisation are related to limited access to capital. This occurs due to the increased costs associated with emission reduction measures and the financial risks involved, as well as the absence of support from insurance companies [162]. Even though ship financiers demonstrate ambition to support shipowners in the transition, the sentiment to tackle these barriers is lacking. In a 2023 publication, shipping financiers were found to believe the transition was still far away and emphasised the need for proper regulation to effectively incorporate climate risks into financing, while perceiving the risk of a ship becoming stranded due to non-compliance as limited [146]. Furthermore, research found that financiers perceive advanced ship designs using innovative technology as high risk, while preferring well-known and secure risk projects [136, 384]. Combined with overcapacity, risks of low resale value and non-performing shipping loans, banks are more cautious to finance shipping, while retrofit costs cannot be covered due to loan security challenges [136, 310].

Consequently, despite green ambitions, it is clear that multiple external factors influence emission reduction decision-making. This is reflected in the existence and imbalance between collective environmental and societal value and individual benefits of stakeholders within larger societal constructs, such as commercial and economic networks [442]. Multiple actors in each domain with different preferences influence the direction of the maritime energy transition. The existence of such conflicting perspectives and utilities results in uncertain development of financial and economic support for maritime emission reduction efforts at each level. For stakeholders involved with a vessel, this complicates the decision on when to reduce emissions while remaining competitive.

1.2 Research motivation

High levels of complexity and uncertainty in decision-making are also recognized as a condition where deep uncertainty or recognized ignorance occurs. Deep uncertainty is defined as: "the condition in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes." [273]. It results in decision makers acting in an ambiguity (uncertainty) averse manner, preferring options where risk is known [388]. A common response to uncertainty is to either ignore or delay decisions [5]. This response is reflected in the current state of the fleet and the sentiment in ship finance [425]. Figure 1.4 shows that vessel age has increased across all ship types as the share of newbuilding orders with respect to the total fleet size has

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decreased. The declining share of newbuilding and the increasing average vessel age reflect a reduction in fleet renewal investment, even though more investment is needed to ensure meeting emission reduction targets.

Instead of ignoring uncertainty or delaying investment decisions, alternative approaches

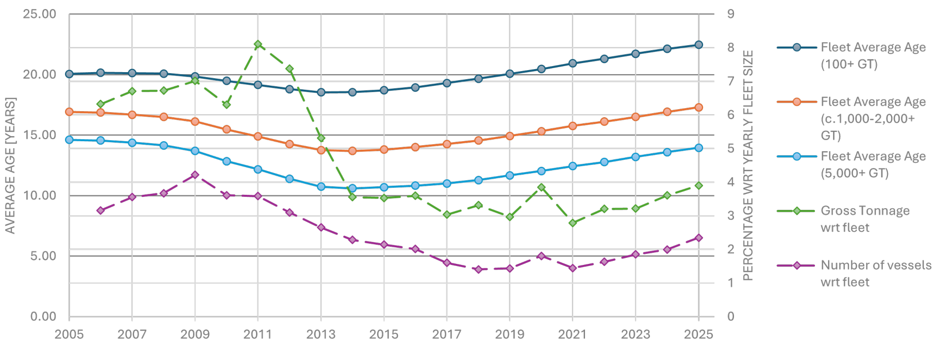

Figure 1.4: Year-over-year fleet development across all ship types. The left figure shows the share of the fleet that is newbuild each year, and the right shows the average age of the fleet, by gross tonnage. The figure illustrates the decline in fleet renewal. The figure is created with 2025 data from [94, 356]

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incorporate deep uncertainty in decision-making by accepting or reducing it [5]. Alternative fuel-capable or fuel-ready vessels already apply such approaches, but it is still only a small percentage of the fleet. When applied in a structured manner, ship design and operational strategies based on acceptance and reduction of uncertainty could offer a way to break through the current state of paralysis in the face of the energy transition.

Adaptive strategies are explicitly mentioned as a way to deal with deep uncertainty and recognised ignorance [185]. Furthermore, it could be especially beneficial for the maritime energy transition, as so-called design for changeability principles are beneficial for systems with a long lifecycle that face rapid technology development, complexity and uncertainty, while incurring high deployment and maintenance costs [147]. Changeability is defined as the ability to change an object's function or properties throughout the lifecycle. Examples of changeability are the change of a ships energy system components or changing operation (speed) to reduce emissions. Multiple authors have confirmed the potential benefit of changeability for maritime applications [93, 305, 324, 349, 402], but stress that its value depends on the level of uncertainty.

Despite its potential, the application of changeability during ship design and operation is difficult, as a ship is a complex, highly integrated system of systems, where any change to one part (such as switching an engine and fuel) may trigger cascading impacts to other systems and the capability of the ship as a whole. Furthermore, the additional innovative activity required to integrate (novel) emission reduction measures, combined with considering changeability, can significantly increase the complexity of the design process.

Besides the increased complexity, the addition of multiple sources of uncertainty further increases the number of options and scenarios to consider when applying changeability for the maritime energy transition. Consequently, to ensure the ship can robustly accommodate changeability [12] as an integral design consideration, it is required to investigate multiple options, their interdependencies and multiple scenarios to anticipate required changes and develop a robust design.

Fortunately, as will be shown in chapter 2, considerable research has been conducted to address uncertainty and complexity in decision-making, both in maritime and other disciplines, whose insights could be beneficial for the maritime energy transition. However, an approach that integrates these tools to support assessing changeability against uncertainty in design and retrofit engineering processes for complex objects, such as ships, is lacking.

Shipowners and other stakeholders who ignore or delay decisions in response to the energy transition run the risk of being forced to use suboptimal emission reduction measures due to their dependency on external decision-making. This includes both regulatory and system developments, but also the strategic responses of other shipowners to the transition. The development of a proactive strategy that accepts or reduces uncertainty through preparation enables stakeholders to respond more rapidly and effectively to emerging developments. Moreover, such a strategy creates opportunities to influence the trajectory of emission-reduction measures and systems, shifting the perspective of stakeholders from reactive to proactive. Besides ship-owners, this also improves support for a broader market of emission reduction measures. Furthermore, ship designers who anticipate uncertainty and include changeability as part of the design phase improve their involvement with the vessel to extend beyond the build phase to the operational lifecycle. Consequently, besides contributing to the advancement of research, the addition of changeability to deal with the deep uncertainty faced in the energy transition also creates opportunities for multiple stakeholders.

1.3 Research objective

The objective of this thesis is to develop and validate a decision-support framework that addresses the wicked decision-making problem posed by the maritime energy transition, where deep uncertainty complicates the when, what, and how of adopting emission-reduction technologies.

As explained in the research motivation, several authors have proposed incorporating changeability or adaptability to deal with such deep uncertainty. Nevertheless, while the benefits of changeability have been widely discussed in the literature, this thesis instead focuses on how changeability can be used as an integral part of ship design and lifecycle decision-making, enabling decision-makers to use changeability as a strategy for the maritime energy transition. This shifts the decision-making perspective from reactive response to a more proactive approach, while also increasing awareness of what changes are possible, when these can be implemented and how to use them to the decision maker's advantage.

To achieve this objective, the thesis develops a decision-support framework that combines decision-support methods and analytical tools. The framework is based on an overview of the approaches that decision-support methods use to address deep uncertainty in decision making. These enable the exploration of emission-reduction measures and preparations during ship design, reducing financial barriers to emission reduction.

The framework is aimed at ship-level decision-makers, such as ship owners and supporting stakeholders who are involved in design, build, and retrofit decisions of a vessel, independent of the type of ship. By improving the awareness of differences between emission reduction measures and the role of change-enablers, the framework supports informed decision-making in response to the energy transition.

The research objective, dealing with the maritime energy transition through enabling changeability, is considered to be achieved when the framework is found to:

1. Support the exploration and comparison of emission reduction strategies.
2. Provide quantitative insight into the feasibility of changing strategies.
3. Inform the decision-maker what preparations enable changes and how these actions influence lifecycle costs.

The framework is applied with stakeholders to investigate whether it provides quantitative insight into how vessels can be prepared for future changes and informed decision-making under deep uncertainty. Lastly, even though the framework is developed for maritime applications, the insights have broader relevance to other domains characterised by long lifetimes and deep uncertainty.

1.4 Research questions

The central question this thesis addresses is:

How can decision-making in the maritime energy transition be supported to enable timely ship design and retrofit decisions under deep uncertainty?

As the maritime energy transition presents a highly complex or wicked decision-making problem, due to its many interconnected challenges and stakeholders, the thesis first analyses the decision-making problem and then investigates existing approaches and develops additional methods to support decision-making for the maritime energy transition. To better understand the nature of the decision problem, the first chapter focuses on clarifying the state of the art to support decision-making for the maritime energy transition. This is supported by the following sub-question:

1. *What makes decision-making under deep uncertainty, such as in the maritime energy transition, particularly challenging, and how can these challenges be systematically characterised and addressed?*

The insights from the first chapter are used to develop the framework to support emission reduction decision-making under deep uncertainty. Through the development framework, the following research question is answered:

2. *How to facilitate decision-making under deep uncertainty in the maritime energy transition?*

The framework is developed in the subsequent chapters. In order, these chapters discuss when to change emission reduction strategy while facing uncertainty, what emission reduction measures can be incorporated and how these can be integrated inside the vessel, to answer the following three sub-questions:

3. *Which existing methods can support decision-making in the maritime energy transition, and what are their limitations?*
4. *How can the evolution of ship system architectures be described and quantified?*
5. *How can ships be prepared to accommodate future system architecture developments?*

To investigate if changeability can be enabled through the use of the framework and whether the last chapter considers a case study with a stakeholder, aimed at answering the following research question:

6. *To what extent can system developments be included in design in a practical case study?*

1.5 Thesis Structure and Contributions

A visualisation of the thesis structure and interrelation of chapters is provided in Figure 1.5. After the theoretical background chapter the next chapters focus on developing each

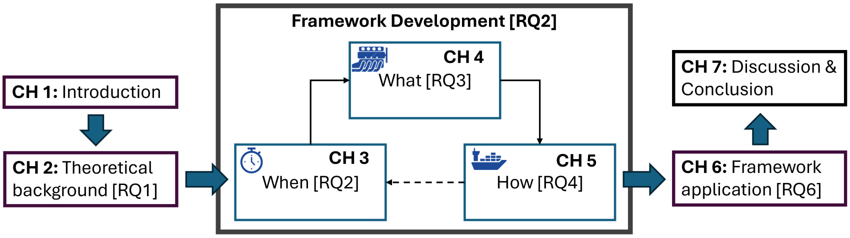


Figure 1.5: Visual representation of thesis structure

module for the decision support framework. Below is an overview of the contents and contribution of each chapter:

1. To answer *RQ1*, chapter 2 reviews decision-support methods from multiple disciplines, including engineering design, operations research, and systems thinking. It identifies the opportunities and limitations of decision-making methods to enable decision-making under deep uncertainty.
Contribution 1: Develops a theoretical framework to structure decision-making challenges and approaches, and provides a structured mapping of different methods and their applicability to decision-making challenges.
2. To answer *RQ2*, the theoretical background is used to subdivide the maritime energy transition decision-problem into three parts: when, what and how to adopt emission reduction technologies in a vessel. These three aspects are used as a basis for the decision-support framework.
Contribution 2: Proposes a multi-disciplinary framework that allows investigation of separate levels of detail using challenge-appropriate methods.
3. To answer *RQ3*, chapter 3 investigates how decision support methods can be applied to a maritime emission reduction measure selection case-study to investigate the

benefits and limitations of different methods. It studies explorative methods, such as dynamic adaptive policy pathways and robust decision-making, to alternative future scenarios and search methods such as stochastic programming and adaptive robust optimisation to guide decision-making during ship design and operation while incorporating uncertainty.
Contribution 3: Investigation of the benefits and limitations of methods dealing with decision-support under deep uncertainty.

4. To answer *RQ4*, chapter 4 describes the methodology used to describe changeable system architectures. It develops a system architecture exploration model that can be used to build and evaluate system models and connects these to investigate interdependencies between changing systems.
   Contribution 4: Proposes a novel network algorithm to hierarchically connect components within a system architecture to evaluate and compare system architectures under uncertainty.

5. To answer *RQ5*, chapter 5 describes the development of the ship integration placement model. It is used to investigate the ability to integrate and change system architectures in a ship layout and evaluate their effect on vessel performance.
   Contribution 5: Proposes a placement algorithm to evaluate changeability, connecting changeable system architecture and the ship design.

6. To answer *RQ6*, the what and how components of the framework are applied to a real-world case study with expert designers, demonstrating how changeability can be embedded during conceptual design stages.
   Contribution 6: Investigates the benefit of incorporating changeability perceived by vessel-level decision-makers.

2

A framework to categorise decision support

Maritime emission reduction decision-making presents a complex design and engineering problem, further complicated by multiple external factors. These include uncertainty regarding emission-reduction requirements, the availability of logistic and economic support, maritime industry-specific characteristics, and the performance of possible solutions due to ongoing developments.

The maritime industry consists of a complex global structure [59], involving many actors with conflicting perspectives and preferences [342]. Because the transition is primarily driven by societal and environmental necessity rather than economic advantage, emission-reduction policies often conflict with economic barriers faced by actors and the high costs associated with the innovation of critical technologies and infrastructure [26, 184, 390, 459]. This is further complicated by the fact that shipping operates globally, while perspectives and support at continental organisations, local governments and constituents differ. Consequently, the pathway to reduce maritime emissions is uncertain, as global targets are subject to change and local rules and regulations are fragmented [139, 390].

At the same time, many emission reduction measures are innovative and still in development, resulting in limited operational experience [25, 71]. This creates uncertainty regarding installation, maintenance and safety [358, 445] as well as deviating estimates for cost and emission reduction potential of technological measures [58, 471] and supporting infrastructure [49, 170, 230, 260]. The impact of these technological uncertainties further depends on ship type [237, 277] and the capacity of shipyards to outfit both new and existing vessels with novel emission-reduction measures at an uncertain time in the future [407]. Within this arena, designers and engineers must investigate different perspectives, requirements, and capabilities to address issues at varying levels of detail.

A large body of literature on design and decision support methods could offer support, but the sheer volume and diversity in context, descriptions, and approaches complicate

This chapter is under review in Research in Engineering Design; the content has been adjusted to align with the thesis context.

application. In maritime decision-making, four dimensions are found to influence the selection of a decision support method:

1. The decision context: the level of detail directly influences what insights can be generated. In maritime studies these typically range from policies [335], port infrastructure [460], fleet management [182], ship operation [386], to ship design [333].
2. The solution direction: industry specific characteristics impact what potential solutions are applicable. This includes differences in ship type and subsequent operational requirements [235, 240, 350], and the working principle of emission-reduction measures, such as operational measures [470], ship design [86, 325] or additions or modifications to the ships Power Propulsion and Energy (PPE) systems [88, 463].
3. The methodological approach suitability: decision-support methods differ in how they deal with decision challenges and are therefore specifically selected to fit the decision problem under investigation [139, 181, 196, 303, 482].
4. The decision evaluation: the ability of a decision support method to include multiple objectives [437, 438], quantifying the effects of uncertainties on value [195, 221] or the inclusion of preference and competition [409, 434].

However, determining which decision support methods to use for what challenge and dimensions remains difficult, as the number of methods increases yearly by transfer from other fields, extension, (re)invention or combination to find new ways to deal with challenges [272]. Three papers that reviewed specific challenge categories in the maritime domain are noteworthy for their extensive efforts. Notably, Agis [5] examines different sources and approaches to deal with uncertainty from the perspective of the maritime industry, Ebrahimi et al. [132] present multiple categories of complexity and how to measure them from the perspective of a shipyard, and Trivyza et al. [438] review methods to deal with challenges to evaluate innovative technological reduction measures.

Despite their contributions, these studies address the challenge categories separately, while the number of studies and applications far exceeds those treated in these papers. As a result, several knowledge gaps remain:

1. Existing reviews generally review challenges separately, thus creating overlapping subcategories and varying descriptions. No review has discussed how to deal with multiple challenges simultaneously.
2. The ever-increasing number of options makes comparing the effectiveness and limitations between methods difficult without significant investigation.

Consequently, determining how to deal with the multiple challenges of the energy transition in the maritime sector is complex in itself. It becomes a question of whether a decision support method is applicable, whether novel, more extensive decision methods are needed, or whether multiple existing methods should be combined. Consequently, decision-makers and researchers are currently confined to approaching the problem with a routinised or preselected method, which can force an ill-fitting approach or limit its effectiveness. Therefore, this chapter reviews the state of the art of decision support methods in order to address the first research question:

What makes decision-making under deep uncertainty, such as in the maritime energy transition, particularly challenging, and how can these challenges be systematically characterised and addressed?

To answer the question, a novel framework is proposed based on design and complementary decision-making theory to categorise methods into general approaches to manage complexity, uncertainty, and valuation challenges relevant to the stakeholder. It divides the decision space into four parts: the context space (external to the boundary of influence), the object space (influenceable decision alternatives), and the value space (reflecting performance and preference), which are connected with mapping functions (relations within and between spaces).

A review of nearly two hundred methods is conducted to identify approaches that address specific challenges in each space. The framework guides the definition of challenges to determine suitable approaches. For problems involving multiple challenges, it supports combining approaches to address critical components. Ultimately, the framework provides structure to fundamental problems like the maritime energy transition by categorising challenges and investigating approaches used by applicable methods.

The review is performed in two phases, following a narrative approach aimed at identifying key works and representative methods and application [110]. Searches were performed using Google Scholar, Science Direct, Web of Science and Scopus, combining the terms uncertainty, complexity and valuation with terms related to decision-making, energy transition, design, management, manufacturing and maritime. The initial selection was then expanded to related themes, such as psychology, policy-making, infrastructure, aerospace and mathematics. Reviews and highly cited papers were further used to identify influential authors, research groups and journals.

2.1 A framework to structure the decision-making process

To structure the decision making process, this thesis proposes the framework shown in Figure 2.1, subdividing the decision space into a context, object and value space interconnected through mapping functions. The figure alligns with the four dimensions that influence the selection of a decision support method discussed in the introduction in the following way. The decision framework consists of a represented decision space (decision context and solution direction) $\mathbb{R}^{(O,C)}$ and a perceived value space (decision evaluation) $\mathbb{R}^V$, which is reflected from the represented space using mapping functions (methodological approach). The represented decision space consists of the context $\mathbb{R}^C$ and object of choice $\mathbb{R}^O$ spaces separated by a boundary of influence ∂I. The figure merely represents the real decision space using two two-dimensional spaces with two independent parameters each, while these spaces are actually multi-dimensional.

On the right side of Figure 2.1, the decision between two emission reduction options is visualised. It includes a context scenario $C = \{C_1\}$ with a fixed fuel price and emission reduction target, and each reduction option has object parameters fuel consumption and emission reduction $O = \{O_1, O_2\}$. The mapping function M is used to create a reflected value V with value parameters cost and emission reduction percentage. Furthermore, the decision maker establishes a target value V_T, including an emission target and cost preferences shown as a gradient.

The framework is grounded in established decision theoretic principles. It adopts the three principles that are required for decision-making [440]: objects of choice (alternatives

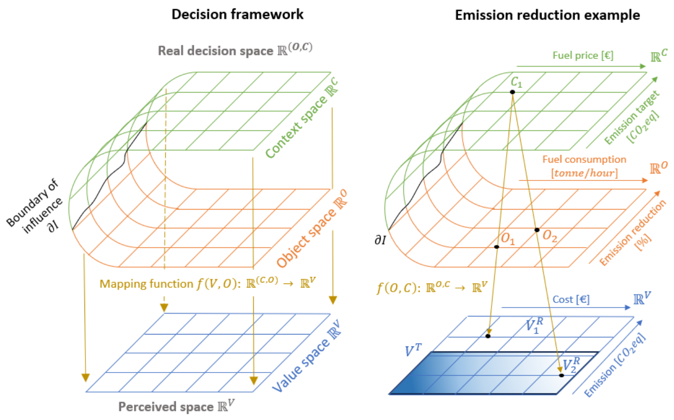


Figure 2.1: Framework structure to relate context (green), object (orange) and valuation of choice (blue) and their mapping (yellow) to visualise an exemplary emission reduction decision between two objects of choice (O_1, O_2) in a fixed context (C_1).

to choose from), a valuation rule (utility to maximise or minimise) and a mapping function (estimating the effects of choice). The object of choice is further subdivided into an endogenous and exogenous space defined by the boundary of influence [299]. The exogenous context of choice represents the circumstance where the decision occurs outside the decision-maker's influence [138, 290, 457]. Furthermore, the framework structure parallels a well established approach from policy-making literature that organizes decision problems in terms of context, levers (object), system model (mapping) and system outcomes (value) [226].

The space and mapping representation allows a decision-maker to subdivide the decision problem into dimensions and challenges. The context space $\mathbb{R}^C$ contains all the entities, scenarios, interfaces and factors external to the boundary of influence. One or multiple points or sets in the space are selected to describe the decision context (C). The object space $\mathbb{R}^O$ contains all decisions internal to the decision maker's boundary of influence, where multiple points or sets (O) contain the objects of choice from which the decision-maker can select (e.g. the emission reduction options to choose from). Mapping functions $f(O,C)$ are used by decision-makers to represent the real decision space and formalise the relationships inside and between the object, context and value spaces. It is directly related to the set selection in the object and context spaces.

The value space $\mathbb{R}^V$ at the bottom exists in parallel to the real space and reflects the performance of each object of choice as they act in the selected contexts V^R. The establishment of value is a precondition for decision-making. Values within the value space represent the preference of the decision-maker [121] to enable the selection of an object of choice amongst alternatives [438]. To evaluate is defined as a synthetic problem, which, rather than occurring naturally, is a product of human and social value systems [443]. As such, not the decision itself but its application results in a value that differs depending on the perspective of the beholder: there is the collective value, including society and nature (environment), and the (psychological) value to the individual [38, 443]. Therefore, besides (external) reflected value, it also includes a set representing the decision-maker's perception of value and their requirements (V^T). The set can be created by directly using context parameters and object inputs or translating these to other key performance indicators, such as cost or utility.

2.2 Challenge categories in the framework

The framework considers two fundamental challenges categories; complexity and uncertainty. Complexity refers to a state where information is abundant and unstructured, with chaotic or non-tractable relationships. It reflects how difficult the problem is to comprehend, even if information is available. In contrast, uncertainty refers to limitations or deficiencies in information regarding states, parameters, outcomes, or preferences, reflecting a lack of information about the decision problem.

Although both affect the decision space, the categories describe different properties of the decision problem and are therefore treated separately. Nevertheless, the interaction of both challenge categories can amplify the decision problem, as is described by deep uncertainty. To clarify the impact of complexity and uncertainty on decision-making and the interaction between both, the challenge categories are visualised in Figure 2.2. The

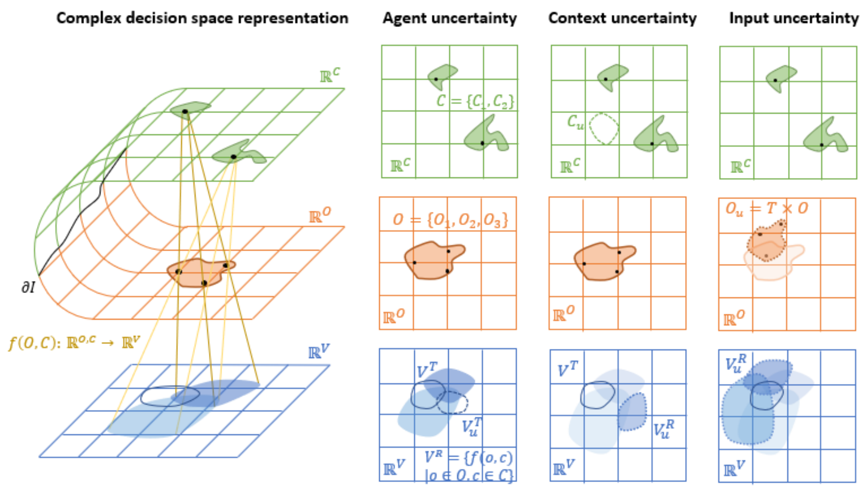


Figure 2.2: Representation of challenge categories in the framework. The left part of the figure shows a complex space representation to relate context, object and valuation of choice and their mapping. The right part of the figure shows the impact of uncertainty (lack of information) and its reflection on other domains.

left of figure 2.2 shows the impact of complexity on the real decision space $\mathbb{R}^{(O,C)}$, where the set of potential contexts and objects of choice has changed from a point into an area. Resulting in (large) reflected value areas in $\mathbb{R}^V$. In the value space, complexity results in an increased number of or the existence of multiple (conflicting) target values. The figure on the right represents the impact of uncertainty within the context $\mathbb{R}^C$, object $\mathbb{R}^O$ and value $\mathbb{R}^V$ space on the other spaces:

1. Agent uncertainty: The value space $\mathbb{R}^V$ includes the reflected value sets V^R and a set

representing the decision-maker's target value (V^T). Uncertainty results in a shift in the target value due to potential differences in indicators and preference, represented by (${V_u}^T$).

2. Context uncertainty: The second column shows the impact of uncertainty on the context and value space. It occurs when parameters take different values than expected, when different parameters are needed or when the parameters change over time and is represented by the difference between the selected context and reality (C_u). Because of the changes in the context and object of choice the reflected value set (${V_u}^R$) translates or deforms.
3. Input uncertainty: occurs when an input might not take the expected value or its selection might not result in the target object in reality, effectively transforming the set (O_u).
4. Model uncertainty: Is not shown in the figure, but can occur when (multiple) novel or crelationships are considered, while the functional response is unclear or unknown. Through the mapping function, uncertainty to propagate through levels and cause the representation in each space to differ significantly from reality.

Figure 2.2 illustrates how complexity primarily expands information in the decision space, while uncertainty distorts or shifts its representation relative to reality. When both occur within a space, the decision-maker faces not only an unstructured, but also limited knowledge about its structure and evolution. To further investigate how uncertainty and complexity can influence each space, literature on each challenge, their definitions, how to measure them and additional characteristics in the decision spaces are investigated separately.

2.2.1 Uncertainty

Even though, uncertainty is a major challenge recognized in literature, its existence is also seen as the reason that the decision-making activity has value [206, 282]. To describe uncertainty, we use the definition of a 'State reflecting the lack, inaccuracy or deficiency of information. Any situation outside pure certainty, independently of the degree of uncertainty.' [5]. The thesis adopts this definition as it reflects uncertainty as a state that occurs in different shapes and situations, while also providing ways to describe its degree of significance and impact. This allows us to further characterise uncertainty into a level [430], time of resolution (either short or long-term) [299], source/location and nature [456]. The sources are reflected in the framework by whether uncertainty stems from the context, object, value, or mapping in the decision space.

Uncertainty is said to always be present in decision-making [458], while the impact and need to deal with it can be described using a level or degree. Five levels are defined in policy-making literature [273]: complete certainty, low uncertainty (known unknowns), intermediate uncertainty (can be represented stochastically), deep uncertainty (many alternatives and unknown unknowns), and lastly, recognised ignorance. The definition of deep uncertainty also considers the effects of a combination of complexity and uncertainty [457]. The addition of uncertainty to complex problems is found to affect decision effectiveness significantly [5, 363]. Furthermore, in risk theory, risk is defined as a subset of quantifiable or measurable uncertainty by using probability, which represents the expected value of an adverse outcome [183]. Additionally, risk theory also recognises a 'higher level' uncertainty subset where the true state of affairs cannot be quantified [321]. This demonstrates the difficulty of dividing challenges into categories when the level of uncertainty is high and not enough is known about the problem.

Besides level, "nature" is also used to describe uncertainty. Uncertainty can be aleatory or ontic (irreproducibilities due to natural or physical causes) or epistemic (due to a lack of knowledge) [51, 135]. These are attributed to the context or object space. Alternative definitions of aleatory and epistemic uncertainty are synonymous with intermediate and deep uncertainty, respectively [105, 411]. Epistemic is also described as the part of uncertainty that can be reduced, while the natural aleatory uncertainty cannot. Ambiguity is often used to describe uncertainty in the value space, when conflicting frames about the issue exist [117].

2.2.2 Complexity

To establish the significance of complexity in the framework structure, we start with discussing several perspectives, as multiple definitions of complexity are proposed that differ depending on the perspective. For example, in an extensive review of complexity in shipbuilding, a complex system is described as: including a multitude and diversity of elements and connections, nonlinear and dynamic relations, the presence of hierarchical levels, variety of possible states, phase transitions and emergence (where the whole is more than the sum of its parts) [132]. From policy-making, Moallemi et al. [290] note how separate categories, like many parts, are not a precondition, as even small deterministic systems can represent chaos. Furthermore, Suh et al. [420] describe complexity as being the measure of uncertainty in achieving the functional requirements of a system within its specified static (deterministic) or dynamic (uncertain) design range. Again, this shows the connection and grey area between complexity and uncertainty, especially when describing the decision-problem. However, complexity is not random, as it is described as something between complete order and disorder [246]. Consequently, this thesis defines complexity as a state where information is abundant or unstructured, with chaotic or non-tractable relationships, which is further described using drivers/sources and level.

Several ways have been proposed to quantify the level of complexity in decision-making, such as measuring the amount of information [155, 278], the growth of memory and processing time relative to input size [56, 246, 278], the logical depth of a problem, and the degree of organization or pattern within a system [246]. In ship design, both the design process and the design itself have been assigned lower (e.g., inland cargo vessels) or higher levels of complexity (e.g., naval vessels). In this case, high complexity is often referred to as wicked or Ill-structured problem (ISP) [15, 72, 333], and low complexity as Well-structured problem (WSP). WSP are distinguished by various attributes, such as clear testing criteria, predictable outcomes, solutions requiring viable time, and well-defined transitions and consequences of alternatives [397]. In contrast, ISP are only fully understood afterwards; the (design) performance is difficult to evaluate [168]; they are characterised by unclear definitions and outcomes and the absence of stopping rules, while each problem is unique and can be a symptom of another (perpetual). Lastly, highly complex problems can be interpreted in different ways [276, 360], which can result in ‘form follows fiction’, where the choice of explanation determines the problem solution [405]. Consequently, regardless of its measurement, the complexity level is defined to range from low to high.

Multiple authors suggest using routine or more 'basic' frameworks from WSP to guide decision-making or limit efforts to important levels for ill-structured or wicked problems [347, 397, 444], using learned decision-making or progression to gain insight into wicked problems. For complex problems, routinised (learned) decisions can also result in a solution bias because of over-reliance on comparable problems [47]. Routine can influence choice despite intentions and is likely to result in decreased information search depth, a tendency to seek confirmatory information, and an underweighting of disconfirming evidence. Time pressure is said to increase the likelihood of routine choices, while changes in the presentation of the decision task result in deviations. Consequently, when routinised decisions are used to deal with complexity, they can also result in insensitivity to it.

2.2.3 Additional characteristics that impact challenges in the decision space

The main challenge categories can be further impacted by additional characteristics like temporal effects, risk and social dynamics. The impact of each characteristic on the main challenges in the decision space is discussed below.

Temporal effects

The impact of time is often included as a source of uncertainty in the literature. However, it is not considered as a separate space in Figure 2.2, as it can occur in each of the four dimensions and also impacts complexity. How to deal with uncertainty is directly influenced by the term of resolution being short, intermediate or long [103, 429]. Dynamic temporal effects can also result in uncertainty about if, when and how parameters can fluctuate. Furthermore, when a decision problem is known to change over time, it can also impact complexity [155]. This adds a time dimension to a decision space to reflect when and how information develops.

Risk

The ability to define preference in the value space is significantly impacted when facing uncertainty or risk. For example, expected value is often used for temporal effects in the value space, but is found to overestimate perceived value (St Petersburg paradox [321]). Furthermore, expected value is also subject to the flaw of averages, as it does not account for potential extreme opposing outcomes [331].

Capturing preference in a measure such as utility while facing uncertainty was proven difficult due to differences between decision-makers in risk-averse behaviour, nonlinear effects when discounting future scenarios, and overweighting of extremely unlikely outcomes (utility [37, 65], discounted utility [144, 377], cumulative prospect theory [220]). Lastly, when faced with higher levels of uncertainty, decision-makers were found to behave in an ambiguity-averse manner, preferring decisions where risk is known, even though an option with unknown risk had higher utility (Ellsberg paradox [388]). Additionally, decision-makers are shown to act irrationally under uncertainty, as predictions from observations are found to be inconsistent (Allais paradox [220]).

Social dynamics

In the value space, complexity can result in an increased number of objectives to consider [403], but also in multiple conflicting perspectives if more stakeholders are involved [464].

This is especially the case when dynamics and interdependencies of stakeholders outside of the boundary of influence can impact the value [385].

Value is often described as a sum of multiple attributes, where preference can differ between individuals, nature or society [121], while the total value is a product of each of these perspectives. Consequently, it cannot be described by a single objective, as outcomes become one-sided, which can result in depletion of resources, accidents or environmental destruction [443]. For example, environmental decisions can be unprofitable for the individual, while individual benefit can result in a depletion of resources. Therefore, recently, multiple objectives have been used more often to represent this balance between perspectives. This has also been recognised for emission reduction in the maritime industry, where, besides the standard cost metric, social, safety, reliability and lifecycle considerations were found to be important value metrics to include in decision-making [438].

Besides the concepts of value and multi-objectives, the number of stakeholders can impact decision-making and the perception of value. This is because of power dynamics between internal and external actors [385], but also the underlying characteristics of the object of choice, such as the collective action problem (no single user is essential, but if not enough contribute, it cannot be provided; people will exert less effort than working alone) and network externalities (where utility depends on the number of users) [443]. The existence of social choice impacts the ability to create a perfect ranking. Four axioms should be met: no decision-maker dictates the final vote (non-dictatorial), there can be no ties in preference, the same input should give the same result (universal), the ranking should not change when a lower-ranked option is added (independence), and if everyone prefers an option, it should also be in the aggregate ranking (Pareto efficient). However, only three of the four can realistically be met (Arrow's impossibility theorem [387]). Nevertheless, if no social choice is considered, as is the case for engineering requirements, perfect ranking is possible. However, social choice can play a role in engineering projects like water management [226]. When it is considered, a perfect ranking becomes impossible due to conflicting frames of reference, called ambiguity [117]. In this case, social dynamics, like competitive or cooperative behavioural concepts, need to be included.

2.3 Approaches to deal with challenges in the decision space

The framework structure can be used by a decision maker to locate the challenges in the decision space, identify uncertainties and complexities and establish whether challenges are modified by additional characteristics in each space.

Five main approaches are defined that decision support methods utilize to deal with the challenges in the decision space:

- Reduction: Simplify the dimensionality of a space or fix information to decrease the size of the space.
- Extension: Add information or dimensions to expand the space.
- Exploration: Explore possibilities or navigate dimensions within a defined space representation.
- Transformation: Change the representation of the space to obtain a novel outlook on the existing information.
- Structuring: Decompose or organize existing information.

In each space, different approaches can be used to reduce or manage challenges. However, not every approach is effective for every challenge. For example, extension is primarily used to address uncertainty, while reduction and structuring are used to manage complexity. Below, methods that apply these approaches in different ways are described for every space.

2.3.1 Approaches used for the Context space function challenges

The context space $\mathbb{R}^C$ represents the set of all entities, scenarios, interfaces and factors external to the boundary of influence of the decision maker. One or multiple points or sets in the space are selected to describe the decision context (C).

- *Contextual complexity* occurs when the context space contains a large number of parameters (dimensions), options, or interrelations between parameters.
- *Contextual uncertainty* arises when the selected representation of the context (C) deviates from reality (C_u), for example, when parameter values differ from expectations, relevant parameters are missing, or parameters evolve over time.

Approaches used to address context space challenges include reduction, exploration, extension and transformation. Reduction approaches primarily address contextual complexity by limiting dimensionality or fixing parameters. Exploration is applicable to both complexity and uncertainty, as it enables the investigation of multiple dimensions (complexity) as well as alternative or uncertain scenarios (uncertainty). Extension approaches increase the dimensionality of the context space or acquire more information to primarily deal with uncertainty. Lastly, rather than using the context space as input to the decision problem, transformation approaches the context space as a function of other spaces.

Reduction

The information used to construct the context space can be reduced either by limiting the level of detail or by describing it as a single deterministic scenario with fixed parameters.

Limit the level of detail: Information can be limited by reusing knowledge from a similar decision problem [276] or by minimising the context space to variables relevant to the problem and decision-support method [192]. Similarly, contexts can be bounded by removing infeasible scenarios. For example, Collaboration Method (CM) uses compatibility criteria to eliminate infeasible contexts. Furthermore, because consultation with stakeholders or field experts are an important source of contextual information, methods like Assumption-Based Planning (ABP), focus on guiding the process of establishing information and assumptions in the context space.

Deterministic scenarios: The context space can also be reduced to one or multiple deterministic scenarios with fixed parameters. In this case, reducing the context space enables the decision-maker to focus on other challenges. For example, Design Structure Matrix (DSM) reduces the context space to focus on structural relationships by investigating mapping functions, Failure Mode and Effect Analysis (FMEA) focuses on failures of the object of choice within deterministic scenarios, and Multi-Criteria Analysis (MCA) focuses on handling multiple attributes in the value space. When the level of contextual uncertainty is low, methods such as Operations Research (OR) reduce the context by representing it as a single deterministic scenario. Multiple deterministic scenarios are also used in methods such as Decision Analysis (DA) and Real Options Analysis (ROA) to investigate actions or performance when possible future contexts are limited.

Reduction in the context space allows the decision-maker to investigate selected temporal effects indirectly, for example by comparing a limited number of discrete deterministic scenarios instead of modelling continuous time. Although reduction decreases perceived complexity, it becomes increasingly difficult to address higher levels of uncertainty. One benefit of a deterministic context is the creation of a detailed representation of an envisioned context, which is easier to comprehend and extend. However, such representations may introduce bias and become demanding to define as the number of scenarios increases. Moreover, reduction can present a biased picture, as contexts derived from experience may focus on success rather than failure, thereby risking the repetition of past mistakes.

Exploration

Instead of limiting the scope, another approach is to gain knowledge by exploring available information. However, for higher levels of complexity and larger amounts of information, this effort increases. Therefore, sampling can be used to explore specific contexts, as is the case with Design of Experiments (DOE), which identifies combinations of variables to test. Alternatively, unlikely contexts can also be dismissed with stakeholders [102].

Sample generation methods aim to populate the space efficiently while also limiting bias. Methods like Monte Carlo Sampling (MCS) can be used to improve the efficient exploration of the context space by using samples from a probability distribution. Additionally, as is the case for Epoch-Era Analysis (EEA), sampling is used first, and a limited context space is selected for detailed research afterwards. For higher levels of uncertainty, context parameters can be explicitly modelled as random or scenario-dependent variables, thereby populating the space with uncertain contexts. As shown in the first two graphs on the left of Figure 2.3, this can range from several points, for low uncertainty, to all points, representing deep uncertainty, where more points allow the investigation of an increasing

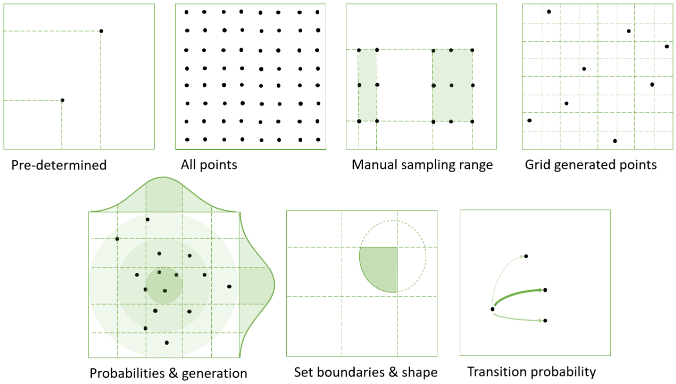


Figure 2.3: Examples of methods populating a 2D space

level of contextual uncertainty. Different sampling schemes can be used to populate the space. Variables are combined using an orthogonal grid with Factorial Sampling (FA), or sampled using rules such as Latin Hypercube Sampling (LHS) or using probability in MCS. Diffusion methods like Geometric Brownian Motion (GBM) or Jump Diffusion (JD) provide ways to sample the continuous or discrete development of a variable. The selection of samples in the context space is exploited in Fourier Amplitude Sensitivity Test (FAST) to establish a frequency-domain context variable and correlate the frequency to output variation. Additionally, context samples are used in Exploratory Modelling and Analysis (EMA) as data for further value space analysis, or in Response Surface Method (RSM) to create mapping functions.

Extension

Extension strategies primarily address contextual uncertainty by acquiring additional information, generating new information, or extending the representation of context variables.

Data analysis: When information is already constrained by what is available, it can be used to generate new knowledge from existing data or generate new data. This is primarily applicable when considering novel or unique contexts [164]. One direction that is used more often for decision-making is data analytics. Descriptive analytics can be used to visualise the decision space and inform the decision maker Sensitivity Analysis (SA), while methods like Bayesian Inference (BYA) use predictive analytics to predict future scenarios for use in decision-making. Prescriptive analytics like Genetic Algorithm (GA) prescribe what "optimal" decisions the decision maker should make Evolutionary Algorithm (EA). Similarly, methods that use autonomous prescriptive analytics like Artificial Neural Network (ANN) learn from data to autonomously make decisions without human intervention [391, 447].

Data generation: Data can also be generated by using experiments or simulations to represent the decision space. The maritime industry often uses physical or simulated experiments to investigate contextual uncertainties (e.g. wave and weather impact) and manage complexity. However, experimentation requires significant time and effort, and the quality of results depends on model and experimental assumptions like scale effects [8, 452]. Nevertheless, investigating the extended contexts from data can help structure the context space and answer specific suspicions. For problems that are difficult to test in reality, simulation offers a good way to still develop a context. Experimenting or prototyping a decision in practice allows fundamental ideas to be tested and explored.

Probability: Besides using existing or generated data, context variables can be extended using probability to deal with intermediate and aleatory uncertainty. Depending on the nature of the uncertainty, it can be determined from experiments or data for aleatory uncertainty, while epistemic uncertainty lacks this possibility [105]. Besides using probability to guide sampling in MCS, it is also used to represent the likely values of a variable directly in methods like Probability Model (PM) or Probability Box Model (Pbox) or to state a belief whether that probability or a variable is true Dempster–Shafer Theory (DST). Furthermore, in Uncertainty Quantification (UQ) multi-dimensional probabilistic fields can be used to research impact and correlations between parameters alternatively, when it is possible to determine the probability over scenarios, methods like Stochastic Programming (SP) use probability distribution as a weight to enable the investigation of the average and extreme cases within in the context space over time [33, 325]. Furthermore, probability is also used in DA to capture the likelihood of reaching a context from an initial starting state to research scenario development or used in Bayesian Framework (BF) to represent causality. Similarly, methods like Markov Decision Process (MDP) define transition probabilities between all context points to investigate development over time without a pre-determined starting state.

Temporal effects in the context space: The context space can be extended to include a temporal dimension when contextual uncertainty and complexity evolves over time. This can be done through the use of discrete sets or events, transitions or a continuous trace. Nevertheless, the extension of the context space with temporal effects can result in increased complexity or uncertainty when considering an extensively detailed timeline or when context variables change over time.

- Discrete temporal sets or events: Independent of the challenge category, temporal effects can be described as a chain of discrete temporal snapshots. For example, Discrete Event Simulation (DES) represents change as discrete events, even though these can occur sporadically over time. Additionally, methods like Dynamic Adaptive Policy Pathways (DAPP) combine multiple contexts into ordered discrete temporal snapshots to research specific temporal developments. In contrast, EEA combines multiple discrete events randomly. Extending on this, Adaptive Robust Optimisation (ARO) connects context snapshots to investigate adaptive responses to different temporal context developments, while Game Theory includes the response of external agents over time in the context space. Petri Net (PN) uses an initial discrete event as an instigator for consecutive contexts to research impact, and Event Trees (ET) investigates the connections of discrete temporal context.
- Transition: The impact of multiple contexts can also be projected onto an initial state by using transitions. This is especially useful when dealing with a context with a clear initial starting point but many outcomes. For example, Distributionally

Robust Optimisation (DRO) projects multiple discrete temporal stages onto the initial context using either a weighted probabilistic distribution and Robust Optimisation (RO) uses an unweighted set of future contexts. Another approach used in ROA, is to extend the initial context by a limited number of pre-determined dependent contexts and a transition probability to reflect potential pathways. Besides this, MDP connects multiple contexts without an intial context using a transition probability. This way, a sequence of temporal context developments is effectively simulated to investigate the response to temporal uncertainty.

- Continuous trace: When the number of timesteps required to capture a parameter's temporal behaviour increases, a continuous time trace is used instead of discrete events. These model temporal development by dividing the interval into sequential steps (SIM).

When investigating a context where patterns repeat over time, like electricity demand, expected continuous patterns can be used to investigate the impact (Forecasting (FO)) of or responses (FAST) to temporal effects. However, even though using a single trace reduces the complexity of the solution, using expected development is insufficient for higher levels of uncertainty. Therefore, the parameter can also be represented using multiple random continuous temporal pathways to represent or test context variable fluctuations JD [138].

Paradigm shifts are events in time that have a significant impact but are difficult to model as they change the context in an unforeseen way, but it is unknown how and when these occur. These are called black swans, and due to their nature, continuous traces or discrete events are not applicable. Instead, the decision space is re-framed to a higher level of decomposition so the decision maker can prepare for consequences on an overarching level, like having sufficient liquidity [429].

Transformation

Besides operating within the context space, transformation strategies change the representation of contextual information itself. Methods can either project onto the context space or approximate boundaries for context variables.

Project onto the context space: To deal with the highest levels of contextual uncertainty, several methods project other spaces onto the context space. They use what is known about the object, valuation, and mapping to search for information about unknown variables in the context space. Several ways are visualised in Figure 2.4. The first figure on the top left represents Info-Gap Method (IG), where data or approximations in the value space are used to search an allowed error margin around a point in the context space (set size) that still meets requirements [190]. The second figure represents the use of UQ to approximate context variables by tuning a mapping function with reference points. Such methods differ depending on their use for aleatory uncertainty or epistemic uncertainty [105, 475]. For example, Gaussian Process (GP) deals with aleatory uncertainty by using probability to represent a confidence interval, Interval Model (IM) deals with epistemic uncertainty by coupling variable ranges and Pbox combines both. As long as enough or the appropriate reference points are available, methods like these can transform the context space and fill gaps in data or represent errors. The figure on the top right shows how Scenario Discovery (SD), uses projecting to establish relevant scenarios for object performance testing [104]. An

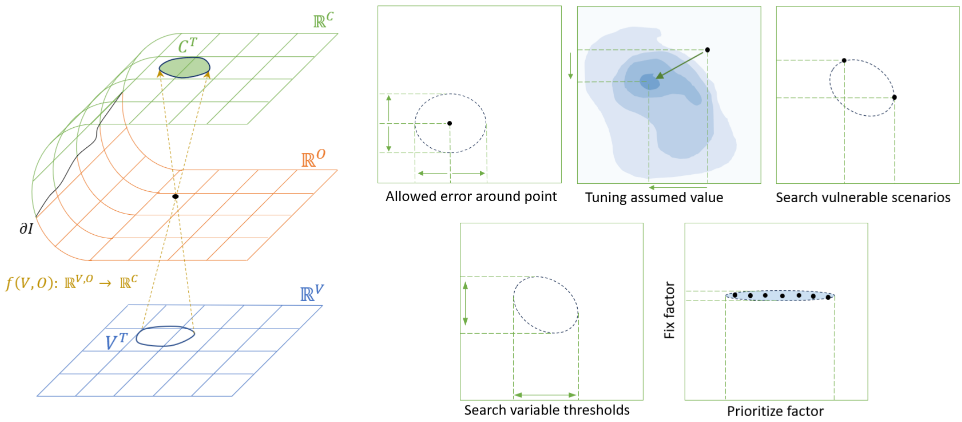


Figure 2.4: Figures representing the process of projecting other spaces onto the context space to search for the impact of context parameters.

extension of this is used in Robust Decision Making (RDM), which searches for the variable threshold at which the object of choice no longer satisfies a set requirement instead. This can be done over many variables and effectively projects a set in the context space where that decision meets requirements. In this case, samples in context space are evaluated with respect to a value threshold. The last figure represents how this principle is also used in SA to identify what variable contributes most (factor prioritisation) and least (factor fixing) to valuation fluctuations, which is responsible for specific fluctuations (factor mapping) or search variable values for which the value remains under a threshold [290].

Approximating boundaries: Because high levels of epistemic uncertainty make assigning probabilities or defining specific points difficult, other methods transform the context space by approximating boundaries instead. For example, IM uses an interval or a set in the context space to establish boundaries in the context space. Similarly, Rough Sets (RS) places bounds on approximated information to determine human-readable rules from incomplete data. Grey Number Theory (GNT) extends bounds with multiplication factors to size the set, while RO uses uncertainty sets, which add a shape function to the bounds to include correlations between variables.

Besides static boundaries (also called crisp sets), dynamic boundaries using probability Chance Constraints (CC) or Fuzzy Sets (FS) are also used to investigate the impact beyond and over the boundary. Furthermore, hybrid methods such as DRO exploit the benefits of both probability and constraint approaches, applying both probabilities and sets to different parameters with varying levels of uncertainty. Alternatively, DST assigns a probability that a variable is within an interval, while Pbox defines upper and lower bounds to probability.

2.3.2 Approaches used for the Object space function challenges

The object space $\mathbb{R}^O$ contains all decisions internal to the decision maker's boundary of influence, where multiple points or sets (O) contain the objects of choice from which the decision-maker can select (e.g. the emission reduction options to choose from).

- *Structural complexity* is represented by the number of parameters that describe an object, the functional interrelation and/or physical arrangement that establishes the location in the space and the number of points or number, size and shape of the set.
- *Input uncertainty* occurs when an input might not take the expected value or its selection might not result in the target object in reality, effectively transforming the set (O_u).

Furthermore, because decision-making can be an iterative or hierarchical process consisting of multiple sub-decisions, complexity and uncertainty can occur when a decision-maker has to make many (iterative) sub-decisions to influence the object of choice. Consequently, complexity makes designers deal with an expanding design space, while uncertainty can make the exact location of the solution within that space unclear. In the emission reduction example, increased structural complexity is reflected by including more detail regarding integration on board for the emission reduction options, incorporating the impact of an option on ship stability, power and energy management. This extends the design space and propagates the impact of one option to other decisions. Meanwhile, object uncertainty can result in information or the parts of the emission reduction option varying in reality.

To deal with challenges in the object space, methods use reduction, exploration, extension and structuring approaches. Reduction is mainly used to deal with complexity and limits the dimensionality of the decision by fixing multiple values or limiting the number of alternatives to focus on other spaces. Lastly, to deal with complexity in the object space, structuring can be used to decompose the object into multiple subdecisions. This decomposition can be done based on the level of detail or based on time. Alternatively, exploration increases information by populating the space with alternatives. This goes well with extension approaches, where dimensionality is increased, or information is modified or added. Lastly, approaches that use transformation in the object space, modify options by incorporating changes between decisions.

Reduction

Methods that use reduction ignore uncertainty to deal with complexity by considering a limited number or static decisions.

Limited number of objects: To focus on challenges on challenges in other spaces instead. For example, SD limits the objects and uses them to investigate how the object space reflects on the context space.

Static object of choice: One efficient way to reduce the object space is to assume it remains static over its lifecycle. When when object parameters remain unchanged over the duration of the life cycle and uncertainty is low, the object of choice can be simplified to a static representation. Similarly, methods that optimise, explore, and search the object space often assume temporally static objects, as the space grows exponentially when also including changing between different objects of choice over time.

Exploration

In the object space, exploration can be used to define and investigate alternative options [128]. The approach is comparable to how the context space is explored, but it deals with the size of the space instead of uncertainty in contexts. The object space is explored by evaluating a manual selection of alternatives (DOE) or generating samples over object variables (MCS). Samples are used in Open Exploration (OE) to visualise trade-offs between object space variables. To deal with epistemic and deep uncertainty, the object space can also be explored using sampling over uncertain variables. For example, in Multi-Attribute Tradespace Exploration (MATE), selected object variables are investigated by populating the object space with samples.

Extension

To investigate more alternatives and add more information to the object space, object variables can be extended with probability, by allowing a dynamic object or by expanding into the context space.

Dynamic object of choice: Some methods classify the object of choice to be dynamic beyond the decision phase, using active robustness, where parameters are actively changed in response to disturbances, to deal with intermediate or deep uncertainty. Change enablers such as flexibility, modularity, and Product Platforms (PP) prepare an object of choice to be more changeable and improve its active robust properties. This effectively increases the number of potential transitions in the object space. Changeability is either quantified top-down using value thresholds for cost and time or bottom-up, measuring the reduction of cost and time for each change enabler [131, 353, 370]. It has been argued that the cost of changeability increases, while change cost decreases for higher levels of changeability [148, 422]. When an object of choice is decomposed, different levels of changeability can be applied to each level [89]. When decomposition has been applied to structure the problem, changeability can be assigned differently across hierarchical levels. Furthermore, changeability can then be propagated, multiplied or absorbed between and inside each level [211]. Several methods aim to investigate the effectiveness of preparations during the design phase. ROA allows testing the benefit of changeability under object or contextual uncertainty, Discrete Choice Model (DCM) using multiple scenarios or MDP simulating alternative decisions. These evaluate the addition of changeability but don't consider when or how to change over the lifetime. To deal with high levels of uncertainty, methods like Dynamic Adaptive Planning (DAP) also prepare for the future, measuring and applying adaptive decisions after the decision phase, identifying which decisions to delay or parameters to add, and proposing when actions should be performed [457]. The definition of a pathway is also used in Technology Foresight (TFO) to establish the planning decision moments in DAPP to establish decisions based on events.

When using changeability with static objects of choice, the function and properties of the object can change despite the object remaining unchanged over the lifecycle (passive robust) [371]. In contrast to search approaches that identify an optimal or robust point in the object space, passive robustness modifies the representation of the object itself by embedding margins or constraints directly into its definition. To do so, instead of optimisation, Robustness Discrepancy Model (RDiM) selects parameters so that the performance is ensured to be within a minimum required value range while facing contextual uncertainty by adding either static margins. Similarly, Probabilistic Design (PD) adds or probabilistic margins to variables, while methods like CC use probabilistic constraints. Furthermore, to deal with intermediate uncertainty, where multiple contexts of choice are considered (versatility), additional attributes can be added, stacking functionality and making the initial object more complex. Even though it simplifies the object of choice and limits the scope to the decision phase, passive robustness can only deal with lower levels of uncertainty, as it can reach a limited number of objects.

Expand influence: This is used when the term of resolution is long and the level of uncertainty is high. Expanding the boundary of influence is specifically useful when the object space and the influence of the decision-maker are found to limit the ability to deal with uncertainty. Instead of reacting to developments in the context space, it aims to influence the context to its benefit, as it recognises an inability to predict the context at high levels of uncertainty [164]. In TFO, the goal is to expand the influence of the decision maker to external parties like politics, and in IG, avenues for research are provided if the uncertainty can be reduced. A desirable future is established, and context parameters that can be influenced to their benefit are included in the object space. The approach is used for long-term planning (8-30 years), as such efforts are more demanding and uncertain but less dependent on external decision-makers, and for short-term planning (1-3 years), where efforts are more dependent, and the decision-maker has a shorter period to react [10]. For the long term, a single strategy is established and re-evaluated over the lifetime. Multiple expected scenarios are established for the short term, and adaptive strategies are developed for each, adapting to the future. However, even though this allows dealing with high-level, long-term uncertainty, when complexity and the number of scenarios and data increase, bias towards one option may eliminate other worthy avenues. Therefore, methods like Adaptation Planning Method (APM) instead look at identifying load-bearing assumptions that would cause the plan to fail if wrong and determine their vulnerability to estimate adaptive plans to mitigate that vulnerability.

Probability: Multiple methods use probability to deal with intermediate uncertainty. For example, MCS combines probability with sampling to extend the object space. Similarly, when dealing with uncertain object space variables, probability can be used to represent aleatory object uncertainty. It is used in Robust Design (RD) to identify how to minimise the probability of failure or variability in object performance. Similarly, probability can be used to represent uncertainty. For example, probability is used in SP to represent the expected value of an object variable to evaluate a strategic decision. This is extended in Multi-Stage Stochastic Programming (MSSP), where multiple subsequent uncertain developments are investigated. The development of uncertainty over time is simulated in Time-Expanded Decision Network (TDN) using a transition probability that connects events and decisions sequentially or indiscriminately. Transitional probability as used in MDP allows returns to the same event. Lastly, probability is also used in UQ as input to reflect the impact of uncertainty on relevant outputs, in Mutual Information Index (MII) to quantify whether its variation is dependent or independent of specific object variables, in BYA to portray confidence of an output, and BF to establish causality.

Furthermore, SA is used to identify which object variable the valuation is most and least sensitive to, and PM to discover connections between input and output variation by using probability or IM using intervals. Methods like Polynomial Chaos Expansion (PCE) use representative models and utilise model properties to estimate behaviour. Nevertheless, Data Envelopment Analysis (DEA) investigates the object variables and their impact directly in the real decision space when the object of choice can be experimented with.

Transformation

Methods that use transformation modify the object space by using projection to search optimal decisions or by simulating the performance object of choice.

Search object space: These methods search the object space for decisions and transform it by projecting knowledge from other spaces onto it. Methods often project information from the value and context space onto the object space to search for the 'best' object of choice (optimisation). To guide the search and reduce structural complexity, constraints CC and logical rules are used to provide direction to the solution and ensure the feasibility of the object. Alternatively, as any value variable can be used in a search, RDM investigates vulnerable objects, which can also be used instead of optimality. As such, SA methods search the object space to gain information about object variables. Principal Component Analysis (PCA) investigate variables to prioritise or which ones to fix Patient Rule Induction Method (PRIM) identify variable thresholds where value requirements are satisfied and Associative Classification (AC) or to determine general decision rules.

When faced with uncertainty, methods like PD can be used to select the choice with minimal variability in performance. To support this effort, CM uses compatibility constraints, CC uses a contraint compliance probability, while Fuzzy Integral (FI) uses fuzzy and RO uses crisp set boundaries. This is further extended in MDP, which even includes temporal effects and searches for decision sequences. For deep uncertainty levels, RDiM investigates the allowed set size around an assumed parameter [39, 190]. In this case, a minimum value requirement can be used to identify a set around an object of choice where it is value robust or where the value threshold is opportunistic or profitable. Alternatively, RDM searches parameter thresholds, using context or value requirements to create a set without identifying one assumed point. Other ways to use this approach are DSM where relations are identified between decision options [36, 66]), PCA reducing object variables to principal parameters and MDP establishing how decisions connect to context scenarios using principal eigenvectors [221].

Simulating the object space: Simulation transforms the object space into a test bed for decisions and is often combined with an extended context space. For example, it has been used in Discrete Event Modelling (DEM) to test decision response to discrete events, in PN to explore concurrency in distributed systems or agent behaviour under uncertainty in Partially Observable Markov Decision Process (POMDP). Additionally, for global or multi-actor decision making, the response of individual agents to decisions in the object space is included in Agent-Based Model (ABM). Furthermore, TDN considers a sequence of decision connections, while Domain Mapping Matrix (DMM) uses exploration to investigate dependencies between variables or the clustering of Spectral Clustering (SC). Lastly, correlation and transitions between different options can also be used to investigate temporal interrelations between objects of choice Responsive System Comparison (RSC).

Structuring

To deal with structural complexity, the object space is structured using tracking knowledge or decomposition of the decision problem over detail or time.

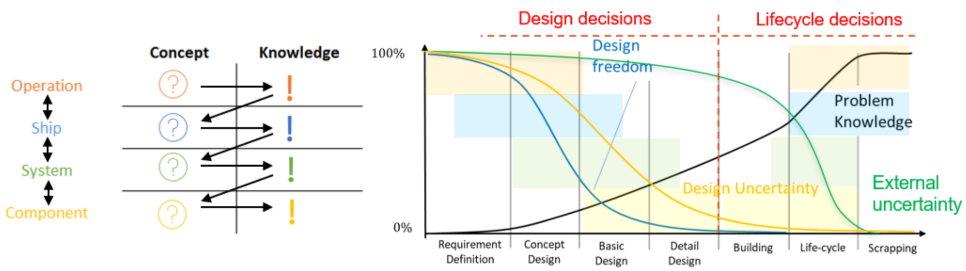
Track knowledge: Tracking information throughout the decision process can be used to reduce structural complexity that occurs due to the existence of sociotechnical interactions in decision-making. Decisions and design often consist of both technical and social considerations, especially when multiple decision-makers are included [69, 336]. As such, in interactions, tacit knowledge, which is gained from experience and considered common knowledge, can lead to reasoning that is difficult to trace or replicate. To address this, decision-makers and stakeholders work simultaneously in Concurrent Design (CD), to make sure decisions are communicated directly. Alternatively, Knowledge-Based Engineering (KBE) records and manages information during the process. Tracking knowledge also used in Quality Function Deployment (QFD) to directly connect requirements to decisions and in FMEA to record information flow and responses so causal effects.

Decompose on level of detail: To structure a decision, it can be decomposed into multiple sub-problems with increasing levels of detail. This can be done non-hierarchically, leaving the decomposition up to the decision maker [347], or hierarchically, guiding decision-makers in defining the required function of the object of choice and then the properties that meet it [155, 286]. This orders decisions in sequence, so the impact of consecutive decisions decreases. Creating a top-down description of the complex decision problem, where an overarching decision meets the target function (high level) through the sum of more detailed sub-decisions (low level). Methods like Systems Engineering (SE) investigate how decisions are connected to previous decisions and the target function [209]. Multiple levels of detail materialise when dealing with structural complexity like this. For example, the left side of Figure 2.5 visualises a standard decomposition of the ship design process into levels of detail. A common way to develop these levels is to use iteration. For example, Point-Based Design (PBD) moves through the hierarchy multiple times, where sub-decisions move each detail level from concept to knowledge and can be used for the next sub-decision [69]. Alternatively, Set-Based Design (SBD) reduces effort by identifying and developing specific components, subsystems, systems, and their direct connections after decomposition. Extending on this, the problem can also be decomposed into discipline-related levels where expert knowledge and routine decisions (experience) can be applied. Additionally, CD develops multiple discipline-specific levels in parallel while stimulating direct communication to increase the speed of decision-making. The different disciplines can also develop multiple global solutions simultaneously, analysing intersecting properties to select what parts of a design to develop further. Methods like SBD delay decisions purposely so successful aspects from different perspectives can be researched. Furthermore, after decomposition, System Dynamics (SDY) is used for subproblems with their own levels of detail, either dealing with more abstract, global properties or, in Simulation (SIM), highly detailed properties of the object of choice. Lastly, instead of focusing on levels, methods like DSM primarily describe connections and dependencies. Besides untangling structural complexity, this is advantageous for innovative decisions [69], where multiple levels are preferably developed in parallel.

2

Temporal decomposition: Temporal effects can increase perceptual complexity when multiple sequential connections. Therefore, the decision can also be decomposed into temporal sub-problems, so it covers multiple stages, like the decision stage and the lifecycle. Similar to decomposition in detail, temporal decomposition can be used to reduce structural complexity. Especially when objects of choice face clear changes in context, object or value variables over the lifetime, so initial and consecutive decisions over time can be defined (change enablers). In Life Cycle Assessment (LCA), this decomposition is limited to describe a single well-defined timeline or in Technology Roadmap (TRM), focus on the long-term goal, while using a single abstract development timeline. Alternatively, APM defines multiple timelines, including preparation and execution phases in response to future developments. When considering temporal effects in a decision process with multiple levels of detail, early sub-decisions directly influence later stages. Because of this, as shown on the right of Figure 2.5 for ship design, several effects complicate decision-making, like problem knowledge development (black), a decrease in decision freedom (blue), and the development of design (yellow) and external uncertainty (green) over time. The design

Figure 2.5: Development of decisions over the design process, showing interrelations between hierarchical levels on the left as adapted from [68] and the placement of these levels in the design process as adapted from [275]



uncertainty only fully decreases after the ship has been built, while design decisions are already established as part of the earlier phases. The design freedom for the higher levels decreases early in the process as the design gradually converges. As such, the design space and structural complexity can be reduced by subsequently converging different levels of detail over time as the variability of design options is smaller at each step [275]. However, relevant challenges in each sub-decision remain. Therefore, within ship design, decision support methods are distinguished as either dealing with the complexity in the process (complex design methodologies) or exploring the effect of uncertainty [17].

2.3.3 Approaches used for the Value space function challenges

The value space $\mathbb{R}^V$ exists in parallel to the real decision space and reflects the performance of each object of choice as they act in the selected contexts V^R. Besides reflected value, it also includes a set representing the decision-maker's perception of value and their requirements (V^T). The set can be created either by directly using context parameters and object inputs or by translating them into other key performance indicators, such as cost or utility.

- *Perceptual complexity* is represented by the size of the requirement set and the number of indicators to describe the perceived value.
- *Agent uncertainty* is represented by the translation or deformation of the set due to changes in the context and object of choice (${V_u}^R$) or potential differences in indicators and preference (${V_u}^T$).

These challenges can be affected by additional characteristics like social choice, in which the collective value influences individual preferences, and time.

Approaches in the value space include reduction, exploration, extension, transformation and structuring. Reduction primarily addresses perceptual complexity by simplifying the representation of preference. Exploration and extension primarily address agent uncertainty by comparing multiple alternatives and adding information to the value description respectively. Transformation changes the representation of value by incorporating temporal and social dynamics into valuation. Lastly, structuring aims to establish connections and identify the sources of value through traceability.

Reduction

Methods that use reduction aim to limit value space information by either fixing prefence before analysis (a-priori), limiting the perceptual complexity by proportionality or reflecting into a single value through aggregation.

A priori: When the level of uncertainty is low, criteria and preferences can be estimated beforehand (a priori), resulting in a single or limited number of value metrics. The first step is to define how to rank options and trade-offs. Performance indices such as cost or utility are then used to reflect increasing preference. A single value metric allows for a more detailed investigation of the sources of value, for example through LCA, or of optimality, as in Particle Swarm Optimisation (PSO). Alternatively, in SD, projections onto other spaces and the establishment of variable thresholds rely on static KPIs to represent fixed requirements. This principle is also applied in TRM to investigate how to reach a target. Predefined value parameters can further be linked to events using Dynamic Programming (DP) or to agents with ABM to guide and evaluate decision-making.

Variable aggregation: in MCA multiple separate value variables can be defined to establish preferences for ranking performance or, as in QFD, to guide decision-making. Criteria and preferences are aggregated into a single metric to rank options in several different ways. For example, methods such as Analytic Hierarchy Process (AHP) establish tangible criteria and preference weights based on personal or domain-specific considerations to arrive at a single best decision. Similarly, Multi-Attribute Utility (MAU) aggregates multiple attributes into a single objective to prescribe an optimal decision. While aggregation is often used within approaches in other spaces, the aggregation itself reduces perceptual complexity within the value space. Furthermore, in methods such as Metaheuristics (MH), an overarching or aggregated value can be used to optimise the performance of an object within a separate context, whereas RO optimises performance across multiple contexts.

Proportionality: One of the most important aspects to consider when using a decision-support method is the proportionality between the challenges being addressed and the perceptual complexity of the approach. This is because the value space is reflective: each change to a space or mapping function introduced by an approach also affects perceived complexity. When a method requires substantial effort to address many challenges, this perceived complexity can make it increasingly difficult for decision-makers to understand both the decision-making process and its solutions. Therefore, a decision-maker should always assess whether perceptual complexity remains manageable and proportional to the challenge [61, 62, 69].

Exploration

In the value space, exploration is used to compare trade-offs, investigate which variables drive outcomes, or to treat value as a context variable to shapes scenarios.

Trade-off exploration: In this case, multiple KPIs are defined to explore trade-offs rather than aggregating attributes. By using multiple objectives, the relationships among the selected objectives are visualised. Epsilon-Constraint Method (EC) creates a set boundary on the value space that reflects the optimum or measures the relative distance to it, while GNT creates a bandwidth around the set boundary. Single objective methods that deal with uncertainty like RDM can also be extended to find the optimal robust decision over multiple objectives using Multiple Objective Robust Decision Making (MORDM). Alternatively, methods like Break-Even Analysis (BEA) inherently compare multiple objectives.

However, when dealing with a high number of KPI or discontinuous or multi-modal data, traditional optimisation may yield infeasible solutions where no boundary is found, or the KPI is inside the set rather than on the boundary [128, 375]. To address this, evolutionary or swarm search algorithms [348] like Multi-Objective Genetic Algorithm (MOGA) are used to determine global optima for multiple objectives [262].

Variable investigation: When social preference is included, ranking can lead to conflicting interpretations of the KPI. This is because of Arrow's impossibility theorem, which describes the impossibility of establishing a perfect voting procedure when subjective social choice is included in the decision problem [387]. As a result, this approach investigates variables directly, reflecting them onto the value space to provide insights and inform a decision rather than ranking. Even though this accommodates social choice, it also increases perceptual complexity due to the exponential increase in parameters and indicators and the difficulty of tracing non-linear mapping effects between them. Exploration is used by multiple methods, such as RSC and RDM to investigate the impact of variables on the value space. Furthermore, exploration is also used by DCM to investigate agent decision-making, DEM to reflect discrete events on the value space and SDY to describe the impact of overarching dynamics on value.

Additionally, multiple methods use exploration to examine the relationship between variables. For example, UQ methods and surrogate methods like Multivariate Adaptive Regression Splines (MARS) populate the design space and use the reflected value to explore the impact of differences in the object and context spaces. This includes methods like Multidisciplinary Optimisation to explore the propagation of value between models, Analysis of Variance (ANOVA) to investigate the influence of dependent variables, Reliability Block Diagram (RBD) to investigate the impact and reduction of failure. Furthermore, Mahalanobis–Taguchi Gram–Schmidt System (MTGS) uses exploration for pattern analysis, PCA creates representative variables, and TRM investigates the development of variables over time.

As context variable: By including value as a context-dependent variable in the context space, decisions can be tested against the impact of changing value Scenario Analysis (SCA). In this case, methods like DEA treat value in the same way as other variables, enabling them to be sampled. Furthermore, in methods like ABM, this also allows the value to function as an instigator for events or actions, creating value-driven scenarios.

Extension

Even though extension allows insight into uncertainty [101], ranking multiple objects of choice at higher levels of uncertainty can be complicated due to additional characteristics. To deal with these, the value space is extended to explicitly reflect power dynamics, risk and robustness and temporal effects. Besides those, extension can also be used to increase the number of objectives or add descriptors such as probability or weight to value variables.

Social choice/Power dynamics: The value space can be extended to consider social choice and power dynamics between multiple internal or external agents. The power relationship can take three different shapes. First, an agent can have "power over" others so that influence from other agents can be neglected, also called a dominance model. Second, an agent can be expected to act following the dominant influence but has the "power to" act otherwise, even though this is unlikely to change the power dynamic (such as striking). Third, a decision-maker can have "power with" other agents, which results in a cooperative or empowerment model where decision-making is shared with others. In this case, the decision can influence value, but others can as well. Agents are found to respond to "power with" relationships by deciding to either act in their interest, create conflict, or choose cooperative stability.

Methods dealing with power dynamics differ depending on the shape of the power relationship. First, when the power relationship does not favour the decision maker, the situation can be accepted as fact and ignored. Second, when the social choice is external to the boundary of influence, it can be investigated by modelling different scenarios as uncertain contexts, as is done for DAPP [436] and Environmental Measures (EM) [290]. Alternatively, Game Theory (GAME) models research fundamental behavioural dynamics, while ABM explores the behaviour of (multiple) decision-makers and DCM explores how decision makers act according to pre-specified or probabilistic decision rules. Third, when social choice occurs internal to the boundary of influence, power relationships between multiple decision-makers can be treated as structural complexity. For example, CD deals with social choice by stimulating direct communication and using different experts for discipline-related sub-problems to be able to dictate ranking. Additionally, methods like SE improve decision-making momentum and establish and track requirements through the process to create consensus amongst decision makers.

Extend with additional descriptors: To deal with intermediate or high levels of uncertainty, the value space can also be extended with additional descriptors like probability or weights on top of the a priori value description. These are used to create a single combined value or increase the information depth. These methods often pre-define multiple criteria and add descriptors (a priori) to aggregate the different criteria, perspectives and preferences into one value [183]. A new KPI for ranking can be created in different ways. For example, Simple Additive Weighting (SAW) assigns preference weights to each KPI, Weighted Aggregated Sum Product Assessment (WASPAS) uses complete aggregation, and Elimination et Choix Traduisant la Realite (ELECTRE) uses partial aggregation. Furthermore, to determine the most important criteria, Normalised Attribute Values (NAV) uses relative weighting, AHP uses pairwise comparison, and Decision Making Trial and Evaluation Laboratory (DEMATEL) uses influence comparison. At intermediate levels of uncertainty, probability can also be used as an additional descriptor to investigate the impact of uncertainty propagation on value SA. Furthermore, ANOVA uses variance to gain insight into dependency, while Shannon Entropy Technique (SENT) uses disagreement in evaluation. For higher levels of uncertainty, PN models propagation as a connection and capacity problem to identify sequences and conflicts of information. Additionally, instead of probability, frequency (FAST) or interval differences (IM) are used as additional descriptors to establish the impact of propagation. Lastly, in GNT a set's boundary is scaled to research the impact of reflected inputs.

When uncertainty is high and probabilities are unreliable, an alternative is to identify weights with comparison ranking (prospect theory). However, in unfamiliar cases, decision-makers are found to assign weights inconsistent with actual probabilities (source theory) and to prefer known risk to unknown uncertainty (ambiguity averse). For instance, people generally overestimate their chances in lotteries, assuming an irrational probability of success. Robustness is also used in RO to deal with uncertainty without assigning probabilities, instead defining ranges of variable values to which the solution must remain robust. Alternatively, IG is used to project a value variable range onto the object of choice. Robustness Measures (RM) uses robustness measures as a single objective, while RDiM uses an objective variation region for multiple objectives. When dealing with structural complexity as well, methods like Gross Tonnage (GT) can be used to investigate the structure or change enablers could be used to include multiple actions or attributes in the decision to improve value robustness.

Incorporate risk and robustness: Uncertainty affects decision-makers differently based on their risk appetite, behaving either risk-averse, risk-neutral, or risk-seeking. Risk-averse agents avoid high-value bets due to an increased perceived risk to limit losses, while risk-seeking agents prefer these due to a preference for high gains. To reflect uncertainty's impact on preference, this approach quantifies risk or robustness. Risk preference is commonly described with expected return and variance, where Risk Theory (RT) often uses the slope of a utility curve to represent risk appetite. Extending value with a quantification of risk for an object of choice is used in RBD to determine what contributes to reducing it. In FMEA, the quantification of risk allows the decision maker to investigate the circumstances under which it increases, and in ET, the impact and what initiates it.

To establish robustness, instead of averaging, RM uses combined measures that assess performance across multiple contexts and minimise the risk of failure. TDN also aims to extend value over contexts, representing each with a separate value development path or probability (SP). Furthermore, parameters or logical operators are extended in FS with discrete steps between values to reflect a degree of membership or agent uncertainty for measures, functions and sets [77].

Structuring

Trace sources: To deal with perceptual complexity, the value space can be structured by tracing the sources of a KPI over the decision space (LCA). This allows understanding its development and sources allows the decision maker to structure the decision space even if the value is established externally. For example, going through a process while analysing each step allows a better understanding of how it has been built up [49]. This also works for temporal cases, as existing data is used in Black–Scholes Model (BSM) to identify what sources contribute to a value, while prediction can be used to structure potential value development and create pathways TFO.

Transformation

The value space can be transformed to incorparate temporal effects in value variables. Furthermore or to evaluate the decision space after mapping (a posteriori).

Incorporating temporal effects in a value: Decision-makers have to deal with the development of preferences over time, which can, depending on the influence and nature of the decision, be assumed to be static (fixed) or dynamic and changing during the life cycle. However, in both cases, future value has to be transposed during the decision process, as it is synthetic and created during its application. As mentioned in section 2.3.1, contextual temporal effects are often described using either discrete methods like DEM or continuous approaches Geometric Brownian Bridge (GBB). However, this primarily deals withthe level of detail. Therefore, to reflect temporal effects on value, this approach includes them as part of the value instead. This is done in Expected Value (EV) by using the expected value, which is the average of a probabilistic description of value. This can, however, result in the so-called flaw of averages, where the average does not represent the majority of extreme (opposite outcomes) [331].

Instead, temporal effects are also described using Discounted Cash Flow (DCF) by assigning a decreasing weight to a value gained further in the future to describe the preference for gaining value in the current period. However, it has been shown that short-term gains, like addiction, are generally negative for the long term due to compounding effects. Alternatively, some valuation methods, such as BSM, incorporate volatility as a weighting or as a separate performance indicator. The main benefit of this approach is the simplicity of a single value that describes temporal preference. However, despite much research, a general definition of temporal preference has not been established. This failure might be due to the uncertainty of future outcomes or non-linearity in utility that affects discount rate computation. Therefore, to describe temporal preference in decision-making, it has been proposed to use a personal or domain-dependent discount rate instead (multiple motives [144]).

A posteriori evaluation: A posteriori evaluation deals with deep uncertainty by defining multiple performance indicators and performing evaluation after mapping (a posteriori). This is because a single aggregated objective is argued to degrade for deep uncertainty, as KPI and preference cannot be estimated beforehand [403]. Therefore, the reflected set is established before defining preference, so pre-selection does not limit the value space investigation. Several variables from the context or object space that are potential performance indicators are sampled and reflected onto the value space, representing multiple objectives. Between these objectives, BEA represents what variable combinations are along a break-even line, Pareto Front (PF) defines an optimal front and Fuzzy Pareto Front (FPF) extends this to define what combinations are close to it. Similarly, EEA reflects variables without creating a front in the value space, preserving as much of the space for a posteriori evaluation.

RDM uses a posteriori evaluation and purposely fixes parameters to improve the object of choice between iterations. While Pareto Archived Evolution Strategy (PAES) changes parameters based on evolutionary rules between iterations. Alternatively, it can also be used with IG to identify information gaps. Besides modelling, data from the actual decision space is utilised in DEA to establish requirements, variables and trade-offs or in DAPP to monitor the strategy. If a lot of data is available, a posterior analysis is used in Grey Relational Analysis (GRA) identify variable relations or for importance and membership in k-Means Clustering (KMC). Methods like Radial Basis Function (RBF) automate this process, aiming to approximate or, like Inductive Learning (IL), learn from data or behaviour. Furthermore, a posteriori evaluation is also used in SIM for detailed simulated behaviour, in PN to test contextual events or in SCA scenarios, or in DCM for the decision-making of individuals with different preferences.

2.3.4 Approaches used for mapping function challenges

Mapping functions $f(O, C)$ are used by decision-makers to represent the real decision space by establishing the relationships inside and between the object, context and value spaces. Because of this, in addition to connecting the spaces, the mapping functions reflect how complexity and uncertainty propagate across them and are directly related to the selection and interaction of sets in the object and context spaces.

- *Model uncertainty* occurs when novel or difficult relationships are considered, and the functional response is unclear or unknown. This can cause uncertainty to propagate across levels, leading the representation in each space to differ significantly from reality.
- *Behavioural complexity* increases when more parameters and inputs are included or when non-linear interrelations are required to describe system behaviour.

Approaches used to address challenges in mapping functions include reduction, extension, structuring and transformation. Reduction primarily limits behavioural complexity by standardising representation and managing fidelity. Extension augments mapping models with additional functionality, uncertainty representation or temporal structure. Structuring involves using mapping functions to organise relations and patterns from data. Lastly, transformation alters the modelling itself, for example when the mapping shifts from analytical to data-driven representation, the transparency of the model is changed, or when the functional representation of the mapping model is fundamentally redefined.

Reduction

For mapping functions, reduction can be used ro manage behavioural complexity through standised mapping functions, changes to the fidelity level and proportionality.

Standardisation and formalisation: Standardised mapping elements consisting of well-established theoretical [118] or empirical relations [421, 486] are used to manage behavioural complexity. These are often grounded in established laws, rules and functions derived from extensive research in their respective fields, which help describe the behaviour of systems or phenomena, whether human or natural. For example, methods like Mixed-Integer Nonlinear Programming (MINLP) use mathematical notation to standardise the mapping. The formulation of the mapping, context, object and value spaces can also be integrated into the method itself [13], as is the case with many evaluation methods. Furthermore, to ensure comparability of results, methods like Environmental Product Declaration (EPD) reduce mapping to the value space by using global standards.

Fidelity level: Depending on the application, mapping models can use different levels of detail (fidelity), which directly impacts behavioural complexity [378]. For example, SIM investigates the real decision space in great detail, while SDY analyses overarching behaviour while simplifying lower-level details. While high-fidelity models are often more accurate, they are also more time- and resource-intensive. Therefore, deliberately accepting lower accuracy through low-fidelity models can reduce behavioural complexity [8]. For example, in ABM, multiple individual decision-makers are either represented as aggregated variables or as active entities with individual behavioural rules [224]. An intermediary approach GP is also used, in which low-fidelity models are refined using data from high-fidelity models to improve accuracy.

Proportionality: Even though standardised mapping can reduce effort, it does not necessarily decrease behavioural complexity, as mappings may still involve non-linearities and numerous parameters. Therefore, the mapping model should remain proportional to the decision problem, provide realistic outcomes (validation), and be adequately constructed (verification). Moreover, when complexity is high, deciding which parameters to include becomes difficult, so adding more should be carefully checked against overfitting [331].

Extension

While reduction limits fidelity or representation, allowing a decision-maker to focus on other aspects of the challenge, this approach extends the mapping with additional functionality. It increases the functionality or information of an existing mapping model without fundamentally changing its structure. Extension can be used to augment inputs, outputs or the mapping function, estimate errors, include decision intervals, or incorporate multi-disciplinary models.

Extend inputs, outputs or mapping: Methods like JD and FO extend input variables to fluctuate over time for use in the mapping model, while PRIM or Random Forest (RF) extend outputs for investigation. Additionally, mapping models like SP extend both inputs and outputs to tune or investigate the mapping between spaces while optimising for a single variable. Similarly, MOGA augments the development of inputs based on outputs to support the investigation of multiple objectives. In contrast, in UQ the chosen mapping model must be extended to enable exploration of the decision space. Alternatively, Concurrent Subspace Optimisation (CSO) extends the mapping by using multiple sub-models. Value variable outputs can also be extended or redefined in Multi-Attribute Expense (MAE) to enable alternative evaluation or to provide different robustness insights RM.

Estimate error: Extension can be used to include an error estimate in the mapping model to deal with mapping uncertainty. This can occur when the mapping model is constructed with potentially erroneous or incomplete information. When uncertainty is low and sufficient reference points exist, errors can be identified by checking whether samples deviate significantly from their expected category. The distance is determined using geometric or structural constructs such as MTGS and Support Vector Machine (SVM), or boundary estimation with IG or angular deviation measures with Ridge Regression (RR). For intermediate uncertainty, RD incorporates probability to represent the likelihood of samples taking a specific value. For high levels of epistemic model uncertainty, methods like GNT add error bounds directly to variables. Alternatively, Axiomatic Design Approach (ADA) incorporates aleatory model uncertainty by performing experiments and representing variability probabilistically. When linear or non-linear relationships are defined from data, Meta/Surrogate Modelling (MMSM) use a static confidence interval around the approximation function. Alternatively, when accurate reference points are available, Multi-Fidelity Model (MFM) extends the mapping by dynamically tuning error bounds, PCE fits the mapping model using representative functions, and PM uses samples to establish static or probabilistic bounds.

Decision interval: The amount of time considered and the available decision-making window directly influence behavioural complexity. Temporal extension augments the mapping model with explicit timing, sequencing and control structure. Consequently, some methods extend the mapping model to explicitly incorporate temporal structure and decision timing. While the decision process can be concurrent with the problem's occurrence, mapping models are often developed separately from the actual decision space.

When a decision interval is long and events are far between, mapping can be represented as a single overarching model (SDY) or multiple discrete snapshots (DEM). However, when the decision space can be modelled as a self-contained system [163, 453] or when sequential development over time is crucial, a continuous-time or equivalent domain SIM can be used to investigate system behaviour and timely response [302].To address short reaction times, autonomous decision models such as Model Predictive Control (MPC) can be developed that utilise feedback from the actual decision space to trigger decision-making. To improve accuracy, high-fidelity models are typically used for lower reaction times (operation), while low-fidelity models can also be suitable for detached approaches (design) [27]. For mapping where decision timing is uncertain, methods like APM and DAPP use preparatorions that incorporate triggers and adaptive responses to contextual developments.

Additionally, because adapting a decision can be complex due to inertia, mapping models are extended to explore the development and impact of decisions over time. This includes extending the mapping to explore multiple decision pathways in parallel with ROA, exploring potential states over time with (TDN), and reflecting adaptation effects with ARO. Additionally, recursive mapping models such as DP use backward propagation to determine decision sequences that lead to a target state.

Multi-disciplinary modelling: The mapping can also be extended to include multiple characteristics and disciplinary perspectives. In this case, multiple sub-models from different disciplines are combined to represent critical aspects of the decision space. Each sub-model may have different fidelity or structural characteristics. Nevertheless, even though using multiple models can enhance model results [251], an increased number of relations and interactions may also increase behavioural complexity. Additionally, to control information propagation through the combined model, the input and output connections are ordered hierarchically, or, in the case of CSO, non-hierarchically.

When properly combined, multi-disciplinary models can be analysed similarly to smaller mapping models while incorporating multiple disciplines and levels of detail. However, optimisation approaches like Multidisciplinary Optimisation extend the mapping to handle combinatorial growth [187, 400]. Several large, multidisciplinary models have been constructed for fields such as ship design (holiship [319]) and aerospace design (KADMOS [159]). Even though constructing separate models and combining them can be demanding, these approaches have been shown to reduce decision-making time and enable exploration of novel decisions while accounting for multiple disciplines and behavioural complexity.

Structuring

Structuring in the mapping space uses models to reveal, organise and formalise structural relations within the decision problem. Rather than reducing fidelity or adding functionality, it focuses on identifying how elements, states and causal mechanisms are connected. Multiple methods reduce behavioural complexity by explicitly investigating structure through mapping. For example, Flow Diagram (FD) is used to analyse elements and actions, FMEA investigates causality and risk propagation, Fault Tree Analysis (FTA) reflects decision and failure propagation, and Markov Chain (MC) incorporates state transitions to formalise system dynamics.

Constructing of a mapping model: When well-established analytical models are not applicable or do not exist, structuring can be performed using collected data to construct the decision space mapping. This is particularly relevant for high levels of behavioural complexity or large datasets, where describing relations is difficult.

The first step is to use existing data or well-defined experiments DOE [95] to identify and investigate which parameters or relationships are necessary to describe the problem space [299]. Experiments can be conducted in a real-world setting or using representative, high-fidelity models when conducting them in reality is difficult. The testing parameters are selected to effectively cover the relevant context, object, and value parameters. However, as experimentation can be time- and resource-intensive, the number of experiments is minimised while ensuring coverage. Second, the collected data is analysed to establish structural patterns. For example, RF is used to identify correlated categories [19, 48], KMC defines membership of a group, and Regularised Class Association Rules Algorithm (RCAR) investigates logical rules from data.

Alternatively, Kernel Methods (KER) identifies the most impactful variables to reduce the size of the mapping model. This is achieved by detecting correlations to limit mapping to influential parameters or by constructing representative parameters through space transformation. Lastly, when data originates from many sources and becomes difficult to interpret, as is the case in Machine Learning (ML), multiple variables can be aggregated using weights to create a more explainable structural representation (FI). Depending on their use, such techniques may either structure the mapping by identifying dominant relations or extend it by enabling uncertainty propagation.

Establish connections: Mapping models are very suitable for investigating and structuring technical and social relations in the decision space. A common first step is to subdivide the problem into physical (spatial), logical (behavioural) or operational (functional) domains [61, 66].

Elements and their interconnections can then be described in multiple ways, including matrix-based representations in DSM, state-based representations in MDP, or topological representations of nodes and links in (GT).

These structural descriptions can be extended with logical rules, such as transition probabilities or conditional dependencies, to represent temporal flow with TDN, the dependency of connections in FD, or causal relations in Bayesian and decision networks [213] and belief networks [52]. Operations on these structures allow the identification of functional clusters or critical relations. By incorporating capacity constraints or operational rules, behavioural aspects of the decision environment can also be reproduced (queuing networks [125]).

Transformation

Transformation in the mapping space refers to a change in the epistemic nature of the model: how knowledge is represented, inferred or validated. When uncertainty is deep or data is unknown, it becomes difficult to assess the accuracy of information, or it may be missing altogether. In such cases, instead of relying on specific empirical data, a mapping model may be defined using fundamental relations, representative cases, or logical reasoning. The choice of modelling approach directly affects the accuracy, quality and reliability of estimates and relations. Consequently, instead of extending or structuring an existing mapping, this approach alters how the mapping function is constructed, represented or interpreted through changing the transparancy or combining submodels.

Transparancy: One important transformation concerns the transparency of the mapping model. White-box models are constructed with decision-maker interaction in mind, allowing their internal structure to be understood and analysed. Examples include MINLP and DSM. Because their mechanisms are explicit, model uncertainty can be investigated through inspection, verification and validation. In contrast, black-box models transform the mapping into a data-driven or algorithmic representation in which internal relations are not directly interpretable. These models are frequently used to address high behavioural complexity, such as in optimisation (Mode Pursuing Sampling (MPS)), evaluation (Adaptive Multi-Algorithm Genetically Adaptive Method (AMALGAM)), behavioural estimation (ANN) or clustering (SC). Even though these are powerful, their low transparency increases model uncertainty, as behaviour and results may be difficult to verify or validate. Alternatively, grey models are proposed, in which the decision maker is included in the part of the mapping prone to model uncertainty to improve confidence or allow adjustment of the mapping.

Multiple models: Transformation also occurs when mapping models combine multiple sub-models with Multidisciplinary Optimisation or combined levels of detail [431]. In such multi-level or multi-model structures, uncertainty from a lower level can propagate through the model, compromising its quality and reliability, and making it difficult to identify its source. To address this, a common approach is to verify and validate the behaviour and parameters of each part of the model, both locally and globally (SA), but it is argued that this can only be done for parameters that are not subject to temporal changes [458]. Consequently, under deep uncertainty, transforming the mapping model inevitably involves trade-offs among interpretability, predictive capability, and epistemic confidence.

2.4 Discussion

2.4.1 Approaches and methods

The framework aims to provide insight into how a method or a limited combination of methods can be used to deal with specific challenges from a decision problem while against an acceptable effort, time, and additional challenges. The chapter reflects that many methods can be applied to different challenges. Nevertheless, despite the large number of methods, decision makers are limited to a small subset. As a result, they may overlook more suitable methods and instead force methods that they are familiar with into addressing the challenge. Therefore, the framework adopts the opposite perspective. Instead of starting from available methods, it first defines the structure of the problem to establish which challenges require a conscious decision-making process [219], which challenges can be excluded, and what compromises must be made. Based on this analysis, the framework can be used to determine what approaches to use, while the overview provides insight into which methods can be used to implement these approaches.

A method can span multiple spaces, challenges and use multiple approaches to populate the framework. Nonetheless, the reviewed methods are found to either focus on one of the spaces or mapping (context, object, value, or mapping), one challenge category (complexity or uncertainty), or one common approach (e.g. reduction, extension). The overview also visualises the limits of a method to identify which parts of the problem it disregards. This is important because, in the literature, the applicability of methods to specific problems is investigated primarily. Authors typically focus on methods, either comparing multiple or investigating the application of an existing, combined, novel, or extended method to a pre-defined problem. Because of this, the potential implementation of the approaches behind the method to different or multiple challenges and spaces is unclear. By defining the use of the five main approaches (reduction, extension, exploration, structuring and transformation) in the framework, the routine and bias for known methods can be overcome by improving awareness of different approaches and more suitable methods.

Besides this, it is found that multiple challenges or weaknesses of a known method are commonly compensated for by using a more extensive method than necessary or by combining or extending familiar methods or models. Even though this can offer additional insight, it is guaranteed to increase perceptual complexity and reduce flexibility in dealing with challenges not considered initially. Additionally, weaknesses in one approach can result in other challenges and a ripple effect, making the problem increasingly more complex when models or methods are combined or extended. Therefore, to avoid unnecessary extensions or combinations, the subsequent framework provides insight into how methods represent the problem space and which approaches are used to address challenges. This allows the decision maker to select a single method proportional to the problem or a limited number of complementary methods.

2.4.2 The maritime emission reduction problem

For the maritime emission-reduction problem discussed at the start, multiple simultaneous challenges can be subdivided over the different decision principles using the framework. First, interconnected decisions on multiple levels for different vessel types (subsectors) result in behavioural and structural complexity (mapping and object). Second, difficulties in predicting behaviour and a lack of information regarding the functioning, readiness, and application of reduction measures and emission targets lead to input, context and model uncertainty (object, context and mapping). Lastly, differences in stakeholder perspectives and preferences result in perceptual complexity in the value space.

As explained in Section 2.1, emergence complicates structuring such a problem. To approach relevant challenges for each level separately, the problem is decomposed into more manageable subproblems that vary in their levels of detail, such as the policy level, the ship level, and emission reduction measures. To ensure addressing coordination and emergent effects, tractability is used to identify and track specific challenges and relevant information within and between these levels.

On the policy level, complexity and temporal effects significantly impact developments. These can be approached by using exploration to incorporate multiple economic, social, and environmental objectives in combination with transformation, where a posteriori evaluation and decision adaptation can enable balancing between value attributes [443]. Power dynamics and social choice should also be considered to align stakeholders and ensure cooperative stability. At the ship design level, extension approaches such as dynamic objects of choice together with transformation to decompose decision-making over time can be used to investigate using adaptive strategies against context space regarding reduction targets and reduction measures. Additionally, by expanding influence, cooperation with technological measure developers can be improved to align capabilities with the ship's requirements. Lastly, on the system level, contextual, structural and behavioural complexity and model uncertainties remain for various reduction measures. Consequently, transformation (search), exploration and extension approaches can be used to approximate

2

system value and behaviour to establish processes and requirements and provide error estimates to support decision-making at both the ship and industry levels.

Although this decomposition of maritime emission reduction challenges does not guarantee success or resolution of all challenges, it aims to facilitate rational decision-making by increasing awareness of limitations and clarifying the problem scope for each stakeholder. Applying the framework encourages a more explicit understanding of where challenges overlap, enabling a structured response to complex problems with multiple challenges, like maritime emission reduction.

2.4.3 Insights from the method overview and further research

Some additional insight can be gained when investigating how many methods from the overview table use specific approaches. It is found that extension in mapping (multi-disciplinary models (5%)), object space (expansion of influence (3%) transition probability (4%)) and value space (social choice (5%)), and object space transformation (temporal decomposition (3%)) are the least used approaches. In contrast several approaches are used more often. This includes reduction in the object space (static object of choice (22%), limit information (25%)) and context space (limit information (25%), deterministic scenarios (25%)). Extension in the context space (variable investigation (25%), single/multiple discrete events (40%)), value exploration (value as a context variable (22%)) and mapping model extension (extend inputs, outputs or mapping (40%)) are more frequently found in the investigated methods.

Underrepresentation can suggest either a lack of research or benefits, which should be investigated before applying a method. Furthermore, it seems that approaches addressing higher difficulty levels are used less often. This discrepancy may be due to the reliance on simplifications to investigate a limited number of high-level challenges or due to the overrepresentation of methods using approaches for intermediate or low levels of difficulty. Additionally, even though the list of methods is extensive, and every challenge and space is covered, the overview is expected to be incomplete and to increase over time. Novel methods or applications will cover challenges, spaces or approaches in different combinations or in more detail. The framework could also provide structure for researchers in describing the application's relevant space and challenge categories for comparison.

When examining how approaches are combined, several aspects can be noted. In the context and object space, similar approaches are used more often than other spaces, while no correlation is found between approaches addressing mapping and value space challenges. For challenge categories, approaches for uncertainty and perceptual complexity are often combined. Investigating the method's collective use of specific approaches shows a high positive correlation between: set constraints and probability or weights, discrete temporal sets and exploring the object space, value as a context variable and object space search, and multi-disciplinary models and black box transparancy of models, which can indicate a dependency between these approaches. On the other hand, searching the object space and a priori evaluation, object space exploration and trade-off analysis are rarely used together by methods, which might be explained by the incompatibility of these approaches or gaps in existing research. Whether these findings are caused by a lack of methods that use certain approaches, limitations in the approach definitions, or an application bias remains unclear within this research.

Decision processes like design, which face increasing knowledge over time or shifting focus, could benefit from further research into easily extendable, combinable, reusable or reiterative methods that use general mapping and detached context, object and value variables. When mapping functions must be redefined for each application, a deterministic representation of contextual and object inputs and a priori value variable selection, decision problem developments require reconstructing the method. Due to mapping effects, using a priori values can result in difficulty changing the value of choice in new iterations, even when applying multi-criteria or multi-objective. By generalising mapping and detaching the selection of the context, objects, and value of choice variables, parts of the input, mapping, and output can be reused, allowing the decision-maker to evolve their approach throughout the decision-making process.

Besides the challenges and approach definition phase of the framework, the impact of decision-support methods in the choice phase is an important aspect to consider during application. As such, the choice whether to provide information (descriptive and predictive), propose a decision (prescriptive) or decide without human intervention (automation) should mirror the problem owner's perspective. This way, the result of a decision process satisfies expectations, while the decision process's perceptual complexity and model uncertainty remain manageable. However, papers describing method applications often focus on the novelty of the method, underrepresenting the reasoning behind the choice phase direction and the perspective of the problem owner.

Lastly, even though this chapter can be used to compare methods qualitatively, identifying the most suitable method is not its purpose. Ranking methods for their application to decision problems are difficult because of valuation challenges. For example, methods could be ranked based on how they deal with the most important challenges within the available time and information. However, as these aspects differ for each problem, the main purpose of the framework is to guide a decision-maker in considering the problem, its time frame, challenges, and criteria before selecting a method. Nevertheless, further research could still benefit from an effort to quantify application, but mainly by testing and improving the implementation and limitations of methods by using a benchmarking decision problem containing multiple relevant challenges, as is commonly found in different research fields like policy decision-making and operations research.

2.5 Conclusion

To answer the first subquestion, this chapter categorises challenges and investigates the underlying approaches of multiple methods, providing structured insight into how to address the increase in decisions, methods, and challenges faced by stakeholders involved in vessel design, build, and retrofit during the maritime energy transition. The decision problem is divided into four parts: the context of choice, the object of choice, the value of choice, and a mapping function that connects these. It makes the decision problem's challenges explicit by including sources, level of difficulty, and additional characteristics into the framework for complexity and uncertainty. The decision maker identifies the most pressing challenges, decides whether to focus on the context, object, or value space, and whether a single approach or a large research effort is necessary. Next, one or more main approaches are selected to address these challenges, and the method overview table can be used to determine which methods are suitable.

The framework was developed through an extensive literature review that identified 193 methods. During its development, it was observed that method descriptions use different terminology when describing the approach and the problem spaces and challenges to which a method applies. This limits others to understand only the initial application and requires investigations of additional individual cases, requiring a rather large body of literature to be able to generalise the generic concepts of the methods. Combined with routine and bias, this limits awareness of other, more applicable methods. Consequently, taking a more fundamental approach to the description of methods, as proposed in this framework, allows decision makers to explore more methods and their suitability, while at the same time forcing them to consider different facets of their decision problem. This could reduce the need to combine methods or even guide the combination to a limited number of complementary methods.

The developed framework's application to the maritime emission reduction decision problem encourages explicitly describing challenges and their limitations to structure decision-making. The problem and challenges are decomposed over the principle spaces and policy, ship and system levels. To deal with behavioural complexity, interconnections and coordination between these could be ensured using traceability. Furthermore, five main approaches are proposed that are often used manage the relevant challenges at each level; reduction, extension, exploration, structuring and transformation. For each space, suitable approaches are selected for each level of the maritime decision problem. This includes a posteriori evaluation to manage multiple objectives at the policy level, using adaptive decision-making over the lifecycle for the ship level, and investigating value estimates and the impact of mapping functions by using exploration transformation (search) methods at the system level. By structuring and categorising the decision space and its challenges first and determining approaches second, decision-makers can identify relevant methods that support their decision problem. Consequently, with the many simultaneous challenges in today's world, such a framework is expected to be useful in many other applications.

The next step in applying the framework to the maritime energy transition problem is to select decision-support methods from the method table. To deal with high levels of input uncertainty, multiple methods exist that apply adaptive decision-making, while also investigating value and behaviour estimates using either search or exploration approaches. In the following chapter, the applicability and insights gained from a range of methods are further investigated.

3

Applying deep uncertainty methods to the maritime energy transition

This chapter further develops the framework to support decision makers in dealing with challenges encountered during the maritime energy transition. The development is guided by the following research question:

How to facilitate decision-making under deep uncertainty in the maritime energy transition?

There are multiple aspects that influence this decision-making, including the development of the emission reduction targets, the support of the economy and infrastructure, maritime industry-specific characteristics and the reduction measures. Combined, the maritime energy transition presents multiple challenges that occur at different, but interdependent levels. It is more than the sum of its parts, which cannot be solved by any single stakeholder. As such, it is a complex, emergent problem for stakeholders who must operate within an ecosystem, taking into account the technical and social interconnections that determine its functioning. The presence of social choice and multiple decision-makers further requires consideration of power dynamics and cooperation among actors. Additionally, each level of expertise may possess domain-specific/tacit knowledge, which can disrupt and lead to misunderstandings in the flow of information between levels [68]. This further complicates insight into the impact of individual actor decisions on other levels and unintentional consequences. Consequently, in chapter 2, the energy transition problem and its corresponding challenges were subdivided and structured into several parts:

- Context: This level combines the policy and commercial level that trigger decision-making and considers environmental targets and financial performance of the ship level. Additionally, it accounts for object uncertainty resulting from temporal effects driven by regulatory and market developments.
- Ship: This level represents the ship level, which faces contextual and structural complexity as part of the design, build, and potential retrofit process, while also facing

contextual and input uncertainty regarding the installation, safety, and operational requirements of emission reduction measure alternatives.
- System: This level represents the system level, including behavioural complexity due to the integration of emission reduction measures within the system of systems, as well as model and input uncertainties.

These levels reflect the different perspectives that a decision-maker can face and can be treated as different decision problems. Consequently, the decision framework can be used to identify appropriate methods for challenges at each level. To properly enable changeability and investigate interconnections and influence between these levels, information exchange between methods needs to be ensured.

3.1 Framework for Exploration of Adaptive Robustness in Vessels

Having identified relevant levels of detail for the maritime energy transition and the importance of incorporating inter- and intra-level challenges, the first step in developing the framework is to determine how the levels are connected. As explained in chapter 2, such behavioural complexity can be reduced by using multidisciplinary modelling. It exploits discipline-specific knowledge by combining mapping models[186].

The approach is used to construct a multidisciplinary framework that enables the use of different methods at separate levels, carefully considering the information coupled across levels. By taking information tractability into account before selecting which methods to use for each level's challenges, interactions are inherently accounted for. This enables decision-makers to select methods to address challenges at different levels, while also exploring the impact across levels. This led to the development of the FEAR, as shown in Figure 3.1. The framework consists of three main modules that reflect the levels of

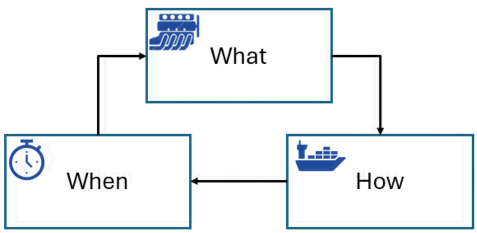


Figure 3.1: Multi-disciplinary model setup of the maritime energy transition problem

decomposition: what, how and when. FEAR is applied to support decision-making for the maritime energy transition challenges as defined in the introduction chapter. These are political, financial, and technological challenges that occur at the context, ship and emission reduction levels. To structure these, the FEAR is subdivided into the following modules:

- When: Pathway selection: This module investigates dynamic objects of choice and the incorporation of lifecycle decisions during the design phase. Aiming to allow the ship to support various transition pathways (with varying levels of success). It mainly addresses the impact of temporal effects in the context, object and value spaces. Information from the other modules can be used to investigate how the ship or system-level strategies perform under contextual uncertainty.

- What: System Architecture: Defines and evaluates the structure and interconnections of on-board systems. It aims to evaluate and compare system architectures, including the connections between systems and the propagation of uncertainty. This allows decision-makers to investigate how emission-reduction measures impact the system architecture. It mainly focuses on addressing behavioural complexity and model uncertainty. The module can be used to explore different system architectures when prompted by the when module and provides system architectures as input to the how module.
- How: System Integration Model: In this module of the framework, the integration of system architectures from the what module is investigated. The ship serves as a platform for installing and exchanging emission-reduction measures. It aims to evaluate the integration of the initial and future system architectures. The results can be used to gain insight into contextual uncertainties and how design choices can address them. Based on the system architecture design space, input uncertainty propagation is evaluated and included during the design phase. This facilitates the creation of alternative designs that support different initial system combinations and their evolution.

3

3.2 When module: incorporating decision support methods for deep uncertainty

Based on the literature discussed in Chapter 2, multiple decision-support methods could be applied to the maritime energy transition. To understand the strengths and limitations of promising methods and determine what is required from the other two modules, this chapter aims to answer the following research question:

Which existing methods can support decision-making in the maritime energy transition, and what are their limitations?

To research the applicability of methods that enable decision support under deep uncertainty, a decision-making problem is defined at the ship level. The study investigates the selection of an emission reduction strategy during multiple stages in the ship's lifecycle using the framework discussed in chapter 2. The decision space structure that is used to subdivide the decision problem in the when module is shown in Figure 3.2.

The decision space representation reflects the temporal development of emission reduction regulation in the context space. To comply with regulation developments, an emission reduction strategy is selected or modified in the object space, by using or changing between reduction options O_i during the ship's lifecycle. The selection is reflected in the value space in the total lifecycle emission and costs associated with each emission reduction strategy. Mapping functions need to be able to reflect the performance of an emission-reduction strategy at different times and the temporal development of the strategy and its relation-

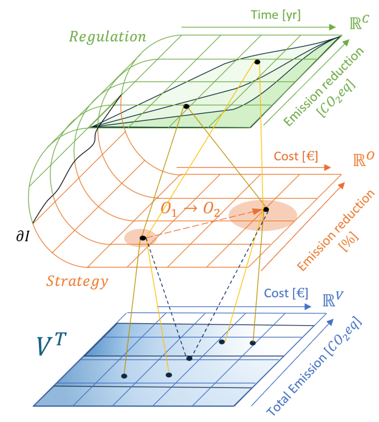


Figure 3.2: Decision space structure for the when module. Including the temporal development of emission reduction targets in the context space, the selection and change between emission reduction strategies in the object space and the reflected value in the value space.

ship to the ship's performance. The main challenges that are considered are related to the complexity and uncertainty that occur in the context and object space:

- Context of choice
  - Contextual uncertainty: The development of regulations is uncertain as it is influenced by different external factors, such as social dynamics (politics), the environmental impact of measures or economic and infrastructure support. The uncertainty in emission reduction targets is reflected in Figure 3.2 by the different colored areas.
  - Contextual complexity: The impact of different external actors and the existence of multiple reduction pathways, and the addition of time increases the complexity in the context space.
- Object of choice
  - Input uncertainty: includes uncertainty regarding the availability, performance and costs of emission reduction measures at different stages during the lifecycle, and the availability of emission-reduction measures.
  - Temporal effects: mainly concerns when a strategy is applied at the start or during the lifecycle, but also includes its impact on uncertainty, regarding the term of resolution and the fluctuation of variables, the increase of complexity due to expansion of the design space, the availability of emission reduction systems and the fluctuation of value over time.
- Value space
  - Value complexity: Besides the two attributes shown in the framework structure, there are multiple attributes that can influence the preference of the decision-

maker. This includes operational performance indices like speed, cargo capacity, bunker capacity and the inclusion of environmental factors in decision-making.

The structure that is followed to address this decision-making problem is shown in Figure 3.3.

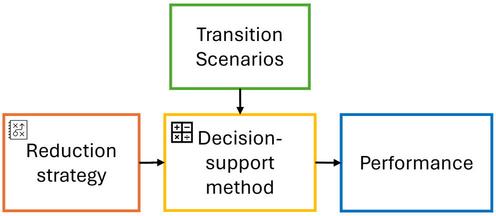


Figure 3.3: When module setup, including object, context and value space. The decision support methods used for mapping are represented in yellow.

The figure shows the context and object inputs and the output to the value space, while mirroring the decision structure figure colors. The methodology to use to explore is investigated from the method table and what approaches can handle uncertainty while also facing a complex decision space, two main groups of methods are identified: those that explore the object space and those that search for optimal objects of choice by projecting onto the object space. To establish the benefit of either group, this chapter consists of section 3.3 that investigates the application of methods using the exploratory approach and section 3.4, investigating the application of the search approach. Both sections consider the decision-making problem as described above, but differ in case study setup and investigated decision-support methods.

3

3.3 Exploratory methods: Ship design methods to deal with deep uncertainty in the maritime energy transition

Much research has been done in other fields on how to deal with high levels of uncertainty in decision-making [273]. Resulting in methods that visualise and evaluate adaptive strategy as part of the decision-making process. Consequently, such methods could offer valuable insights for the maritime energy transition. However, besides experimental application [228, 352], such methods have, to the author's knowledge, not been applied to the maritime energy transition problem.

As the ship design process deals with deep uncertainty, it could potentially benefit from several aspects of exploratory methods that support decision-making under deep uncertainty. First, exploring performance across different scenarios enables designers to identify a design's vulnerability to uncertainty. Such an ability can provide insight into how a design can cope with external changes while remaining on track to meet its objectives [280]. Furthermore, a visualisation of sensitivity to parametric uncertainty allows designers to better understand and be cautious of deterministic pitfalls [324]. Second, besides identifying the vulnerabilities of a single design, the process would benefit from the ability to investigate multiple alternative designs. Moreover, assessing the ability to change between alternative designs dealing with uncertainty could also be valuable (Rehn 2019). Third, the preparation and adaptation of a design to changes is also recognised as an effective way to deal with deep uncertainty [176]. Therefore, besides the analysis of vulnerability and design exploration, the design process would also benefit from developing strategies that can be used in other situations than those for which the vessel is designed. By continuously developing this adaptive strategy, the ship might be more proactive and better able to deal with uncertainties over time. Lastly, the use of a method should be supportive instead of exhaustive. So the designer's focus can remain on design.

From the method table, three promising methods that could be used to support decision-making and meet these aspects were identified. First, DAPP evaluates alternative options and develops possible pathways to compliance [176]. Second, RSC determines the performance of a design in established scenarios (epochs & eras), also allowing evaluation including retrofit (changeability) [369]. Third, RDM explores the effect of uncertainties on a pre-specified design and analyses its vulnerability [253]. The methods are compared on their ability to include scenario analysis, alternative design exploration and adaptive strategy in the ship design process to a desirable level. Each method is applied to a general cargo ship case to allow for a first comparison. The goal is to better understand the usability and potential of each method for the energy transition in shipping. The setup of comparison criteria, the case study and the data used are presented in the methodology section. Next, the setup and the results of each method are discussed. Lastly, the methods are compared and evaluated using the comparison criteria.

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3.3.1 Methodology

A set of criteria and sub-criteria is used to compare the three methods. These are based on the aspects identified in the introduction that could potentially improve the ability to deal with uncertainty during the design process. The criteria are measured on a scale from 1 (worst) to 5 (best).

- Uncertain scenario vulnerability assessment
  - Scenario-specific analysis
  - Uncertain parameter sensitivity
- Alternative design exploration
  - Initial design robustness
  - Evaluation adaptive design
- Evaluation of an adaptable strategy
- Supportive method setup

In this chapter, a supportive method is defined as being (partly) reusable, with clear modules, input and output, that is easily applicable to new cases. Besides the criteria, the level of uncertainty that the method can deal with is compared as well. These levels go from complete determinism (0), clear enough (1), probabilistic representation (2), a few possibilities (level 3), many possibilities (4), to unknown (5) [273]. Of these, levels 4 and up can be considered deeply uncertain, which is encountered by ship designers in the maritime energy transition.

Case study setup

This research aims to establish what insights the three exploratory methods provide by performing a case study into the effects of uncertainty on the performance of the general cargo vessel. The basis of each method is equal and includes a general cargo ship, alternative options, and a set of uncertainties. A general cargo vessel has been chosen because these cargo-type vessels present a large share of total maritime emissions, which has resulted in many energy transition studies. This specific vessel has been used for a case study into the application of ammonia and methanol, which is used as a reference for verification [54]. The vessel parameters are presented in Table 3.1. The ship dimensions, tank volume, tank weight, endurance and speed are used to set operational targets for evaluation.

Table 3.2 presents relevant data of several alternative fuel-converter combinations; the values have been compiled from literature and contain lower, mean and upper bounds to represent best and worst-case scenarios. Fuel density includes the storage system effect and is assumed to be constant. Ten different energy carrier options are considered, which are either converted using an internal combustion engine (CI or SI) or a fuel cell (SOFC or PEMFC). Onboard conversion performance is represented by a conversion efficiency range. Capital expenses are defined separately for storage and converter systems. Besides this, a broad range around the reference value is used for operational expenses.

Table 3.1: Design and operational parameters of the reference vessel

Parameter	Value	Unit
Length overall	150	m
Breadth	15.9	m
Draught	8.6	m
Cargo weight	10200	t
Cargo volume	13644	m^3
Fuel type	MDO	
Fuel volume	900	m^3
Fuel weight	873	mt
Design speed	11.5	kn
Target distance	8000	NM

Table 3.2: Alternative energy carrier and converter options and indicative performance/cost ranges (low, medium, high). Contents are based on [445][1], [50][2], [29][3], [26][4], [7][5], [28][6], [123][7], [188][8], [114][9]

Energy carrier/ converter	Emission factor[4]	Gravimetric density[1,2]	Volumetric density[1,2]	Conversion efficiency[2,3]	CAPEX storage[3,6]	CAPEX converter[3,6]	OPEX[4,6,7,8]
	gCO_2eq/kWh	MJ/kg	GJ/m^3	%	€/kWh	€/kW	€/MWh
MDO–CI	620,700,780	30	29	35,40,45	0.08,0.09,0.10	451,575,821	40,120,200
MDO–SOFC	620,700,780	30	29	45,50,55	0.08,0.09,0.10	573,868,1296	40,120,200
LNG–SI	580,690,770	27	13	35,41,47	0.28,0.31,0.33	451,575,821	60,90,180
LNG–SOFC	580,690,770	27	13	45,52.5,60	0.28,0.31,0.33	573,868,1296	60,90,180
Methanol–SI	700,800,980	16	12.6	45,48.5,52	0.13,0.14,0.15	451,575,821	90,105,130
Bio-methanol SI	10,100,160	16	12.6	45,48.5,52	0.13,0.14,0.15	451,575,821	70,140,200
Ethanol–SI	100,200,300	18	16	45,48.5,52	0.13,0.14,0.15	451,575,821	90,110,180[9]
Ren NH_3–SI	5,30,50	14	10	45,48.5,52	0.13,0.15,0.17	451,575,821	80,140,230
NH_3–SI	801,002,805	14	10	45,48.5,52	0.13,0.15,0.17	451,575,821	160,260,370
Bio–LNG–SOFC	210,350,470	27	13	45,52.5,60	0.28,0.31,0.33	573,868,1296	60,90,180
Bio–LNG–SI	210,350,470	27	13	35,41,47	0.28,0.31,0.33	451,575,821	60,90,180
Bio–liquid–CI	140,200,270	27	25	35,40,45	0.08,0.09,0.10	451,575,821	130,230,270
LH_2–PEMFC	0,590,1000	11	5	40,50,60	0.80,0.83,0.85	500,730,900	75,300,590
Batteries	0,500,1000	1	2	85,90,95	150,260,500	—	30,200,370

The interrelations within the vessel are described using a simplified model, which is shown in Figure 3.4. The ship design is subdivided into three main components: the energy carrier, the energy converter and energy users (operational power). Additional systems or vessel changes are shown in circles and include exhaust treatment (i.e. scrubbing, CCS), energy-saving (i.e. waste heat re-usage), power assistance (i.e. sails) and operational changes (i.e. speed reduction). Only the operational changes are researched.

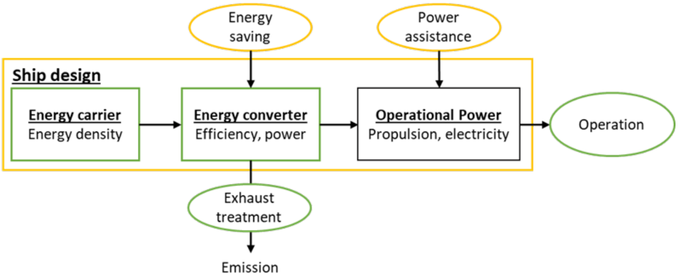


Figure 3.4: General vessel model

The vessel relations are modelled using the functions described in Eqs. (3.1)– (3.4). The outputs include costs, emissions, necessary tank size and mass and are normalised with respect to the current situation (Maritime Diesel Oil (MDO)). Starting from the left part of the general vessel model, the necessary fuel stored for operation P_{store} in MJ is

$$P_{\text{store}} = 3.6 \frac{s_{\max}}{V_s} \left(\frac{W_e}{\eta_e + \eta_{\text{save}}} \right), \tag{3.1}$$

where η_e is the effective engine efficiency, which is dependent on the energy carrier and converter choice, V_s is the design speed, $s_{\max}$ is the maximum target sailing distance, and$\eta_{\text{save}}$is the efficiency increase due to energy-saving engine measures. The total stored fuel power is translated to volume and mass using the volumetric density ρ_{vol}, gravimetric density ρ_{grav} and Specific Fuel Oil Consumption (SFOC), respectively. The total necessary engine power in kW W_e is

$$W_e = \left(P_{\text{aux}} + \frac{c_1 V_s^3}{\eta_D\, \eta_{\text{TRM}}} - P_{\text{ass}} \right), \tag{3.2}$$

where c_1 is the factor of proportionality, P_{aux} is a constant auxiliary power from the hotel and operational load, η_D is the total propulsive efficiency, η_{TRM} is the total transmission efficiency, and P_{ass} is any power assistance that decreases the amount of total power. It is assumed that the total transmission and propulsive efficiencies are constant, and the vessel's propulsion chain is simplified to a single propeller and engine. The global warming potential in tCO2eq is

$$\text{GWP} = \text{EF} \cdot P_{\text{store}}, \tag{3.3}$$

where EFis the emission factor CO2eq/kWh, which depends on the type of carrier, and $P_{\text{store}}$is the fuel stored for operation from Equation (3.1). The system cost $C_{\text{tot}}$is

$$C_{\text{tot}} = \text{CAPEX}_{\text{conv}} \cdot W_e + (\text{CAPEX}_{\text{storage}} + \text{OPEX}) \cdot P_{\text{store}} + \text{GWP} \cdot C_{CO_2}, \tag{3.4}$$

where $\text{CAPEX}_{\text{conv}}$ is the capital cost of the converter system per installed kW, $\text{CAPEX}_{\text{storage}}$ is the capital cost for storage per kWh, Operational Expense (OPEX) is the operational expense for fuel, Global Warming Potential (GWP) is the emission in tonne and C_{CO_2} is the potential cost per CO2eq.

3.3.2 Application and results of each method

The usability of each method is investigated by applying the methods stepwise. For every step, relevant criteria and insights for the application are discussed. Furthermore, it should be noted that the main goal is to use the case study to compare methods, rather than presenting insights for the maritime energy transition. Because of this, the case (ship model) is simplified, and its findings should not serve as a basis for decision-making, but rather as an indication of applicability.

Dynamic adaptive policy pathways (DAPP)

DAPP has been used to investigate alternative decisions in water management [176]. The method is an expansion of DAP [245], which focuses on designing adaptive plans together with stakeholders. DAPP aims to further analyse multiple alternative decision sequences (pathways) to overcome deep uncertainty. The general setup of the method, as adapted from Marchau et al. [273], is shown in Table 3.3, which also includes the maritime energy transition case study approach.

Table 3.3: DAPP and case study setup

Step	Contains	Substeps
1	Define decision context	Problem framing, system, objectives, outcomes and uncertainties
2	Vulnerabilities & opportunities	Assess tipping points and develop (transient) scenarios and options
3	Identify & evaluate options	Option efficacy
4	Design & evaluate pathways	Create and explore pathways
5	Design adaptive plan	Select pathways, assess short-term actions and long-term options
6-7	Implement and monitor	Apply and assess/change plan using signals

DAPP step 1: Define decision context

During the context definition step, the decision environment, inputs, outputs and system relationships are established. This context definition is equal for all methods. The objectives of the case study are to comply with emission reduction, minimise cost and keep operational capability at a satisfactory level. Even though regulation compliance is dynamic (uncertain), the reduction of emissions is calculated relative to the current situation. Which is the initial general cargo vessel design, sailing on MDO, which is assumed to have no emission reduction measures? The design capabilities, including mass, volume, sailing distance, speed and endurance, are used as a benchmark.

DAPP step 2: Vulnerabilities and opportunities

Step two is to further analyse the problem and determine tipping points, when the current situation can no longer meet target objectives. To establish tipping points, the original DAPP setup uses subjective scenario evaluation for a small number of extreme cases. However, because the performance of emission reduction measures can differ substantially due to input parameters, a quantitative method is deemed to be more suitable. Therefore, the vulnerability of the design to uncertainty is investigated using parameter ranges for cost (OPEX and CAPEX), energy conversion efficiency, and emission reduction performance instead. Furthermore, to research regulatory effects, an emission penalty of 0, 100 and 400 euros per tonne CO2eq is also simulated for the case study. The best, mean and worst-case performances are calculated using the general vessel model. The tipping point identified for the current situation is reached immediately, because the emission reduction is measured with respect to the current situation. Because the DAPP setup does not offer specific scenario and parameter sensitivity analyses, additional information has to be created outside of DAPP for the maritime energy transition decision problem.

DAPP step 3: Evaluate action efficacy

The efficacy of actions to outfit the initial design with other alternative fuels and converter technology is calculated using the vessel model for each indicative cost and performance range value from Table 3.2. The results are shown in Figure 3.5.

	Total CAPEX			Total OPEX			Total OPEX+CAPEX			CO2eq cost			Total cost		
Energy carrier-converter	**Best-case**	**Mean**	**Worst-case**	**Best-case**	**Mean**	**Worst-case**	**Best-case**	**Mean**	**Worst-case**	**Best-case**	**Mean**	**Worst-case**	**Best-case**	**Mean**	**Worst-case**
MDO-CI	96	100	107	30	100	190	36	100	183	0	58	297	23	100	296
MDO-SOFC	99	106	117	24	80	148	31	82	145	0	47	231	20	82	232
LNG-SI	103	108	117	43	73	171	48	76	166	0	56	293	31	83	283
LNG-SOFC	104	113	125	33	57	133	40	62	133	0	44	228	26	67	222
Methanol-SI	97	101	108	58	72	96	61	75	97	0	55	290	40	82	236
Bio-methanol SI	97	107	108	45	96	148	50	97	144	0	7	47	32	68	123
Ethanol-SI	97	101	108	58	76	133	61	78	131	0	14	89	40	59	138
NH3-SI	97	101	108	103	179	274	102	172	259	0	7	83	67	116	218
ren-NH3-SI	97	101	108	51	96	170	56	97	165	0	2	15	36	64	116
Bio-LNG-SOFC	104	101	125	33	57	133	40	61	133	0	22	139	26	53	169
Bio-LNG-SI	103	115	117	43	73	171	48	77	166	0	28	179	31	67	215
Bio-liquid-CI	96	100	107	96	192	257	96	183	243	0	17	103	63	130	220
LH2-PEMFC	116	127	138	42	200	492	48	193	459	0	39	333	32	150	498
Batteries	2606	4700	9484	11	74	145	248	497	999	0	19	157	162	336	746

	Emission reduction			Volume usage			Mass usage		
Energy carrier-converter	**Best**	**Mean**	**Worst**	**Best**	**Mean**	**Worst**	**Best**	**Mean**	**Worst**
MDO-CI	21	0	-27	39	44	51	86	97	111
MDO-SOFC	36	20	1	32	35	39	71	78	86
LNG-SI	29	4	-26	84	96	113	92	105	123
LNG-SOFC	45	25	2	66	75	88	72	82	96
Methanol-SI	23	6	-24	78	84	90	140	150	162
Bio-methanol SI	99	88	80	78	84	90	140	150	162
Ethanol-SI	89	76	62	62	66	71	124	133	144
NH3-SI	91	88	64	99	106	114	160	172	185
ren-NH3-SI	99	96	94	99	106	114	160	172	185
Bio-LNG-SOFC	80	62	40	66	75	88	72	82	96
Bio-LNG-SI	74	51	23	84	96	113	92	105	123
Bio-liquid-CI	82	71	56	46	51	59	96	108	123
LH2-PEMFC	100	33	-43	171	205	256	176	212	265
Batteries	100	68	33	270	285	302	1226	1294	1370

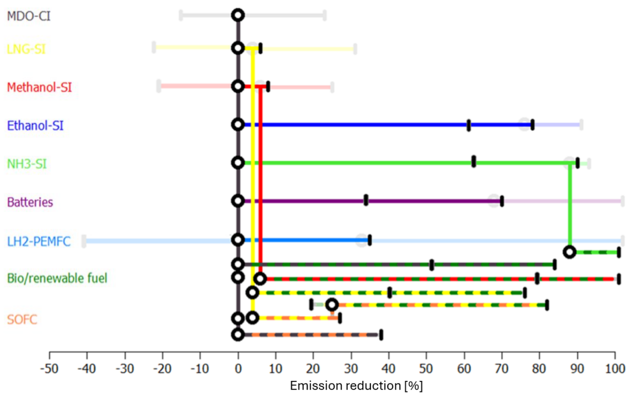
Figure 3.5: Colored ption results for DAPP

Figure 3.5 shows the best, mean, and worst-case impact on CAPEX, OPEX and emission taxation costs, emission reduction percentage and vessel constraints (available mass and volume for energy options) of each action. The emission reduction values are normalised relative to the mean MDO case, with total capital expenditure normalised to the newbuilding cost. Batteries are found to be too expensive for the sailing distance, showing that full electric solutions would only suit short sea shipping. The total CO2eq cost is normalised with respect to the mean operational expense and represents the additional costs due to emission penalties. Many of the energy carrier and converter combinations perform poorly in mass and volume categories. Besides this, the cost range for many options remains broad. Nevertheless, the inclusion of emission penalties can reduce cost disparities between alternative fuels and fossil fuels, potentially stimulating the uptake of low-emission energy carriers.

DAPP step 4: Pathway map and evaluation

The next step is the use of the pathways generator software tool developed by Deltares [113], which implements DAPP as described by Haasnoot et al. [177, 178]. It is a tool that allows the user to manually add actions (alternative fuel and converter combinations), pathways (how actions connect), scenarios (when changes can occur) and a scorecard to evaluate pathways. The result is a pathways map and scorecard that summarises the option results in Figure 3.6.

The Figure shows the pathways map on the left, which includes multiple options on the



Pathway	Volume	Mass	Rel. cost	Safety
	-	+/-	+/-	-
	+/-	-	+	-
	+/-	-	+	-
	-	-	-	---
	---	--	----	-
	---	---	---	--
	-	+/-	+	-
	+/-	+	++	-
	+/-	+	++	-
	+/-	+/-	-	-
	+	++	+	+/-
	-	-	+	---
	+/-	-	+	-

Figure 3.6: Pathways map and scorecard illustrating DAPP results for the general cargo vessel energy carrier-converter combination selection under uncertainty.

vertical axis and emission reduction on the horizontal axis. Each option is assumed to start at the same point as MDO. The uncertainty range has been added to visualise the best and worst-case emission reduction potential. The use of fuel cells in combination with other carriers or the use of renewable feedstocks is added as additional options and are shown as dashed lines from an initial energy carrier. The current EU emission reduction target of 55% GHG reduction by 2030 can only be reached by 7 out of 13 pathways. The scorecard on the right visualises pathway performance from Figure 3.5 regarding volume, mass, relative cost and safety. By providing such pathway information for a specific ship during its design phase, the decision-maker gains a global overview of the impact of different options on the capability and cost of the design. Furthermore, the future actions and uncertainty range offer a perspective of opportunities and vulnerabilities.

DAPP step 5: Designing an adaptive plan

Using the pathway evaluation, an adaptive plan is designed to outline how to reach target objectives. This plan includes preparation that enables promising pathways. Additionally, monitoring procedures are established to continually assess whether the plan proceeds as expected or if another pathway should be followed instead. For the case study, the requirements for several promising carrier-converter combinations are reviewed in Table 3.4. The preparations in Table 3.4 focus on specific measures to take to implement the pathways at the energy carrier, converter and distribution levels. Additionally, it also includes safety and additional notes. Further development is necessary before these

Table 3.4: Adaptive plan example including preparations for four energy carrier - converter combinations that meet emission reduction requirements.

Pathway	Energy carrier	Converter	Safety	Distribution	Other
Methanol-SI + Bio/renewable fuel	tank + cofferdam, cargo mass decrease	Double-walled piping, 0.8m from hull plating, special vent placement	low toxicity, low flashpoint, flammable	Increase 'green' production	
NH3-SI + Bio/renewable fuel	new tanks pressurised & refrigerated, special placement, large cargo mass decrease	Double-walled piping, 0.8m from hull plating, special vent placement, reactor.	High toxicity, flammable	Feedstock problems	NOx problem
MDO-CI + Bio/renewable fuel	small cargo mass decrease	no changes	Toxic to the environment	Feedstock problems	NOx problem
Ethanol-SI	tank + cofferdam, cargo mass decrease	Double-walled piping, 0.8m from hull plating, special vent placement	low flashpoint	Feedstock problems	

options can be implemented, but it does provide insight into direct steps. Updating the pathways and adaptive plan with developments in safety measures, system requirements, and availability allows to understand when to adjust course.

DAPP step 6 and 7

The last two steps, adaptive plan implementation (step 6), monitoring and adapting (step 7), concern the application of the plan during the lifetime. For the case study, the implementation will have to be executed together with a yard and a shipowner, during the building or retrofit phase of the vessel. By regularly monitoring the development of technology and logistics, the plan can be adapted to ensure compliance. Besides this, ship owners can proactively contribute to technology development that suits their pathways. Nevertheless, because of the nature of ships, design preparation can be difficult and will involve large investments. Therefore, it is important to include a more detailed exploration of different path enablers as part of the adaptive plan to be able to evaluate the costs and impact of these measures.

DAPP findings

The focus of DAPP is to create and implement adaptive plans that allow decision-makers to map a pathway toward meeting set targets. This proactive way of dealing with uncertainty could be effective for ship design, because the delivery and continual adaptation of a plan stimulates dealing with deep uncertainty. Furthermore, DAPP can be used to structurally implement the development of adaptive plans in the ship design process.

However, to gain detailed information about pathways and uncertainty effects, additional methods are needed. It is important to carefully select a method, as it affects DAPP input quality from the action efficacy step onward (steps 3-5). For example, the best- and worst-case range method that was used in this case study lacked detailed scenario analysis. Therefore, it was difficult to track outcome sensitivity to specific inputs, which is necessary for vulnerability analysis. Besides this, even though the pathways map and scorecard allow clear insights, the number and detail of options and outcomes that can be visualised are limited. DAPP offers a beneficial framework to create adaptable plans for dealing with uncertainty during the lifetime, but it needs to be expanded with more detailed inputs and modelling.

RSC
RSC is an extension of EEA and MATE and can be used to explore the effect of uncertain scenarios by evaluating alternative decisions in multiple short-term events (epoch) and randomly combined epochs (era) [371]. The setup of the method is shown below. It primarily differs from EEA, because of the additional changeability assessment in terms of the filtered outdegree [369]. The method was previously used to evaluate the flexibility of retrofits to deal with market changes [352]. It offers multiple ways to analyse design performance and could provide valuable insights into the maritime energy transition.

1. Value driving context definition
2. Value-driven design formulation
3. Epoch characterisation
4. Epoch analysis
5. Multi-epoch analysis
6. Era analysis and multi-era analysis
7. Changeability assessment

RSC step 1 & 2: Value driving attributes and design variable definition
The first two steps ofRSC are to establish performance measures and define what design options to investigate. In the case study, the objective is to determine an emission reduction strategy that is able to deal with uncertain technology development and emission reduction regulations. Performance measures are to be identified in discussion with stakeholders. For the case study, the estimated cost and operational capability are treated separately. The value driving attributes, which primarily capture aspects that are not easily expressed in monetary terms, are defined in Table 3.5 combined with a utility to represent preference.

Table 3.5: Definition of the value-driving attributes and associated performance ranges and utility scales used in the case study.

Attribute	Values	Unit	Utility
Emission reduction	0 – 100	%	0 – 1
Endurance	20 – 50	Days	0 – 1
Distance	0 – 8000	NM	0 – 1
Speed	10 – 14	kts	0.6 – 1
Cargo volume	1000 – max	m^3	0 – 1
Cargo weight	9000 – max	tonne	0 – 1

The objective is to maximise both the total utility and minimise cost. The attributes can also be investigated individually, and the contribution of each to the total utility can be adjusted to influence the overall performance of a design. However, although the utility-based approach is effective in identifying suitable design options, it remains subjective and therefore subject to bias. To represent different emission reduction strategies, several design variables are defined and shown in Table 3.6. The different combinations of speed, endurance, and energy converter and carrier design variables result in a total of 97 different design alternatives.

Table 3.6: Definition of the design variables used in the RSC case study.

Design variable	Values	Unit
Speed	10, 12 ,14	kts
Distance	4000, 8000	NM
Converter-Carrier option	MDO-CI - … - Batteries	-

RSC step 3: Epoch characterisation

The next step is to determine epochs to represent typical context situations that describe a combination of future emission regulation, technology availability and cost that the ship can encounter. These are combinations of several predefined values, as shown in Table 3.7.

Table 3.7: Definition of the variables that are used to create epochs in the case study.

Epoch variable	Values	Unit	Number of steps
Emissions	0, 1, 2	g/kWh	3
Emission tax	100, 250, 400	€/tonne	3
Tech availability	0, 1	yes or no	2
η_{conv}	0, 1, 2	-	3
$\text{CAPEX}_{\text{storage}}$	0, 1, 2	€/kWh	3
$\text{CAPEX}_{\text{conv}}$	0, 1, 2	€/kW	3
OPEX	0, 1, 2	€/MWh	3
Total epochs			1458

The values 0,1 or 2 correspond to the technology-dependent worst, average or best case from Table 3.2. The vessel model is used to calculate the performance of every alternative design in each scenario.

RSC step 4: Epoch analysis

RSC provides multiple tools to analyse the performance of an epoch, of which most are so-called trade-space visualisations. For example, Figure 3.7 shows the total utility versus cost for all epochs and all designs. The figure represents the performance of each

Figure 3.7: Total utility versus cost for different options over multiple epochs, with varying design speed and sailing distance. The total utility has been reversed to ensure the preferred options are in the bottom left.

combination of design variables within each epoch, where the bottom left represents the preferred designs in terms of utility and cost. The inclusion of sailing distance in the total utility shifts all options with lower endurance to the upper left, as shown by the red circle. For lower distances, ammonia (grey) is shown to have a better total utility, while bio-methanol (brown) is a better alternative for higher distances. For more detailed epoch-specific information, epochs need to be inspected manually.

RSC step 5: Multi-epoch analysis

RSC can also be used to research the robustness or performance of a design in multiple scenarios (epochs). An example of a parameter occurrence plot has been visualised in Figure 3.8. The Figure shows the fuel volume that is necessary to meet the 8000 NM endurance objective in different design combinations in different epochs, including the initial bunker volume as designed for MDO(red line at 900 m^3). As expected, most traditional energy carrier-converter combinations are able to meet the requirement below the current bunker volume. Due to lower volumetric energy density, alternative fuels require more storage volume, while batteries are evenoutside of the storage volume axis range. Graphs like this can be used to determine whether the ship design should be altered (e.g., by increasing fuel volume or reducing endurance) to support future emission-reduction measures. Furthermore, when the range of storage volume is broad, as is the case for liquid

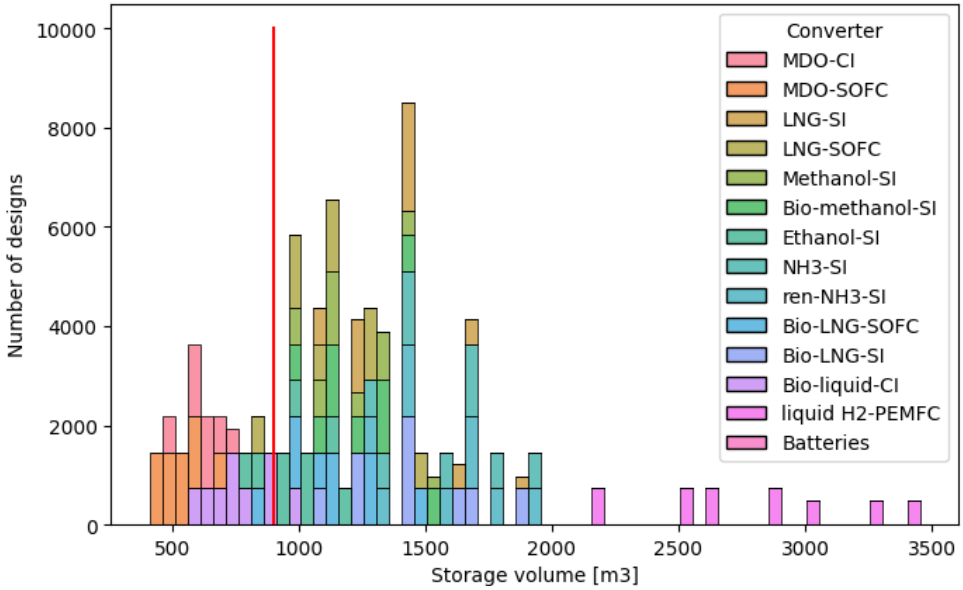


Figure 3.8: Fuel storage volume occurrence plots, for the 8000 NM endurance requirement including the current bunker volume for MDO.

hydrogen PEMFC, the combination is especially impacted by different epoch variations and might have to be adjusted or avoided.

RSC step 6: Era analysis

By analysing eras, the performance of designs during a lifecycle (random combination of epochs) can be investigated. For example, Figure 3.9 shows the performance of emission reduction options in an interesting lifecycle for the case study. The scenario starts with an

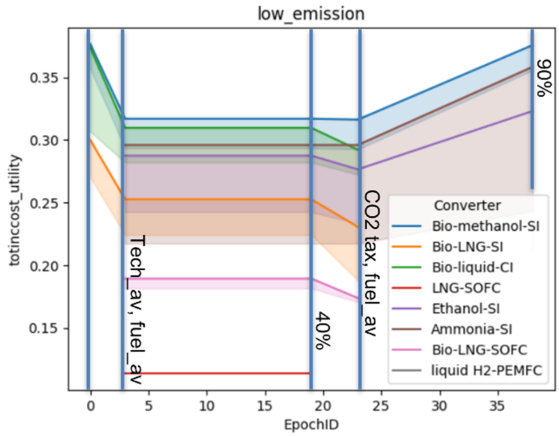


Figure 3.9: Era analysis consisting of 5 different relevant epochs

epoch that represents the current situation, without regulation, while much of the emission reduction technology is still under development. Next, technology becomes available, but fuel availability is still low (fuel cost increases). In the third epoch, a 40% reduction is regulated, which results in an omission of LNG. Next, additional emission taxes are charged, and fuel demand increases (cost increase). Lastly, a 90% reduction regulation is mandated. Single eras like these can be used to investigate specific scenarios. Furthermore, a multi-era analysis can again be used for sensitivity analysis.

RSC step 7: Changeability assessment

RSC evaluates the possibility of transitioning between multiple design options (e.g. retrofit) by using the filtered outdegree measure [371]. This measure represents the number of designs that an initial option can be changed to below an acceptable cost threshold C. First, a set of transition rules on what can be changed has to be defined. For example, the rules that are considered in the case study are to either increase fuel storage size, change emission reduction technology or add on-deck storage. For each transition rule and epoch, a transition matrix must be created that represents design relations, such as the cost of transition and its impact on capability (cargo volume and weight).

An example of the filtered outdegree plot versus investment cost per kWh is shown in Figure 3.10. For each initial energy carrier-converter combination, the graph visualises the

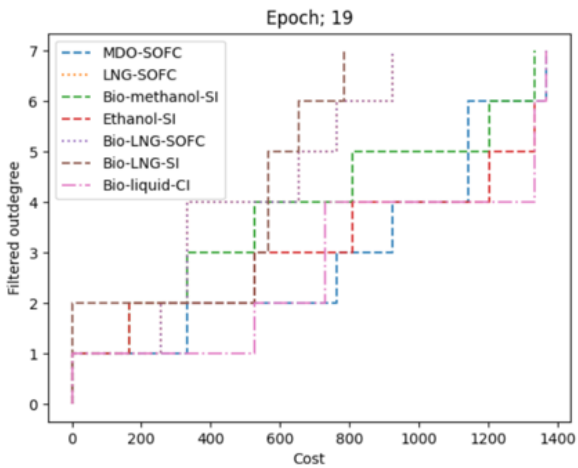


Figure 3.10: Filtered outdegree for multiple start options versus investment €/kWh

number of other options that can be reached for different CAPEX investment costs in an epoch. A higher filtered outdegree at low cost reflects more changeability. For example, in the case study, bio-LNG (brown and purple lines) is found to be cheaper to change from. However, it should be noted that this filtered outdegree representation is mainly focused on measuring changeability; it is not time-bound (epoch-specific) and does not show subsequent options or emission performance. Consequently, even though an option is more changeable, subsequent options could result in worse emission reductions than the initial design; the starting options could be more expensive, or the transition might not be feasible in practice.

RSC findings
When value, design, and context variables are carefully assigned, many context (epoch) and object (design) variable inputs can be explored, using tradespace visualisations, occurrence plots and the filtered outdegree. However, more tools are needed to reduce the tradespace as the use of multiple attributes increases dimensionality, making the analysis extensive and complex. This could be done by adding metrics that can be used to search for interesting eras, analysing performance over many eras, and investigating the sensitivity of different attributes to epoch and design variables.

Robust decision-making (RDM)
RDM is typically used to evaluate the robustness of a decision in multiple scenarios, while iteratively developing decision improvements [253]. The steps of robust decision-making are described below. To apply RDM to the case study, the exploratory modelling and analysis (EMA) workbench was used [243].

1. Pre-specify alternatives
2. Explore scenarios using sampling
3. Measure robustness
4. Vulnerability analysis
5. Iterate new alternatives

RDM step 1: Pre-specify alternatives
The first step is to identify decision options (levers), uncertainties, outcomes and a model that approximates relationships. For the case study, the simplified vessel model from Figure 3.4 has been coupled to theEMA toolbox. The decision options (levers) are different emission reduction technologies. The decision-maker selects relevant uncertain values for research. Table 3.8 shows the value range that should be researched. The speed and distance are also selected to be able to explore the effect of these parameters on outcomes. The outcome parameters that are specified for the case study are fuel volume, fuel mass, cost, possible emission reduction, and vessel attainment (how much distance travelled with a fuel volume).
RDM step 2: Explore scenarios
To explore the effect of the uncertain factors,EMA uses range sampling. Specifically, Latin hypercube sampling (LHS) has been used for the case study, as it aims to describe the full range. The emission range is dependent on each emission reduction. The conversion and fuel costs per kW and the storage cost per kWh are varied to reflect technological uncertainty.
RDM step 3: Measure robustness
Several measures for robustness are available to explore the robustness of a design against uncertainty and to establish the vulnerability of alternative designs. TheEMA toolbox provides measures like max-regret, satisficing and signal-to-noise. Figure 3.11 shows two examples of the max-regret measure for the case study. The max-regret shows the difference in performance between the best and worst scenarios for several attributes, including emission reduction, required volume and mass, and the vessel attainment (distance travelled with each fuel). A low value represents less difference between the outliers. In the left figure, the values are normalised, but skewed due to the inclusion of batteries in the

Table 3.8: Definition of the scenario variables that are used in the RDM case study.

Input	**Lower**	**Upper**	**Unit**	**Note**
Emission tax	100	400	€/tonne	
η_{conv}	0.3	0.8		
$\text{CAPEX}_{\text{storage}}$	450	1300	€/kWh	
$\text{CAPEX}_{\text{conv}}$	0.1	0.9	€/kW	
OPEX	150	1000	€/kWh	
Emission	0	1	g/kWh	Fuel dependent
Speed	12	14	kts	
Distance	4000	10000	NM	

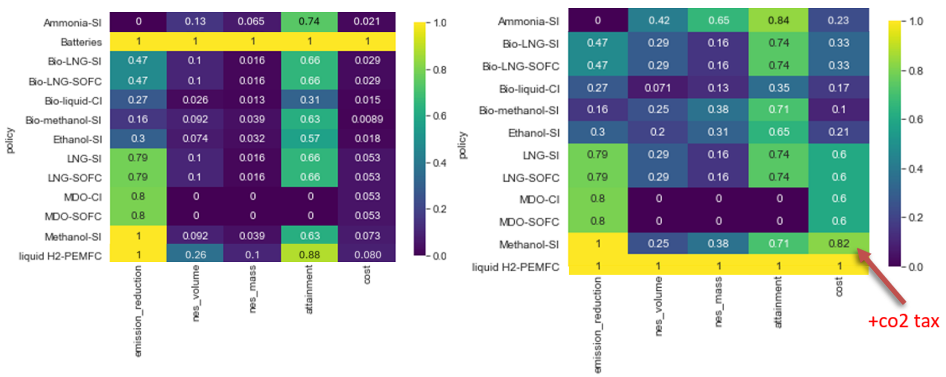


Figure 3.11: EMA max regret robustness measure for the case study energy carrier-converter combinations. The left figure includes batteries, and the right figure excludes batteries to allow a better comparison. The red arrow shows the impact of carbon taxation on methanol when compared to bio-ethanol.

comparison. Therefore, batteries are removed in the figure on the right. Biofuels are shown to have low variability, while ammonia is more sensitive to attainment. Additionally, the potential inclusion of carbon taxation in different future scenarios increases the variability of fossil fuels, as shown by the red arrow. Max-regret measures allow the decision-maker to understand how sensitive an option's performance is to different scenarios.

RDM step 4: Vulnerability analysis

Scenario discovery is used to identify under what circumstances (scenarios) a target outcome can still be met. Such information can be used to investigate the vulnerability of an option to specific uncertain parameters. Figure 3.12 shows a vulnerability scoring analysis that visualises the circumstances (combination of uncertain parameters) for the case study under which a design option meets an emission reduction target. The scenario variables are shown on the sides with a range from 0 (low) to 2 (high). Four variables are included: speed, distance, emission and conversion efficiency. The performance of variable combinations is shown through the colored squares. The square colour from dark blue to yellow represents zero to full compliance with the target emission reduction. Besides vulnerability, the

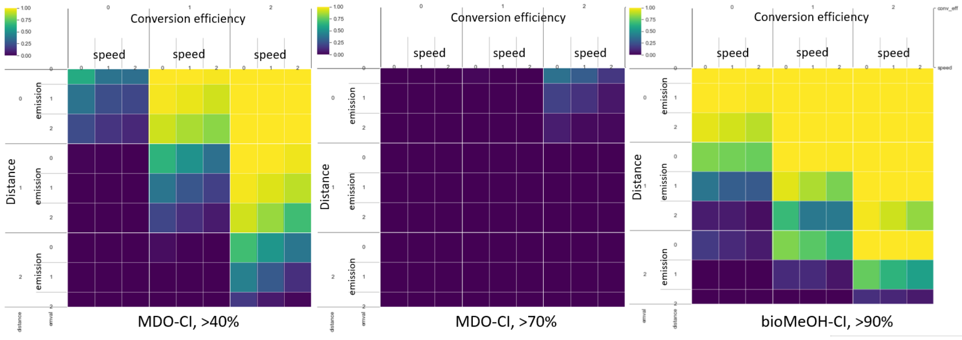


Figure 3.12: RDM vulnerability feature scoring analysis for different energy carrier-converter combinations and emission reduction thresholds for the case study. The figure represents the impact of different scenario variables.

figure can be used to establish trade-offs between parameters. By including more variable parameters in the analysis, such as speed and distance, the decision-maker can determine which measures they can take instead of more drastic actions. TheEMA toolbox also offers a more detailed compliance range estimation with the PRIM algorithm. As shown in Figure 3.12, such an algorithm can be used to enable decision-makers a straightforward way to explore more detailed scenarios. For example, the minimum technological performance (conversion efficiency, emission reduction performance) for compliance can be established. This information can be used by designers to understand and reject unrealistic expectations and focus on other options. Nevertheless, it is important to use a large enough sampling size and to ensure convergence in EMA.

RDM step 5: Iterate new alternatives

After establishing the vulnerability of different options, other alternatives could be iteratively researched. For example, promising carrier-converter options can be reassessed in combination with power assistance or energy-saving options. However, this has not been done for the case study.

RDM findings

RDM is a versatile method that allows for detailed exploration of the effect of uncertain parameters. As found in step 4, by cleverly determining what research parameters (uncertainties) to analyse, the method can be used for a type of backwards analysis, to find compliance ranges for a wide range of scenarios. This allows for detailed parameter sensitivity and specific scenario analysis, without pre-definition of scenarios and their ensuing bias. Furthermore, because scenario assessment is undertaken as a part of the final analysis, value and outcome parameter estimation is less complicated when compared to other methods. Nevertheless, the proper modelling of system relationships is still a crucial part, but it might be modelled in such a way that reusing (of parts) becomes possible. Further research should be done by developing a system model that can be used for multiple ship types for application during the design process.

Besides modelling, the number of design options is limited to the levers and uncertain parameters. This might be solved by going through multiple iterations (step 5), but when many options are needed, this could become exhaustive. To deal with this, methods that expand upon RDM, like MORDM, might be used. This method adds an initial design optimisation step, which is also easily applied using the EMA toolbox. However, even with extensions, RDM lacks a framework like DAPP that guides decision-makers on how to deal with the identified vulnerabilities.

3.3.3 Comparison of results

The performance of each method in the comparison criteria as defined in subsection 3.3.1 are scored and compared in Table 3.9. The DAPP is used during the whole lifecycle: the

Table 3.9: Method comparison criteria scoring

Criterion	DAPP	RSC	RDM
Max uncertainty level	5	4	4
Uncertainty vulnerability	2	4	5
Scenario analysis	2	5	4
Parameter sensitivity	1	3	5
Design exploration	4	3	4
Design robustness	4	3	5
Adaptive design	4	3	3
Adaptive strategy	5	3	2
Supportive setup	3	2	4

design stage (strategy creation), the production stage (implementing strategy) and the operation stage (measuring and adapting strategy). Because of its continual development during the ship's lifetime, it can include many alternative system models, options, outcomes, and scenarios, even those that were initially unknown. This is reflected in the maximum uncertainty level criterion. However, while it does provide an adaptive strategy during the lifetime, it needs other methods for initial analysis of scenarios and parameter sensitivy. Furthermore, because of its global nature, the scenario analysis pathway scorecard output is limited to a low level of detail. This results in a low scenario analysis and uncertain parameter sensitivity score, which are combined into the assessment of vulnerability to uncertain scenarios. The pathway description does represent different option, combinations and tipping points (adaptive design) using pathways, combined with the scorecard, this results in a comprehensive representation of robustness and adaptivity. The main strength in using DAPP for the maritime energy transition is the implementation of an adaptive plan, monitoring tipping points, and further adapting the strategy during the lifetime of a ship. Lastly, as it uses external input, different methods can be used to extend its capability to allow more detailed design exploration. However, such a method should be comprehensive by itself, because nuances are neglected in the global output of DAPP. Therefore, to apply DAPP in the design process, uncertainty identification and pathway map input should be standardised.

RSC deals with level 3 and 4 uncertainty as it can be used to initially research many future scenarios. It strength is in scenario analysis due to the use of epochs, to reflect interesting situations and eras, that combine epochs into scenarios. However, the selection of epochs is subjective and limited to a few scenarios due to the large amount of output, resulting in a lower score for the parameter sensitivity assessment criterion. The method also offers a wide range of analysis tools, like the filtered outdegree, which can be used to evaluate adaptive design. Additionally, because of its explorative setup, many alternative designs can be evaluated in many epochs and eras. This can provide detailed insight into technology options in specific scenarios, while also evaluating of strategy transition in a scenario. However this detailed analysis is limited to a selection of scenarios and alternative designs, to decrease computational strain, resulting in an average score for design exploration abd adaptive strategy evaluation. Additionally, the supportive method setup score is low because of the significant workload of identifying transition matrices, method variables and extensive modelling of functional relationships.

RDM deals with level 3 and 4 uncertainty and uses range sampling to define scenarios and enable the investigation of a large trade space for each uncertain parameter. The method defines allows a detailed exploration these parameters and the circumstances (scenarios) under which these result in a desired outcome. The use of theEMA toolbox also presents an advantage, because it can be added to create a toolbox for the ship design process. Consequently, RDM performs well in terms of uncertainty vulnerability assessment. However, because the method is focused on establishing the vulnerability of an option to uncertainty, it is especially useful to identify proactive designs rather than exploring many design options. Because of this the initial method only deals with a limited number of design options, but could lead to unknown solutions due to its iterative nature. Nevertheless, adaptive design an adaptive strategy improvements have to be defined by the user. However, since the identification and improvement of vulnerabilities are iterative, the method can fit well within the current design process. Furthermore, increasing the number of alternative designs and adding multiple objectives is possible by using an extension of RDM [273].

From Table 3.9, it is clear that the strengths and weaknesses of each method lie in specific parts. DAPP provides a strategy overview that can further be developed during the lifecycle, but it lacks a detailed option and scenario exploration. Alternatively,RSC and RDM allow a more detailed analysis of specific scenarios and parameter sensitivity, respectively. However, they are less suitable to develop an adaptive strategy. By using RSC or RDM as input for DAPP, a lifetime strategy can be developed from the extensive analysis. By using such a method in parallel with the ship design, it can be better equipped to deal with deep uncertainty. Nevertheless, further research is required to develop a combined method that is able to satisfactorily meet the criteria. Both RSC and RDM might be used as input for the DAPP framework. However, in this case study, RDM performs better than RSC in most criteria. More importantly, RDM is identified as a more suitable method for the selection of emission reduction strategies. Nevertheless, much should be done to properly combine DAPP and RDM. Besides coupling, to ensure valuable results and proper usability, a general setup and modelling framework needs to be created, while carefully integrating it into the design process.

3.3.4 Exploratory methods conclusion

Three promising methods from different research fields were applied to a preliminary case study of a general cargo ship. The methods were compared to research what insights could be gained on uncertainty and alternative fuels, and establish how such methods might be of use to the ship design process. DAPP evaluates alternative options (compliance limit) and develops possible pathways to compliance. The RSC method combines EEA and MATE, which evaluates the performance of a design in established scenarios (epoch), also allowing evaluation including retrofit (changeability). Robust decision-making (RDM) explores the effect of uncertainties on a pre-specified design and analyses under which circumstances objectives are met.

Based on this evaluation, each of the researched methods delivers different but valuable insights into option performance in uncertain conditions during the early design stage. DAPP provides a global but clear overview of the possible future pathways toward emission reduction compliance of the design. RSC provides more detailed insight into technology options in specific scenarios (including an evaluation of changeability in each scenario). RDM enables more in-depth research of uncertain parameters and the circumstances under which an option might comply. By applying a method that combines aspects from DAPP with RDM during the ship design process, the ship designer can explore the vulnerability of design options and develop a continual adaptive strategy to deal with uncertainty.

3.4 Search methods: Optimal ship fuel selection under life cycle uncertainty

According to many studies [58, 112, 122], alternative fuels are the only technical option to drastically reduce emissions from shipping. Depending on the fuel and feedstock, reductions are deemed to be substantial and reach close to zero emissions on a well-to-wake basis [259]. Nevertheless, each alternative fuel has distinct advantages and disadvantages in aspects such as safety, combustibility, availability, storage density, etc. [123]. Depending on the preference for these aspects, the choice of the 'best' fuel may hence differ between stakeholders.

Even when reducing the range of aspects to be considered to technoeconomic criteria, the choice of fuel may not be obvious. Multiple studies [122, 237, 265] show that the choice is strongly dependent on cost assumptions, in particular on relative differences between the different feedstocks. These feedstocks can be fossil, bio or renewable energy sources and open up a large range of conceivable price trajectories, which can be viewed as scenarios. Most studies [122, 265], evaluate alternative fuels within multiple scenarios. Less frequently, the fuels are evaluated across all possible scenarios, i.e., taking the large range of uncertainty with respect to fuel and carbon prices into account explicitly. Fuel prices are impacted by many external factors, like logistics, regulation, supply and demand, and are therefore subject to change and difficult to forecast. For example, the heavy fuel oil (HFO) price has varied between 145 and 1126 USD/tonne in the last decade alone [394]. Excluding this in energy system selection could result in future economic infeasibility. Substantially different fuel prices are even plausible when considering the impact of long-term political development and thereby emission reduction requirements or incentives. Last but not least, flexibility is seldom valued within fixed scenarios as it is difficult to do so. In the presence of uncertainty, however, flexibility can be a suitable design strategy [107].

This section investigated how including uncertainty using methods applying the search approach provide important insights into the potential of a fuel. To achieve this, the application of two different methods is explored, namely robust and stochastic optimisation [45, 233], on a relatively simple case study. This will allow for a clearer comparison of the methods and allow the reader to pick the best option for their application. Robust optimisation includes uncertainty by adding it as a constraint and having the decision maker select an uncertainty level to be robust against. Stochastic optimisation approaches uncertainty in a probabilistic manner in the objective function by assigning probabilities to possible scenarios. The methods are tested on their ability to investigate a techno-economic selection of alternative fuels under fuel price and carbon price uncertainty. As these methods are relatively new in this field, the chapter addresses multiple questions. First, it aims to investigate how solutions that include uncertainty differ from a deterministic solution. Second, the methods are compared to understand if the difference in their approach also results in a difference in recommendations. Third, further insights from each method for ship designers are examined. Lastly, it is investigated if the methods are sensitive to assumptions and if the amount of work to implement these methods is compensated for by

This section has been published in the Sustainability journal the insights they provide.

3.4.1 Methodology

As a basis, this chapter uses the Mixed Integer Linear Programming (MILP) setup from [249]. Below, the setup of the deterministic model is reiterated, and the extensions towards the robust and stochastic optimisations are further explained.

Deterministic model setup

The variables and parameters used for the deterministic problem setup are shown below:

Table 3.10: Sets, parameters, and decision variables for the optimisation model

Symbol	**Description**	
T	set of discrete *time periods*, indexed by t	
S	set of ship *energy systems*, indexed by s	
F	set of *fuel options*, indexed by f	
Ω	set of *scenarios*, indexed by ω	
U	set of uncertain cost values, indexed by z	
Parameter	**Description**	**Modelling Comment**
C^N_s	*newbuild cost* of system s	
$C^R_{s'\|st}$	*retrofit cost* from system s' to s at time t	
C^{LO}_{st}	lost opportunity cost of system s at time t	
C^F_{ft}	*fuel cost* of fuel f at time t	
C^C_{ft}	*carbon cost* of fuel f at time t	
B	*energy consumption* per time period	assumed constant over time
EF^{WTW}_f	well-to-wake emission factor of fuel f	
Decision variable	**Description**	
y_{st}	1 if system s is installed at time t, 0 otherwise	
y_{s0}	1 if system s is chosen initially, 0 otherwise	
x_{ft}	1 if fuel f is used at time t, 0 otherwise	
$r_{s'\|st}$	1 if retrofit from s' to s occurs after time t	

The problem consists of two objective functions. The cost of ownership;

$$\min \sum_{s\in S}\left(C^N_s\, y_{s0}+\sum_{t\in T}\left(\sum_{s'\in S}C^R_{s'|st}\, r_{s'|st}+C^{LO}_{st}\, y_{st}+\sum_{f\in F}B\left(C^F_{ft}+C^C_{ft}\right)x_{ft}\right)\right), \tag{3.5}$$

where the cost consists of a newbuild, lost opportunity and operational element. And global warming potential GWP in tonne CO2 equivalent;

$$\min \sum_{t\in T}\sum_{f\in F} B\cdot x_{ft}\cdot \mathrm{EF}_f^{WTW} \equiv \mathrm{GWP}, \tag{3.6}$$

which consists of an emission factor EF_f^{WTW} which is calculated with emission data estimates for each fuel. The following constaints allow only one energy system and fuel each timestep, the remaining constraints are used in combination with the retrofit decision variable to change systems between timesteps:

$$\begin{aligned}
\text{s.t.} \quad & \sum_{s\in S} y_{st} = 1, && \forall t\in T,\\
& \sum_{f\in F} x_{ft} = 1, && \forall t\in T,\\
& y_{s'(t-1)} + y_{st} - 1 \le r_{s'|st}, && \forall s', s\in S,\ \forall t\in T\setminus\{0\},\\
& y_{s'(t-1)} + y_{st} \ge 2\, r_{s'|st}, && \forall s', s\in S,\ \forall t\in T\setminus\{0\},\\
& r_{s'|s0} = 0, && \forall s', s\in S.
\end{aligned} \tag{3.7}$$

To be able to solve the multi-objective problem and create a proper front, the GWP objective is rewritten as a constraint that is stepwise (n) relaxed.

$$\min \ \mathrm{GWP} \tag{3.8}$$

$$\sum_{t\in T}\sum_{f\in F} B\cdot x_{ft}\cdot \mathrm{EF}_f^{WTW} \le \mathrm{GWP}_n. \tag{3.9}$$

Robust optimization

Robust optimisation focuses on finding solutions that are insensitive to changes in parameter values due to uncertainty. It does so by including the bounds of a parameter as a constraint in the optimisation problem. As we consider the uncertain variables to be fuel and carbon price, the objective function for cost is rewritten to be a constraint and the uncertain variable C_{ft}^{FC} is located in red.

$$\min \ \theta \tag{3.10}$$

$$\text{s.t.} \quad \sum_{s\in S}\left(C_s^N\, y_{s0} + \sum_{t\in T}\left(\sum_{s'\in S} C_{s'|st}^R\, r_{s'|st} + C_{st}^{LO}\, y_{st} + \sum_{f\in F} B\cdot {\color{red}C_{ft}^{FC}}\, x_{ft}\right)\right) \le \theta, \quad \forall C_{ft}^{FC}\in U. \tag{3.11}$$

The uncertainty is a combination of carbon and fuel cost, which can be represented using a mean and deviation as;

$$C_{ft}^{FC} = \bar{C}_{ft}^{FC} + \hat{C}_{ft}^{FC} z. \tag{3.12}$$

Where the deviation is scaled with the uncertain variable z , which is used to guide the solution toward the proper robustness level against the cost deviation. The cost constraint becomes

$$\text{s.t.} \quad \sum_{s\in S}\left(C_s^N\, y_{s0} + \sum_{t\in T}\left(\sum_{s'\in S} C^R_{s'|st}\, r_{s'|st} + C^{LO}_{st}\, y_{st} + \sum_{f\in F} B\left(\bar{C}^{FC}_{ft} + \hat{C}^{FC}_{ft} z\right) x_{ft}\right)\right) \leq 0, \quad \forall z \in U. \tag{3.13}$$

The decision to switch between options can be made at each time step t. The next step is to rewrite Equation 6 such that the uncertain variable z is constrained by its uncertainty set. This is done by separating the variable and writing the support function δ^*,

$$\text{s.t.} \quad \sum_{s\in S}\left(C_s^N\, y_{s0} + \sum_{t\in T}\left(\sum_{s'\in S} C^R_{s'|st}\, r_{s'|st} + C^{LO}_{st}\, y_{st} + \sum_{f\in F} B\,\bar{C}^{FC}_{ft}\, x_{ft} + \delta^*\left(\sum_{f\in F} B\,\hat{C}^{FC}_{ft}\, x_{ft} \,\middle|\, U\right)\right)\right) \leq \theta. \tag{3.14}$$

Uncertainty Set selection

The next step is to select the uncertainty set that the constraint should satisfy, for which the support function is rewritten accordingly. Multiple sets have been proposed in literature that aim to guide the selection toward a proper level of conservativeness and correlation [149]. These include research into flexible sets by [479], the connection to risk measures from risk theory [84], the addition of stochastics in the form of distributional robust optimisation [40] and robust constraints based on probability [44]. Such directions show the potential for further developments of robust optimisation for ship energy system selection. However, to show the principle and benefits of using robust optimisation, this comparison uses less complex uncertainty sets. Figure 3.13 shows the uncertainty sets that are used in this chapter. We use two different uncertainty sets to account for two different types of correlations, namely within a feedstock/fuel group and across feedstock/fuel groups. Within a fuel group, we use a box uncertainty set with fuel prices bounded by ρ_F, shown in red. This reflects the direct correlation within bio, fossil and electro-fuel groups, where each fuel would reach its worst case at the same time. In between feedstock groups, indirect correlation is reproduced by using an ellipsoidal uncertainty set bounded by $\rho_F G$, shown in green. In this way, either feedstock can be worst-case, but not both at the same time. On top of these correlations, carbon prices are added with a box uncertainty set bounded by ρ_C.

$$U = \begin{Bmatrix} \|z^C\|_\infty \leq \rho_C \\ \|z^F\|_\infty \leq \rho_F \\ \|z^{FG}\|_2 \leq \rho_{FG} \end{Bmatrix}$$

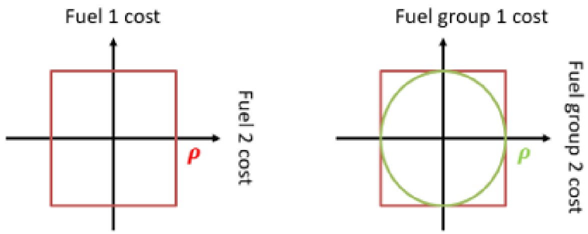


Figure 3.13: Uncertainty set visualisation.

The selection of each scaling factor can be done separately to also research relative deviations. The size of the set is typically defined using the Central Limit Theorem (CLT). In effect, the uncertainty set represents all possible combinations of samples of each uncertain variable, but it constrains the extremes. The deviation from the mean can be scaled ρ to cover a larger space. Therefore, by increasing ρ, the selection can be forced to be more conservative.

Adaptive robust optimization

The most important decision is the selection of a start design while taking future price fluctuations into account. ARO splits the problem into a "here-and-now" decision y_{s0} and "wait-and-see" decisions y_{st} and x_{ft} in the future. By accounting for uncertainty in the future, the initial decision can be made more robustly.

$$\text{s.t.} \quad \sum_{s\in S}\left(C_s^N\, y_{s0} + \sum_{t\in T}\left(\sum_{s'\in S} C^R_{s'|st}\, r_{s'|st} + C^{LO}_{st}\, y_{st} + \sum_{f\in F} B\left(\bar{C}^{FC}_{ft} + \hat{C}^{FC}_{ft} z\right) x_{ft}\right)\right) \leq 0, \quad \forall z \in U. \tag{3.15}$$

Which results in the following equation when the ellipsoidal uncertainty set is substituted for the support function;

$$\begin{aligned} \text{s.t.} \quad & \sum_{s\in S}\left(C_s^N y_{s0} + \sum_{t\in T}\left[\sum_{s'\in S} C^R_{s'|st} r_{s'|st} + C^{LO}_{st} y_{st} + \sum_{f\in F} B\bar{C}^{FC}_{ft} x_{ft}\right]\right) \\ & + \rho \left\| \sum_{t\in T}\sum_{f\in F} B\hat{C}^{FC}_{ft} x_{ft} \right\|_2 \leq 0. \end{aligned} \tag{3.16}$$

Stochastic Optimization

The stochastic programming model is a bi-objective two-stage optimisation model. The full model, including all constraints, is described in detail by [248]. From the deterministic model presented above, two additional steps are required to derive the mathematical formulation for the stochastic programming model. In short, these steps are a split of decision variables into fuel x and system y, plus the introduction of probabilities, utilising sampled scenarios and respective weighting in the objective function. The split of the decision variable into $x_f t$ and $y_s t$, i.e., into the fuel and systems for each time period, is made to better distinguish the most urgent decision of the choice of a system from the slightly less pressing decision of the fuel, which in practice can be substituted by any fuel compatible with the selected system. With this step, the objective function reads as;

$$\begin{aligned} \min \sum_{s\in S}\Bigg[& \underbrace{C_s^N\, y_{s0}}_{\text{building cost}} + \sum_{t\in T}\Bigg(\underbrace{C^{LO}_{st}\, y_{st}}_{\text{lost opportunity costs}} + \sum_{s'\in S} \underbrace{C^R_{s'st}\, r_{s'st}}_{\text{retrofit cost}} \Bigg)\Bigg] \\ & + \sum_{t\in T}\sum_{f\in F} \underbrace{B x_{ft} \cdot \left(C^F_{ft} + C^C_{ft}\right)}_{\text{fuel cost}} . \end{aligned} \tag{3.17}$$

As the second step, the uncertainty is accounted for by means of a set of scenarios that the model optimises across. That is, the model applies a risk-neutral expected value formulation.

The scenarios are sampled, based on the probability distributions discussed in [248]. The sampling of scenarios from probability distributions implies that probabilities are implicit in the scenario set. Each sampled scenario ω, therefore, obtains the probability $P_\omega = 1/|\omega|$. The resulting formulation of the objective function thus becomes;

$$\begin{aligned} \min \sum_{s\in S} \Bigg[\underbrace{C_s^N\, y_{s0}}_{\text{building cost}} + \sum_{\omega\in\Omega} P_\omega \Bigg[\sum_{t\in T} \Big(\underbrace{C_{st}^{LO}\, y_{st\omega}}_{\text{lost opportunity costs}} + \sum_{s'\in S} \underbrace{C_{s'|st}^{R}\, r_{s'|st\,\omega}}_{\text{retrofit cost}} \Big) \Bigg] \Bigg] \\ + \sum_{\omega\in\Omega} \sum_{t\in T} \sum_{f\in F} \underbrace{P_\omega\, B\, x_{ft\omega}\, C_{ft\omega}^F}_{\text{fuel cost}} . \end{aligned} \tag{3.18}$$

Scenario sampling applies probability distributions for both fuel and carbon prices. The sampled prices are then stored for each fuel as $C^F_{ft\omega}$. Hence, there is no explicit distinction between fuel and carbon price contributions in the mathematical formulation. As for the second objective, the global warming potential, the formulation becomes;

$$\min \sum_{\omega\in\Omega} P_\omega \sum_{t\in T} \sum_{f\in F} B\,\mathrm{EF}_f^{WTW}\, x_{ft\omega}. \tag{3.19}$$

By changing the decision variables and introducing the scenario sampling concept. For the implementation in the commercial solver, this objective is rewritten as a constraint with the right-hand side subsequently lowered in order to identify solutions on the front, i.e. solutions with a lower expected GWP but higher expected TCO.

3.4.2 Case study

For the setup of the comparison, the considerations with regard to the uncertain parameter selection are discussed first. Second, the input data, which is kept equal for both methods, is presented in Table 3.12. Lastly, the aspects that are compared are specified.

Uncertain parameter selection

The comparison of methods has been limited to two parameters that, when changing, could highly impact the optimal selection. This provides a good basis to test the ability of robust and stochastic optimisation. However, besides carbon pricing and fuel price, multiple other parameters are uncertain for alternative fuels. We would like to stress that uncertainties outside of the scope of this research can still impact and skew the results in various ways. To highlight important uncertainties, several categorised parameters are included in Table 3.11 below. Table 3.11 identifies possible reasons that parameters could shift and what their perceived impact would be on the final selection. References that discuss the impacts mentioned for each parameter are also included. Nevertheless, not all of the factors mentioned are covered by the references. From the perspective of the model, input factors, like costs, will directly influence the results. On the other side, market factors reflect the ability to generate revenue, which could be impacted in different ways by alternative fuels, e.g., generally higher freight rates or different speeds. Furthermore, the development and availability of technology, like energy conversion, carrier and exhaust treatment systems, will only become clear over time and could therefore highly impact

Table 3.11: Uncertain parameter categorisation and impact factor overview

Category	Parameter	Impacted by	Perceived impact	References
Market	Lost opportunity	Market, capability reduction, safety measures	Medium	[346]
	Mission requirements	Endurance, speed, cargo requirements	Medium	[240]
Input	Retrofit cost	Timeframe, lost revenue, component costs	Medium	[482]
	Fuel price	Logistics, market supply and demand, availability	High	[260]
	Newbuild cost	Timeframe, manhour & material cost, inflation	Low	[182]
Technology	Energy converter	Novel system development, public perception	High	[43]
	Maintenance	Crew ability, degradation, system complexity	Medium	[455]
	Energy carrier	New storage mediums and feedstock	High	[171]
	Exhaust treatment	Development, costs	High	[365]
	Availability	Location, production upsizing, infrastructure, development, TRL	High	[3]
Process	Production (WTT)	Supply chain emission accounting, feedstock availability, supplier	High	[339]
	Conversion (TTW)	Energy system losses, treatment	Medium	[462]
Regulations	Scope	WTT/TTW, CO_2(eq), SOX & NOX	High	[390]
	Magnitude	Penalty cost, enforcement	Medium	[250]
	Lost opportunity	Market, capability reduction, safety measures	Medium	[227]

the fuel selection and ability to reach emission targets. More importantly, other fuels and systems could be developed besides the current options that are included in the comparison. The potential emission reduction of fuels also greatly depends on the process and ability to decrease the environmental impact in the production and transport (WTT) and conversion (TTW) stages. Finally, the focus and magnitude of regulatory measures can stimulate or deter the use of a fuel type. These uncertainties should be addressed when applying any of the methods in practice.

Input data

The case study is based on a supramax bulk carrier as an example vessel. Any value given here should be reconsidered for another vessel type. Table 3.12 shows the different fuels that were considered and their respective feedstock groups (fossil, bio or electro). The environmental impact expressed in GWP100 has been split into a production and conversion equivalent. The economic impact has an operational part, which includes an uncertain range that has been based on estimates from Lindstad et al. [259], and a fixed capital cost part. The retrofit cost has been elaborated in [248]. The newbuild, lost opportunity, fuel consumption, and retrofit costs should be recalculated for vessels of different sizes and functions.

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Table 3.12: Model inputs including environmental impact and economic impact with upper and lower bounds to reflect uncertain fuel costs.

feedstock	Fuel label	Environmental impact		Economic impact				
		GWP WTT per fuel energy unit [gCO_2eq/kWh]	**GWP TTW per fuel energy unit** [gCO_2eq/kWh]	**Upper bound fuel cost** [USD/MWh]	**Mean fuel cost** [USD/MWh]	**Lower bound fuel cost** [USD/MWh]	**Newbuilding price** [mUSD]	**Lost opportunity costs per 5 years** [mUSD]
Fossil	VLSFO	47.5[1]	284.1[1]	95[2]	66.5	38[2]	30	0
Bio	bio-Diesel	70.0[1]	150.0[1]	128[3]	110.4	93	30	0
electro	e-Diesel	0.0[1]	4.5[1]	423[2]	277	232	30	0
Fossil	LNG	66.6[1]	238.8[1]	812[5]	56.5	32	37.5	0.5
Bio	bio-LNG	49.7[1]	6.0[1]	119[3]	103.7	89	37	0.5
electro	e-LNG	0.0[1]	6.0[1]	358[2]	236.5	192	37.5	0.5
Fossil	LPG	30.0[1]	237.5[1]	98.3[2]	68.8	39.3	33	0.1
Fossil	Methanol	112.7[1]	253.4[1]	210[3]	83	43	31	0.2
Bio	bio-Methanol	112.68[1]	3.24[1]	97[3]	81.5	66[3]	33	0.3
electro	e-Methanol	0.0[1]	3.5[1]	385[2]	250.5	116[2]	32	0.3
Fossil	Ammonia	87.1[1]	19.0[1]	202[2,4]	138	56[2]	37.5	0.5
electro	e-Ammonia	0.0[1]	19.0[1]	220[2]	150	80[2]	37	0.5
Fossil	LH2	108.7[1]	0.0[1]	245[2,6]	150	55[2]	47.5	3
electro	e-LH2	0.0[1]	0.0[1]	245[2,6]	162	79[2]	47.5	3

[1] [259] [2] [260] [3] [237] [4] assuming 80% CCS efficiency [5] [424] [6] Upper bound 100% of electricity-based pendant, lower bound 70% of electricity-based pendant.

Comparison setup

To properly compare both methods, Table 3.13 examines how each method handles important aspects like time dependency and correlation between fuel costs. The value of the

Table 3.13: Important aspects to compare between robust and stochastic optimisation.

Aspect	Robust	Stochastic
Within-group fuel price correlation	Independent, box uncertainty set.	Fully correlated.
Out-of-group fuel price correlation	Correlated using an ellipsoidal set; other correlation structures via alternative uncertainty sets.	Independent.
Carbon pricing	Gamma value can be shifted to examine the impact.	Beta variate probability distribution developing over time.
Time-dependency	Discounting; shifting gamma value for different time steps; adaptive robust optimisation.	Discounting; history-independent fuel prices; history-dependent carbon prices; recourse.
Objective function	Edge-case performance.	Expected performance.
Extra criteria	Minimum regret; result deviation.	VSS.

comparison can be guaranteed only by being aware of the differences between each approach. Table 3.14 shows the tests that are designed to highlight the ability of the methods, while remaining able to compare both. The first test serves as validation and is used for

Table 3.14: Comparison tests

		Robust		Stochastic	
Test	**Purpose**	**Fuel**	**Carbon**	**Fuel**	**Carbon**
Deterministic case	Verify code	Mean fuel price	0 carbon price	Mean fuel price	0 carbon price
Uncertain scenarios	Compare direct output of methods	Gamma scenarios, grouped	Gamma scenarios, shifted over time	Triangular fuel price distribution	Beta variate probability distribution developing over time
Measurement criteria	Test evaluation of impact of different gamma (min regret)	–	EVPI, VSS, ECIU	–	–
Impact of mean change	Sensitivity to assumptions	1/3 of mean	Gamma scenarios	1/3 of mean	Beta variate probability distribution developing over time

3

later comparisons. Next, the methods are compared to understand if the difference in their approach also results in different solutions. The third test uses the output and additional measurement criteria to examine what insights could be provided to ship designers. Lastly, the sensitivity of the methods to assumptions is identified. By completing all tests and implementing the methods, the difficulty of implementation versus the insights can also be addressed.

3.4.3 Results

Deterministic case study

The front for different start ships and pathways is visualised in Figure 3.14. It shows the total cost of ownership versus the total GWP100 over the lifetime. The figure also includes the performance of non-flexible solutions that stick to a single fuel (coloured crosses). The coloured fronts identify the total GWP that a pathway from a start ship can reach (line colour). The same result was found for both the robust and stochastic optimisation codes. By using deterministic optimisation, a decision maker can already gain an understanding of the potential price to reduce emissions, including the starting ship and pathway that could be followed to meet these targets. However, as values might change, do these results hold under uncertain conditions?

Robust optimization

Figure 3.15 shows the multi-objective Pareto fronts for static (crosses) and flexible solutions when the conservativeness level is as large as the identified uncertainty ranges. The

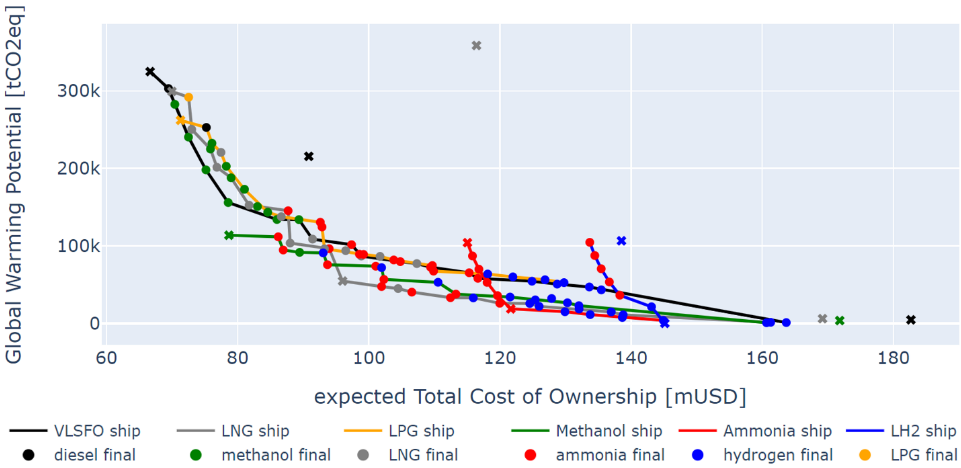

Figure 3.14: Multi-objective plot for the deterministic case with mean fuel prices and zero carbon price.

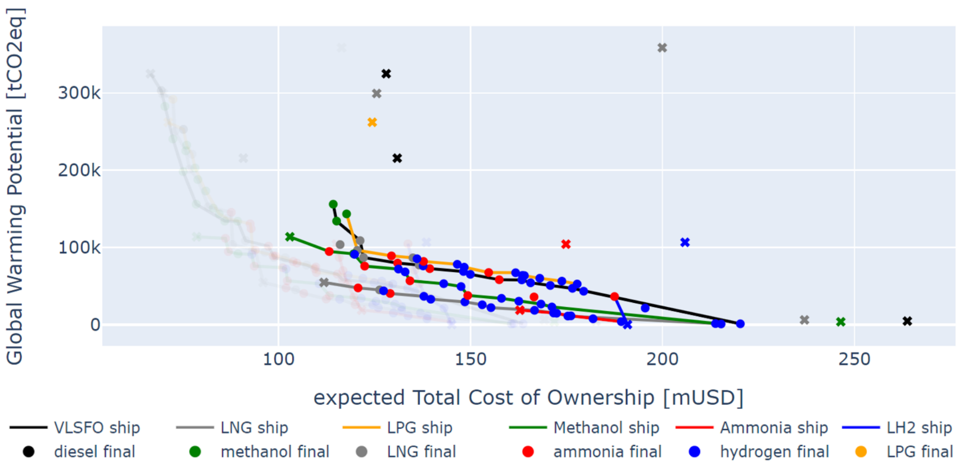

Figure 3.15: Multi-objective plot for the robust optimisation case with high conservativeness level.

deterministic Pareto-fronts are visualised as well. The large conservatism against carbon pricing shifts fossil and biofuel options with higher emissions beyond the Pareto front. This shows that robust optimisation advocates switching focus toward starting with methanol and LNG ships instead, as other vessels are costly and cannot meet reduction targets or need to switch fuels regardless. To further visualise the impact of fuel price uncertainty, Figure 3.16 shows results when negating carbon pricing.

Conservativeness level selection

One of the valuable properties of robust optimisation is the addition of the conservativeness factor. It allows the decision maker to select a preferred robustness level. To better understand the impact of conservativeness selection, different values and combinations of

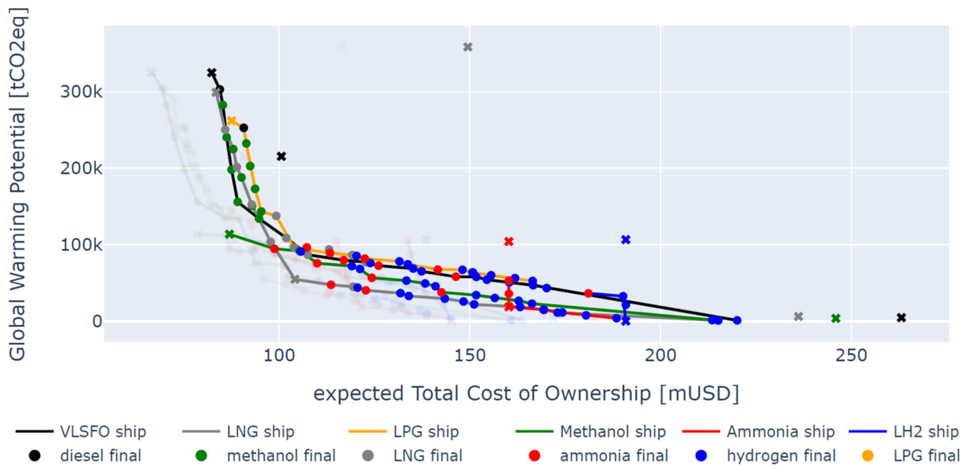

Figure 3.16: Multi-objective plot for the robust optimisation case with zero carbon price and high fuel price conservativeness.

ρ_F and ρ_C can be explored. However, as the additional dimension makes the multi-objective results more difficult to interpret, the GWP objective is rewritten toward two linearised GWP constraints that represent reduction targets from the IMO and the European Union (EU). The resulting robust selections with added conservativeness levels ρ_F and ρ_C are compared with respect to the mean deterministic solutions in Table 3.15 for both reduction targets.

Table 3.15: Single objective robust optimisation solutions for different levels of conservativeness for IMO and EU GWP targets.

			Pathway				
Design	**Target**	**Start**	**2025**	**2030**	**2035**	**2040**	**2045**
0	EU-deterministic	VLSFO ship	VLSFO	Bio-methanol	Bio-methanol	Bio-methanol	E-Ammonia
1	IMO-deterministic	VLSFO ship	VLSFO	Bio-methanol	Bio-methanol	Bio-methanol	Bio-methanol
2	EU-robust	LNG ship	Bio-LNG	Bio-LNG	Bio-LNG	Bio-LNG	Bio-LNG
3	IMO-robust	Methanol ship	Bio-methanol	Bio-methanol	Bio-methanol	Bio-methanol	Bio-methanol

In the EU-robust solution, the increased carbon pricing conservativeness incentivizes shipowners to transition to biofuels early on. In contrast, the deterministic solution starts initially favors vessels operating on conventional VLSFO, while the development in fuel price leads to more retrofits over the vessel's lifetime. This operational flexibility in response to fuel prices is predominantly observed for lower carbon price levels. The vessel's ability to switch between fossil, bio and e-fuels allows operators to capitalise from on fuel price fluctuations while higher carbon price levels constrain owners to more rigid fuel

selections.
For the IMO target, which represents less strict reduction targets, bio-methanol is selected independently of the conservativeness level. Only when being less conservative for carbon and fuel price, the optimisation selects cheaper fossil fuels as a start, which have a higher carbon content but a lower price range. More importantly, only for a very high carbon price conservativeness ($\rho_C = 1.5$), the selection is similar to the EU GWP target. Consequently, carbon pricing primarily affects early pathway decisions, while the GWP target is more impactful regardless of carbon pricing.

Measurement criteria: impact of gamma selection
Selecting a higher robustness level will result in different starting points. Effectively, the optimisation results in three different ships and four different pathways, which are selected depending on GWP targets and conservatism levels. To examine the examine the impact of uncertain inputs on these solutions we use the principle of uncertainty quantification [380] to see if adaptive robust optimisation actually selects robust options. This is tested by generating a dataset of future scenarios to evaluate the performance of the selections. The sampling is comparable to stochastic optimisation, where future prices are sampled from a normal distribution, while carbon price scenarios use a beta-variate distribution. The results of the selected options for 10000 different sampled futures are shown in Figure 3.17. In both

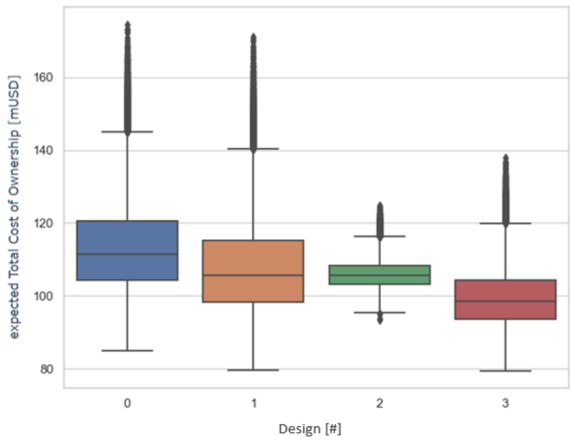

Figure 3.17: Single objective robust optimisation solutions for different levels of conservativeness for IMO and EU GWP targets.

cases (designs 2 and 3), the method selects options with low variance, whereas the deterministic selection results in much larger perturbations. Surprisingly, the robust options seem to prefer a static pathway for each GWP strategy. This can be explained by the variance being so low that the retrofit cost becomes a significant investment. Therefore, adaptability seems to be neglected, but its benefit is apparent when looking at the multi-objective figures.

Impact of changing variability
Biofuels are found in many pathways on the Pareto fronts. This could be explained by

its low variability (15-18%) versus e-fuels (50%) and fossil fuels (40-60%). However, there are multiple barriers like availability, manufacturing cost and government actions that could increase this variability [230]. Therefore, the variability for biofuels is increased to 50% to examine if the robust optimisation selection is impacted. The results for both ranges are presented in Figure 3.18 for medium carbon price conservativeness ($\rho_C = 0.5$) and high fuel price conservativeness ($\rho_F = 1$). There are a few interesting changes due to

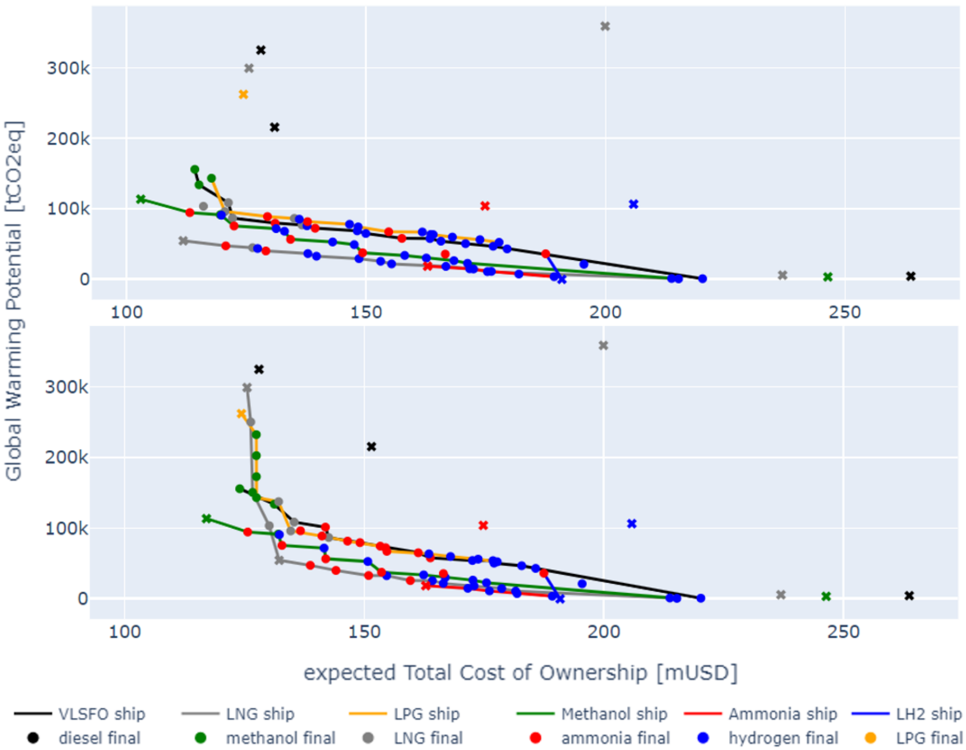

Figure 3.18: Results for original (above) and increased biofuel prices (below).

increased biofuel variability. First, the fronts shift to the right, such that fossil options are in the range of the Pareto fronts, while e-fuel options at lower GWP do not change. More notably, the biofuel shift primarily impacts the mid-range or transition options, where, despite cost increases, biofuels still offer a large reduction potential against a low-cost increase versus fossil fuels. Second, the methanol and LNG ship Pareto shift slightly closer, because the LNG front is found to be more dependent on biofuels. This is also apparent from the heavier focus on ammonia, which is switched to earlier instead of balancing out the GWP from cheaper bio-LNG by switching to hydrogen later on. Nevertheless, even though pathways are impacted, start ship decisions (Pareto fronts) seem to be unaffected by variability changes. More importantly, this shows that there is significant value in being able to retrofit to deal with uncertainty after having selected a starting point.

Discussion

Robust optimisation was shown to be able to select a set of robust solutions from a large number of options. Furthermore, in the case of alternative fuel selection, switching fuels during the lifetime can be included by using adaptive robust optimisation. It can be used to understand the adaptability gap, which is the difference between the static (fixed case) and adaptive robust solution (flexible case). Robust optimisation methods shift the focus of a decision-maker from one assumed value towards properly establishing an uncertainty range by adding conservativeness. However, although this allows the decision maker to immunise against the selected uncertainty, the solution can become too conservative. This can be dealt with in two ways: the correlation can be changed using a different uncertainty set, or the conservative factor itself can be reduced. The impact of uncertainty sets has been discussed extensively in the literature [149], while this chapter primarily discussed the conservativeness factor selection. The impact of these is preferably explored, but this is found to be difficult due to the increased dimensionality. However, a big advantage of robust optimisation against other methods is its tractability. This allows the number of uncertain parameters to be increased at a low computational cost. Overall, the addition of uncertain parameters for ship design works well with single and multi-objective optimisation, but sensitivity exploration is more complex.

Stochastic optimization

This subsection will briefly present the results obtained from the stochastic model. The first part presents the results from the base case as described in Section 3.4.2. The next part describes the value of a stochastic solution, and the last part discusses the results when adjusting the bounds for biofuels.

Stochastic optimisation base case

The Pareto front of solutions from the stochastic optimisation is shown in Figure 3.19. The plot shows that the expected emissions can be lowered by roughly 50% for a marginal increase in expected costs. Reducing emissions all the way down to zero would result in an approximately 60% increase in the expected costs. In terms of optimal power system choice for the newbuild, methanol is suggested as a favourable abatement option for up to 60% emission reduction, while an LNG power system would be optimal between 60% and 90% reduction. Abating the last 10% of emissions would require ammonia or hydrogen configurations from the beginning.

Value of stochastic solution

The value of the stochastic solution (VSS) characterises the cost delta between implementing the first-stage decisions of a deterministic program based on expected values vs implementing the first-stage decisions of the stochastic program. That is, the optimal first-stage decisions of the deterministic expected value formulation are simulated under the stochastic setting.

As for this case study, Lagemann et al. [248] have found that the VSS expressed in monetary terms is generally low. That means that the first-stage decisions suggested by the deterministic expected value problem do not perform much worse than the first-stage decisions suggested by the stochastic model. However, the suggested first-stage decisions in the deterministic problem alternate frequently with decreasing target GWP. This feature is not present in the stochastic solution. Thus, the deterministic solution suggests artificial

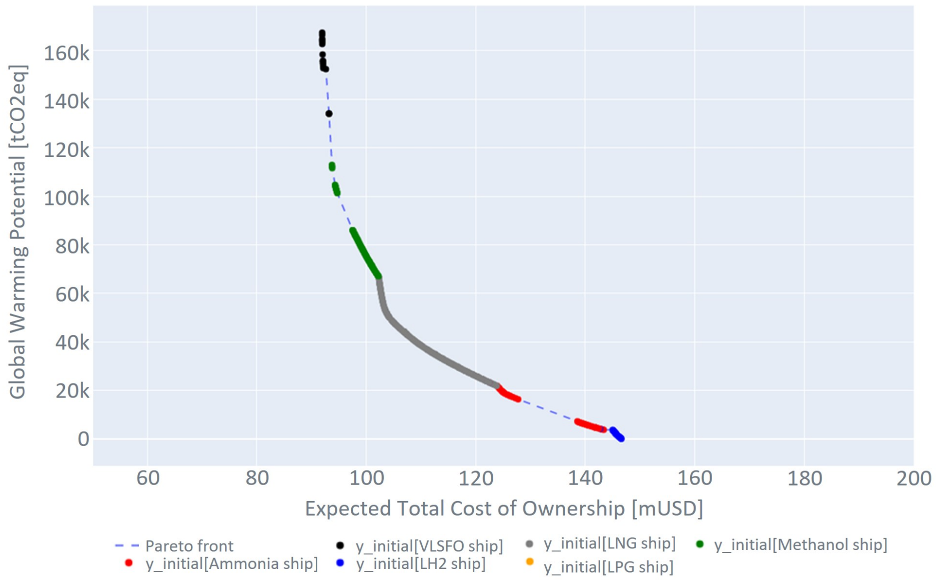

Figure 3.19: Pareto front for initial power system configurations, 100 scenarios with a stochastic carbon price.

chaos, which is not present in the data but rather stems from the discreteness of the problem. More precisely, it is the limited number of possible combinations that generate this alternation of optimal first-stage decisions. The VSS in this case could be better measured as "insight produced".

Stochastic model with adjusted bounds for biofuels

In Subsection 3.4.2, we have shown that the results of the base case might be biased due to low variability in biofuel prices. In order to investigate a change in bounds, we keep the lower bound as is and adjust the upper bound such that the difference between the original mean/mode is now 50%, as for most other fuels. As a result, the triangular distribution becomes asymmetric, with the mode assumed as the original mean, and the new mean is higher due to the adjusted upper bound. Pantuso et al. [316] have shown that stochastic programs are often relatively insensitive to the actual probability distributions while being sensitive to the mean. We will discuss this hypothesis in the light of this case study. When plotting the suggested first-stage decisions, i.e., what initial system to invest in, there is little difference to observe in the Pareto front. The effect of adjusted upper bounds for biofuels differs, however, when it comes to retrofits. This can be seen in Figure 3.20, which uses a brute force technique. That is, it traces fixed combinations of fuels and systems over time across the same scenario set as the optimisation model. The line's colour indicates the first-stage decision (the initial system), while the dot's colour indicates the final system in the last period. This technique has been shown to yield relevant insight [248].

Applying the brute force technique to the adjusted biofuels brings to the surface some secondary effects, namely potential retrofits: Retrofits towards ammonia become more frequent along the Pareto front for adjusted biofuel bounds, while retrofits towards hydrogen

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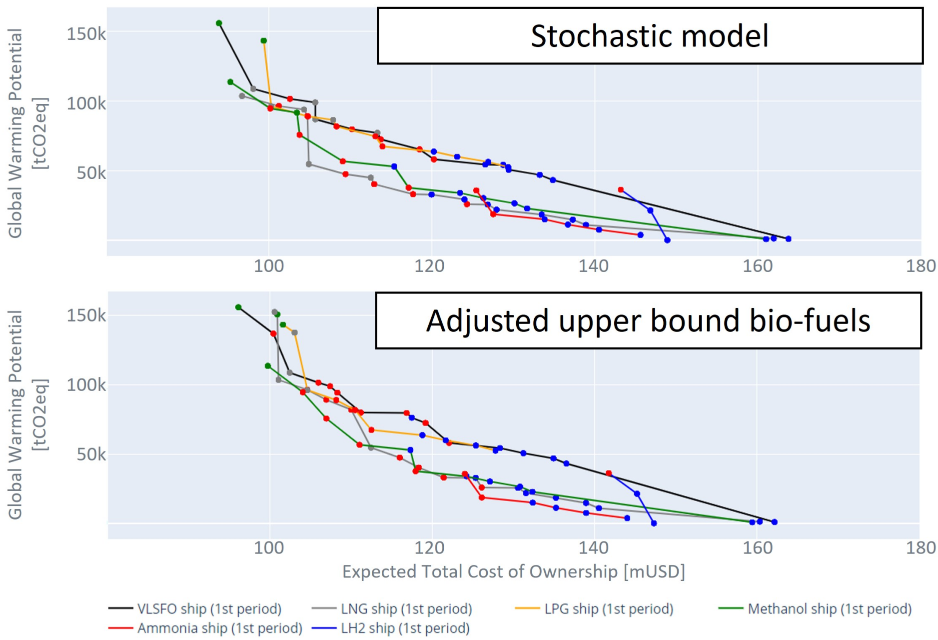

Figure 3.20: Adjusted upper bound for biofuels, brute force results.

are less frequent. Our hypothesis for this is that adjusting the upper bound for biofuels naturally renders them more expensive. The model is thus inclined to switch earlier to e-fuels, for which the retrofit to ammonia is cheaper.

Stochastic optimisation discussion

Stochastic optimisation offers the ability to balance optimisation by weighting uncertain outliers stochastically. In this way, the method allows selecting from many options while taking uncertainty into account explicitly. Furthermore, by using two-stage stochastic optimisation, the method is able to separate the problem into initial (here-and-now) and future (wait-and-see) decisions. This shall reflect the position of a shipowner today because it models the future that is unfolding only after the initial selection. The use of probability shifts the focus of decision-makers toward identifying distributions instead of single values and allows for specifying a nuanced belief in the likelihood of scenarios. Nevertheless, one still needs to specify these probability distributions explicitly, which is challenging, especially for high uncertainty levels. In the case of additional uncertainties, the probability distributions can possibly lead to a non-convexity of the problem. Even though several approaches exist to deal with non-convex stochastic optimisation problems [20, 261], such mathematical limitations must be kept in mind for future extensions and adaptations. Robust optimisation was shown to be able to select a set of robust solutions from a large number of options.

Discussion across methods

By applying both methods to the same problem, the output, methodological assumptions and impact for this specific use case can be compared. When comparing the methods to the deterministic solution, it is apparent that taking uncertainty into account results in different selections, which focus on improving robustness while also incorporating the value of flexibility. The following paragraphs each comment on one of our initially stated aspects for comparison. Looking at the representation of uncertainty, either conservativeness factors or stochastic distributions are used. However, despite a different approach, the fronts offer very similar insights. On the one hand, for robust optimisation, the impact of robustness is clarified when it is compared to the deterministic solution. On the other hand, stochastic optimisation offers smoother Pareto fronts and is less dependent on the initial solution. Regarding insight for ship designers, it is shown that the gamma values in robust optimisation offer much freedom to research different scenarios, even though it increases the dimensionality of the problem. Otherwise, stochastic optimisation is more static, but it has several criteria that offer detailed insights into the differences from the deterministic solution. To research the sensitivity of assumptions, the variability and probability distribution were changed for biofuel. Robust optimisation was found to be sensitive to increasing variability, while the selection of the mean is more impactful when using stochastic optimisation. Overall, in this case study, these impacts are primarily found at the pathway levels and ending option, respectively, while the start selections remain similar. When comparing recommendations from each method, outcomes are very similar, especially regarding the optimal start ship. Table 3.16 further summarises the pros and cons of each method, while showing the aspects that are deemed to be of specific importance for this case study in bold. The setup of the MILP and collecting reliable input was found to be more demanding than subsequently constructing either method. Therefore, in our opinion, the difficulty of implementation primarily depends on the choice to use optimisation, rather than the choice between robust and stochastic methods. Nonetheless, for robust optimisation, the uncertainty set and conservativeness level selection effort proved significant, while for stochastic optimisation, the computational effort, due to the use of probability and sampling, is more pressing. Above all, besides the insights from the method output, the knowledge gained through structuring such a problem is deemed to be especially valuable in the face of uncertainty.

3.4.4 Search methods conclusion

Robust and stochastic optimisation methods are found to present similar solutions for the selected uncertainties under the same assumed input conditions. Robust optimisation offers more extensive scenario research capabilities by using different conservativeness levels and uncertainty sets. However, its results are more readable compared to a deterministic solution, while they were found to be primarily sensitive to variability changes in the uncertainty set. Stochastic optimisation provides smoother fronts with fewer alternations, while it offers several criteria to gain more detailed insights into the differences against a deterministic solution. Its results are primarily impacted by the selection of the mean of the probability distribution. The required computational effort is more significant, in particular for larger scenario sets. By using both methods, it is found that confidence in final solutions can be improved and additional insights can be gained. For the selection of alternative fuel

3

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Table 3.16: Advantages and disadvantages of the two optimisation methods.

Method	Pros	Cons
Robust optimisation	takes uncertainty into account in the modelling stage	can become too conservative
	Immunises against uncertainty	Uncertainty set and conservativeness selection
	Adaptive robust decision making	Dimensionality due to added factors
	Very tractable: low-cost extension to multiple uncertainties	
Stochastic optimisation	Risk is taken care of explicitly	Probability distribution is difficult to specify reliably
	Wait-and-see and here-and-now decisions	Probability can make the problem nonconvex and difficult to solve
	Can treat extreme scenarios as unlikely using low probability	Too large to solve with multiple uncertainties

and power systems, the success of these methods primarily depends on the level of uncertainty and the ability to set up the input for each method. Nevertheless, both methods shift attention toward defining either probabilistic or conservativeness factors and encourage the decision-maker to consider uncertainty in the problem explicitly. As demonstrated, many different uncertainties can impact the results in a decision problem such as maritime energy carrier selection. While this chapter only looked into two uncertainties, many more are preferably included in the decision problem. An extension of uncertain factors should be covered in further research. For this purpose, robust optimisation seems to be promising, due to its tractability, but this remains to be proven. From a more practical standpoint, the methods show that methanol and LNG ships allow a cheap but large reduction in emissions through the use of biofuels. However, flexibility is key for these options to be able to follow possible shifts in fuel or carbon prices as modelled in this chapter. The ability to switch toward other fuels during the lifetime was found to become even more important for values that occur outside of the assumed ranges. This was shown for a potential variability change for biofuels, which was still selected as an important intermediate solution for emission reduction, despite the shift of the mean and the increase in the price range. Consequently, under the conditions of the case study, including uncertainty in such a selection problem is more important than the choice of a specific method. Furthermore, applying both methods to the same dataset can increase confidence in the practical results. We have shown that the suggested decisions of both methods are very similar. Thus, the choice of method, in our case, affects the decisions to a much lesser extent than the assumptions made for the input parameters. Further research should be done on different case studies to corroborate or refute the benefits of flexibility and opportunities of biofuels. This chapter indicates that the application of fuel selection methods for any ship to meet the IMO emission goals can benefit from including life cycle uncertainty.

3.5 Conclusion

To answer the research question, contextual uncertainty and value challenges have been addressed by applying methods that use search or exploratory approaches to a practical case study. Furthermore, these methods were selected based on their ability to support decision-making while facing temporal effects, multiple objectives and the existence of different uncertain variables and scenarios. The methods evaluate different pathways while using adaptation to switch between emission reduction measures. To investigate their applicability and limitations, the decision problem setup is similar in both sections (the selection of emission reduction measures during the lifecycle), but the specific uncertain variables and scenarios were adapted for the method setup.

Exploratory methods such as DAPP, RSC or RDM can be used to gain a broader insight into the design space, even when it is non-convex. However, the complexity of evaluation increases with the size of the design space, especially when multiple objectives and scenarios are also considered. On the other hand, search methods such as two-stage stochastic programming and adaptive robust optimisation can be used to investigate optimal solutions, even when considering a large design space and multiple objectives. Nevertheless, when the number of uncertain variables and objectives increases, and solutions become non-convex, algorithms may struggle to find feasible solutions, requiring heavier search algorithms. As such, the use of one of these methods for the maritime energy transition problem depends on whether the decision-maker prefers insights into the broader design space or optimal selection.

Even though these methods offer meaningful insights into the maritime energy transition problem, there are several limitations that remain to support decision-making under deep uncertainty:

1. Investigation of the impact of improved changeability in ship design: A more detailed investigation of aspects that influence the dynamic objects of choice is needed. For example, in both sections, a global estimate is used to reflect the time and cost of changeability, but specific change enablers are not included. Consequently, while an adaptive vessel is crucial for responding to uncertainty, specific adaptations can be investigated to support preparation and retrofit decision-making. More importantly, it is hypothesised that reducing the cost of changeability with dedicated change enablers could impact the Pareto fronts found for search methods, as shown in Figures 3.14 - 3.19 and lower the threshold for decision-making.

2. More detailed insight into uncertainties related to emission reduction measures: The uncertainties discussed in the chapter mainly considered variables describing the cost and performance of different measures. However, the behavioural complexity and model uncertainty at the system level can affect these and other variables in different ways that are currently not included in the methods. For example, the change or addition of emission reduction measures to the system architecture will also influence existing systems and often require additional systems and changes to the ship design. Besides that, the ship size and shape further constrain the application of emission reduction measures. Furthermore, combining emission reduction measures or operational approaches such as a change in ship speed or autonomy has propagating effects on the whole system. As such, the addition of

system-level information is crucial to provide insight into the impact of structural and behavioural complexity and properly estimate input uncertainties.

Consequently, the methods discussed in this chapter can be used to investigate when to apply emission reduction measures, while considering different uncertainties. The methods apply dynamic objects of choice to deal with temporal effects, while also providing trade-offs between multiple objectives. However, to improve insight into the application of dynamic objects of choice in the maritime energy transition, additional research is necessary. First, the specific components of different system architectures, and the ability to use the ship as a platform for and switch between emission-reduction measures, should be investigated as part of decision-making. Besides that, as defined in table 3.11, there are multiple categories of uncertain parameters that impact the energy transition. As such, the uncertainties are preferably subdivided over the levels and components. The relevant uncertainties can be included as part of these methods. The next chapter establishes the requirements for supporting maritime energy transition decision-making and proposes new sub-questions to guide the remaining research.

4

System architecture model and integration

A ship is a complex system that consists of integrated subsystems [14, 132], so introducing emission reduction measures requires altering multiple parts of the system architecture and impacts its performance. This challenge is amplified when emission reduction measures are added during the lifetime, as they need to be integrated within an already established system architecture. Consequently, to support decision making under the maritime energy transition, understanding and quantifying changes and additions to the system architecture is essential.

This chapter develops a methodology to describe the system architecture and its evolution when emission reduction measures are added. The methodology is developed as part of the what module of the FEAR framework, which focuses on what systems to select to prepare or respond to the maritime energy transition. The chapter addressses the decision making challenges related to architectural change and aims to answer the following research question:

How can the evolution of the ship system architecture be described and quantified?

Even without considering alternative fuels or automation, a ship already consists of many hundreds of thousands of components [133, 312]. As a result, the selection of components has been a topic that has been intensively researched in ship design and marine power and propulsion literature [18, 318, 417]. With the emergence of alternative fuels, EST and hybrid propulsion and power generation [158], the number of options to include in the system architecture has significantly increased. To research and approximate the performance of novel systems, experiments and simulation models are used. However, these approaches typically focus on fixed system configurations, rather than modelling and exploring different and evolving a system architectures.

To structure and describe system elements, relationships and principles of its design and evolution, decision support methods like SE or Model-Based Systems Engineering (MBSE) can be used to manage complexity [143, 204, 448]. These methods enable the description of interconnected components inside the vessel to support its operation. The novelty of the methodology developed in this chapter lies in extending this representation to describe system architecture evolution and quantify the ability to add or change emission reduction measures.

Additionally, for many future emission reduction measures, information regarding performance, integration and relations within the ship's system architectures is often still limited. This makes it difficult for vessel-level decision-makers to investigate how a system architecture will evolve and decide whether and how to prepare. To structure the development of the system architecture description the theoretical decision making framework introduced in Chapter 2 is used and visualised in Figure 4.1.

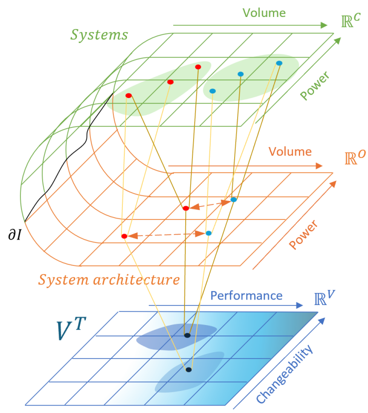


Figure 4.1: Decision space structure for the what component. Systems from the context space are combined into selected system architectures in the object space. The value space reflects the trade-off between the changeability and performance and the shaded area reflects preferred performance. The yellow lines represent mapping from system components into system architectures, overlap between architectures and their performance in the value space.

The context includes geometrical details and performance of systems, such as size, emission reduction and the connections each component needs to other parts of the system architecture. As part of the object space, the combined components form a system architecture. This includes power plant and propulsion components, such as the energy carrier and converter, and additional components to support the reduction or reduce emissions directly. The value space can include multiple performance indices, such as the performance of the system architecture in meeting operational requirements, cost, size and emission reduction performance, but also the ability to change between system architectures. The mapping between the context, object and value spaces enables the comparison of system architectures, including their performance and changeability.

The challenges to deal with for the system architecture are described below:

- Context of choice:
  - Contextual complexity: The differences of system characteristics can also be considered as uncertain. However, because systems are considered mature

during the integration in the system architecture, changes in system characteristics are represented as alternative systems. This increases the number of systems to select from, and is visualised by the shaded area around the points in the context space and is also reflected in value space. The approaches taken to describe contextual complexity are described in section 4.2.2.

- Object space:
  - Object complexity: Different systems might be placed or need to be fitted within a previously selected system architecture when they become available over time. This effectively increases the object space as not only the initial and final system architectures need to be considered, but also architectures that are prepared to incorporate a new systems. The approach used to represent the change of components is described in section 4.2.3.
- Mapping:
  - Behavioural complexity: To describe the relations between, interaction with, behaviour and functionality between multiple existing and future system architecture components. The methods selected to deal with this challenge are described in section 4.1. These are described first, as they are more substantial, guiding the selection of other approaches. The insights that can be gained regarding the interrelations between system components and different system architectures are described in section 4.2.1

The structure that is followed to address this decision-making problem is shown in Figure 4.2.

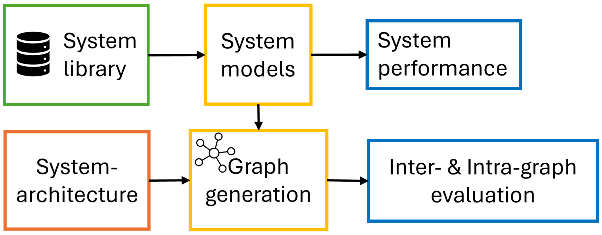


Figure 4.2

The figure shows the context and object inputs, the output to the value space, externally developed system models and the methodology developed for mapping systems into system architecture graphs in the middle.

4.1 System network development

To account for behavioural complexity, while investigating the impact of object uncertainty, a representative system architecture could be used to experiment with the addition or change to emission reduction measures. However, due to the significant cost, the continuous development and the limited availability of emission reduction measures, models offer valuable research tools. In systems engineering and research regarding mechatronic, thermodynamic and chemical systems, it is common practice to model the internal processes of a system to investigate efficiency and operational performance [238]. As such, system developers and researchers have built models for both innovative and existing components of the ship system architecture. Nevertheless, to investigate the (propagating) impact that the addition or change to different novel emission reduction measures have on the ship, these system models need to be investigated as part of the full system architecture and compared based on the physical properties of the system architecture (capacity) and the connections between systems (system topology).

Furthermore, for the analysis of novel system architectures, multiple supporting systems should also be included. Particularly in the context of automation, system architectures and interconnections become increasingly complex due to the addition of sensors and control systems. Consequently, the ability to add or change systems during the lifecycle is also dependent on the similarity of systems on board and whether their capacity and capabilities differ between the initial and retrofit system architecture.

From the framework, relevant approaches to reduce behavioural complexity are to structure technical relations in the decision space (establish connections approach), while multi-disciplinary modelling can be used to exploit discipline-specific knowledge. Approaches such as exploration or searching over the object space can be used to deal with object uncertainty in system architectures, depending on the level of uncertainty.

4.1.1 System models

Various models have been built that provide mapping models for systems relevant to the maritime energy transition, approximating physical properties such as energy flow and emissions.

For each system, an essential consideration is the selection of the appropriate fidelity level (level of detail). When the descriptions of relations necessitate a higher level of granularity, model complexity within a system model increases. A system architecture consists of multiple interconnected systems that also influence one another. Nevertheless, system dimensions are often based on data that is only available for known systems. Alternatively, models can also use principal relations to couple dimension prediction to physical relations of system components [449]. The working principle is shown in Figure 4.3, where a combustion engine is subdivided into several main components that determine its dimensions and mass. For instance, engine performance and size are directly related to cylinder dimensions and count. By identifying and tuning such principal relations for specific systems, the operational and dimensional requirements can be connected. Similar approaches have been applied in research to investigate the relation between ship size for different energy carriers [327, 416] and the impact of operational load profile on the system selection while considering multiple attributes like dimensions [383].

With the continuous development and variety of system models, the What component has to allow for the incorporation and addition of different system models. Consequently, as a proof of concept, this thesis incorporates multiple system models developed in the Technical University of Delft's maritime and transport technology department. The system models used in this thesis were developed as part of the work of Stapersma and de Vos, as

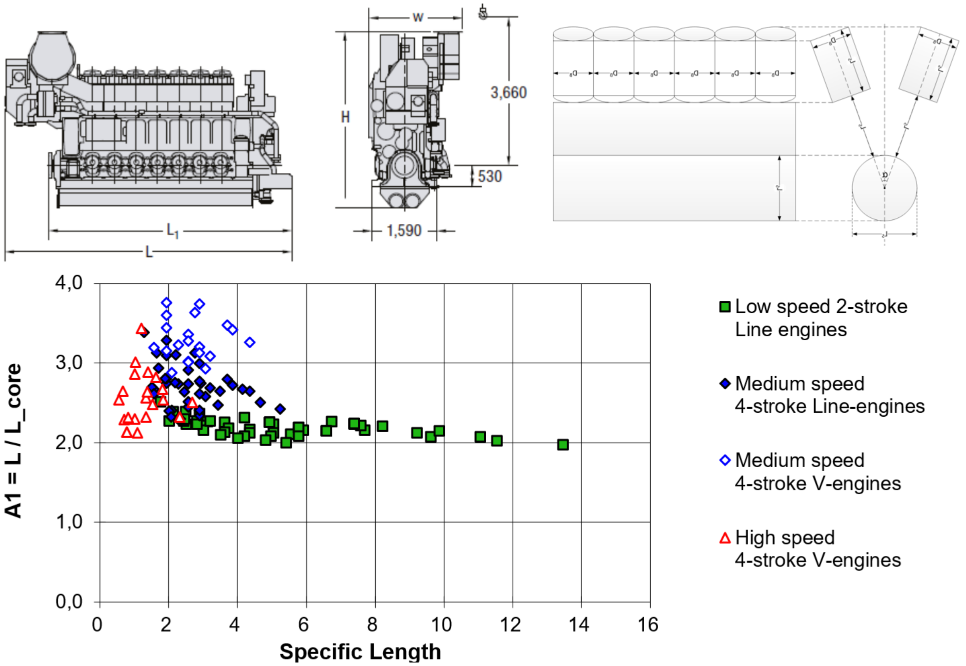


Figure 4.3: System dimension predicion using first principles to couple system performance [449]

well as that of J. van Dijk and T. van der Schueren [120, 383], who developed a number of system models describing components such as dual fuel engines and fuel cells, but also gearboxes, batteries and switchboards. The models have been collected in a Python library, which offers a generic platform where system models can be extended, changed or added. Each system model is described as a class with symbolic mathematics using the sympy package. This symbolic description represents variables using symbols, so systems of equations can be solved symbolically, and different sets of inputs and outputs can be investigated. To reduce computational time, in a first step, all known variables (constants) are substituted, and the remaining symbolic equations are transformed into a surrogate function using the lambdify module. The surrogate function reflects the relationships between variables and can be used to reflect object uncertainty regarding design decisions and investigate the impact of system-specific design decisions, especially regarding novel systems.

4.1.2 Graph generation

To investigate the interactions of components within a system architecture, methods such as networks, schematics, or design structure matrices are highly useful [66, 238]. Depending on the purpose, these representations highlight the physical, operational, or topological architecture between systems, agents, or other structural components [61]. Even though all three relationships are relevant for changeability, the system level is mainly considered with the logical (topology) and operational (capacity) architecture. To capture the logical architecture, graph theory is used to connect each system through its shared media. Similarly, networks have been used to explore the topology of marine system architectures [109], using a genetic algorithm to generate system combinations, while also including operational system capacity, increasing the number of options to research.

Contrastingly, this thesis proposes a different network algorithm to explore network topology in two steps. First, systems and edges are added to a graph based on logical connections. Second, the system models are used to evaluate the operational system capacity afterwards. To qualitatively describe the system architecture, a node library is built that mirrors the system model library. In the node library, each system model is defined as a node with edges that represent a dedicated connection medium. This connection medium represents the energy that crosses the system boundary [293], like fuel, mechanical power, electricity, heated air or cooled water. Besides energy, the connection mediums can also be used to describe alternative interface categories as defined in systems engineering, such as data and signals [239], as long as the interfaces used in the schematic node library and the mathematical system library are modified to be complementary [238]. A system model is connected by searching the library for similar edge mediums, and another system node that supplies the input medium or demands the output medium can be connected. This allows the system architecture to be represented as a directed graph, where systems are connected in hierarchical order. However, to do this, it is important to have a starting point. Fortunately, in every vessel, there are required and recurring marine systems to provide power for propulsion or electrical power for users. This list of systems can be extended based on the additional systems that are required for the ship. Furthermore, because the schematic directed graph is purely qualitative, the library can also be extended with nodes and node-edges that represent systems or mediums that do not actively exchange mass or energy, but have material interface with operational relevance [238], such as cargo holds, anchor chain lockers or sleeping quarters.

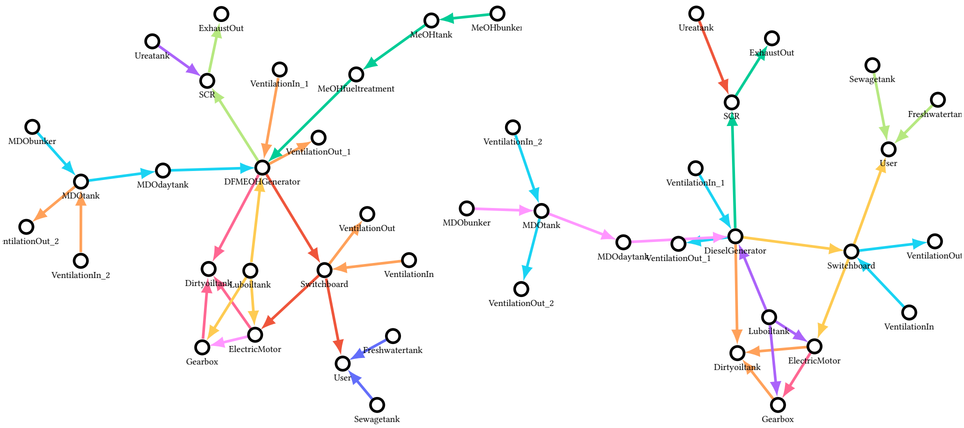
The list of pending systems is added to an initial (unconnected) graph G_0. For each node in this graph, the branch search algorithm below is used to search the library to connect its edges, creating branches with new nodes that are searched until all edges have been explored and the graph is complete. When an edge does not exist, the algorithm creates a source or sink node to provide information to potentially extend the library or show the need for medium input (such as outside air ventilation or a seachest). The new nodes are added to the pending system list, and to ensure the algorithm connects all systems within the graph, the open edges of each system are collected. This way, instead of searching the library, a medium can also be connected to a node that is already in the graph when its edge is open. However, having connected or open edges presents a challenge, as some edges can connect multiple times (like electricity), while others are dedicated (like ventilation). To include edge connecting behaviour, each node is assigned a type: ’distributing’ or ’separated’. The edges of a distributing node can be connected to multiple different systems as long as they use that medium. The edges of a separated system are dedicated and can only be used once, so a new system is needed when the medium is used. Furthermore, when multiple nodes in the library supply or demand the same medium (e.g. different energy converters), parallel copies of the graph are made where each node is branched further.

Algorithm 1 Branch-and-Connect Network Construction

Input: Initial graph G_0, system node library $\mathcal{L}$, supplier/consumer maps
Output: Set of completed graphs $\mathcal{G}_{\text{final}}$

```
Initialize stack with $G_0$
$\mathcal{G}_{\text{final}} \leftarrow \emptyset$
while stack not empty do
    $G \leftarrow$ pop from stack
    if $G$ is complete then
        add $G$ to $\mathcal{G}_{\text{final}}$
        continue
    if no pending systems remain then
        mark missing connections
        add $G$ to $\mathcal{G}_{\text{final}}$
        continue
    Select next pending system $u$
    $\mathcal{B} \leftarrow \{G\}$                         ▷ working branch set
    for all required inputs of $u$ do
        expand $\mathcal{B}$ by connecting to candidate suppliers
        if no suppliers exist then
            record missing link
        else
            branch on each valid supplier
    for all required outputs of $u$ do
        expand $\mathcal{B}$ by connecting to candidate consumers
        if no consumers exist then
            record missing link
        else
            branch on each valid consumer
    for all $H \in \mathcal{B}$ do
        mark $u$ as processed in $H$
        if $H$ is complete then
            add $H$ to $\mathcal{G}_{\text{final}}$
        else
            push $H$ back on stack
return $\mathcal{G}_{\text{final}}$
```

As shown in Figure 4.4, the output from the algorithm is multiple directed graphs that represent the potential system architectures.



(a) Generated system architecture G_1 including dual fuel methanol generator and electric propulsion

(b) Generated system architecture G_2 including diesel generator and electric propulsion

Figure 4.4: Graphs branched at generator, medium colors and locations are randomized

4.1.3 Graph evaluation

Having created the system topology, the next step is to quantify the interdependencies between systems that affect the performance of the full system architecture. The system models are used to connect operational and dimensional descriptions, enabling the investigation of key performance indicators for each separate system. Nevertheless, when connecting multiple systems, the selection and influence of system-specific variables propagate toward other systems, resulting in behavioural complexity. Consequently, to investigate and quantify the evolution of a ship system architecture, we need the ability to explore the impact of interrelations between systems. For example, changing the mix ratio of two fuels in a dual fuel engine can reduce emissions, but reduce efficiency and increase fuel use, while uncertainty in this data might influence the exact performance when a different fuel ratio is used. As discussed in Chapter 2, this challenge can be approached using multi-disciplinary optimisation. It can deal with multiple coupled models that are preferably solved as a whole, but are limited due to the increase in complexity and computational time when some models have higher fidelity, creating a bottleneck for the evaluation of the whole system architecture. Instead, it aims to solve each model separately while still including the interrelations. As such, models are connected and solved either hierarchically or non-hierarchically, while preferably representing the seperate models with low-fidelity surrogate functions that capture the behaviour but reduce computational time [186].

System model extention

The separate model surrogate is already captured through the symbolic representation of system models, that provide the ability to generically adjust variables and analyse the sensitivity of assumptions. The local solver is used to investigate design decisions within a system model. For example, for a diesel engine, there are several discrete design considerations such as the number of cylinders, stroke and bore size and the rotational speed that impact multiple different performance indices such as efficiency, mass and emissions [451]. Besides that, to model decisions such as cell voltage for fuel cells continuous variables also need to be modelled. Consequently, the internal solver follows a multi-criteria optimization shown in Figure 4.5 that distinguishes between discrete variables and continuous variables. Furthermore, to reduce global re-computation time for the full system architecture, this solver is added to each system model. The symbolic equations that

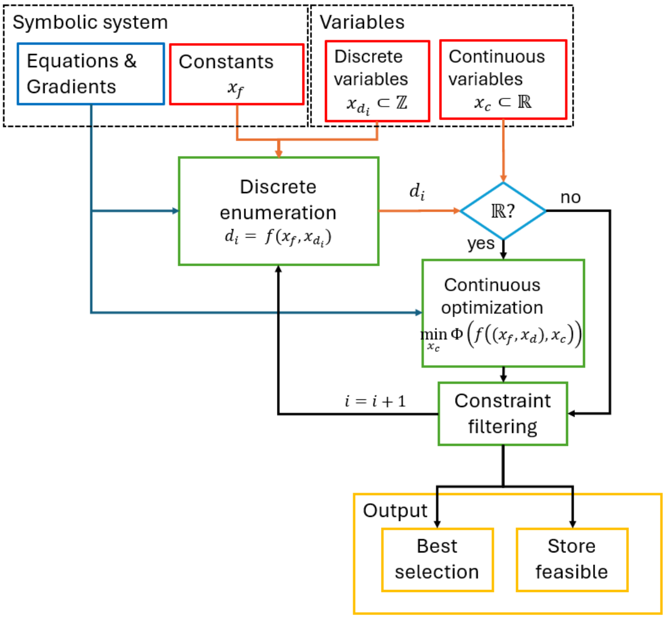


Figure 4.5: Extention of symbolic system description using continuous optimization and trial inputs created from individual and grouped discrete variables

contain constants x_f, equations and gradients to describe system behaviour, are extended by defining additional discrete x_d or continuous x_c variables that can be used to describe either uncertain variable ranges or decisions. First, discrete variables, such as the number of engines, are defined as $x_d \in C$, where C is a finite set of alternatives. If required, discrete variables may be grouped and treated as a combined choice.

If no continuous variables are present, the system is evaluated directly with the discrete candidate inputs $c \in C$.

Continuous variables are defined as $x_c \in \mathcal{X}_c = \{x \in \mathbb{R}^q : l_j \leq x_j \leq u_j\}$ and are solved in an inner loop. The continuous optimization problem $\min_{x_c \in \mathcal{X}_c} \Phi(f(c, x_c, x_f))$ is solved using the L-BFGS-B algorithm. Gradients from the symbolic system description are used when available. The objective function $\Phi : \mathbb{R}^m \to \mathbb{R}$, maps selected outputs to an objective value using weight factors [383]. To ensure feasibility, each system is also subject to inequality constraints,

$$g_k(f(c, x_c, x_f) \geq 0, \qquad k = 1, \ldots, r.$$

A selected solution or the direct evaluation from the discrete enumeration is output for further analysis. Among feasible candidates, we select the best one according to the objective:

$$(c^\star, x_c^\star) = \arg \min_{(c,x_c) \in \mathcal{F}} \Phi(f(c, x_c, x_f)).$$

The algorithm returns the optimal design $(y^\star, x^\star, \mathcal{F})$, where $x^\star = (c^\star, x_c^\star, x_f)$ is the selected design, $y^\star$ are the corresponding outputs and $\mathcal{F}$ contains all feasible solutions for further exploration. Figure 4.6 visualizes the output for a diesel generator model.
The figure is taken from an interactive plot that can be used to explore different variables

4

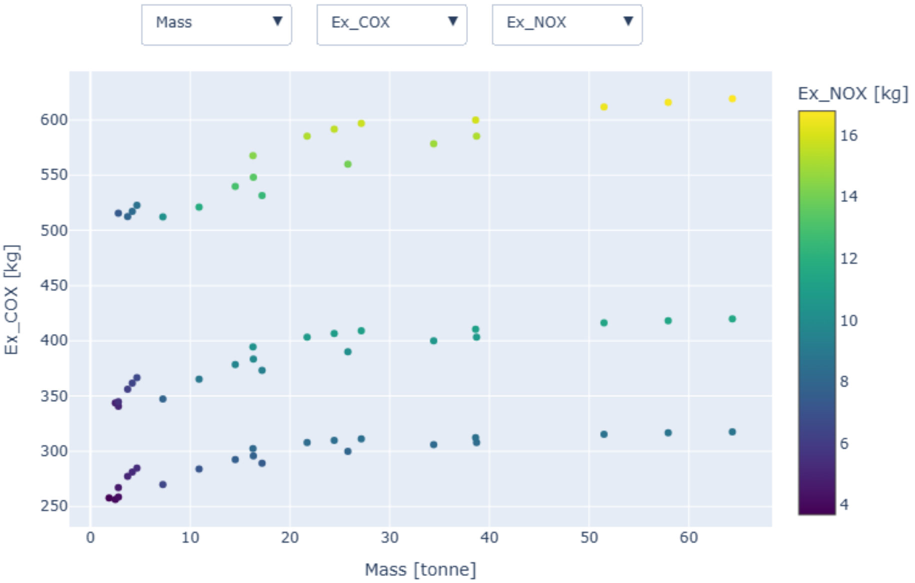


Figure 4.6: Tradespace visualization of the discrete variables of a single system. The CO_{2eq} and NO_X emissions for different diesel generator sizes are shown, also including the interactive dropdown to explore the design space.

from the design space of the system. The figure shows NO_X and CO_{2eq} emissions and the representative engine size in mass, hovering over each point shows discrete design variables. Besides design variables, input uncertainties can be explored by including these as discrete variables.

Graph connection

With the separate model surrogates built and computed locally, the next step is to connect the models. Luckily, the graph representation already offers a hierarchical order of connections between each system model. Each edge represents inputs and outputs to the function that can be used to identify what variables are supplied or demanded by connected systems.

In graph theory, variables that are associated with an edge can be collected as additional information or attributes for further analysis of the graph.

To build the hierarchical solving order, the attributes are used to create a new evaluation graph G_{eval}. This graph connects each node using edges that represent the variables that occur along each edge of a graph G in $\mathcal{G}_{\text{final}}$. Starting with the symbolic variable-edges that are known (global), the evaluation graph can be sorted in topological order to determine the solution order. Each system model then uses throughput variables from previous systems to build a representative function and solve variables locally. Additionally, when a system is of the type distributing, outputs or inputs can be used multiple times. To deal with this, the symbolic system definition is extended with a preprocessor that tells the system model how to handle multiple inputs. To evaluate a system architecture, the decision maker should provide an initial graph, the design variables for each system, and design variables for the system architecture (like the required power and autonomy or a load profile). The results of each system model are then propagated until the full system architecture is solved.

However, besides the evaluation of system performance such as emissions, efficiency and size, approximating the capacity, size and existence of connections between systems is also critical when assessing placement and re-placement of systems on board. Connections differ depending on the flow and safety requirements and the flow medium. Therefore, a library of connection models is created based on the same code as the system models; the connection models are solved after the system models, to reduce the impact on the computational time.

The output of the graph evaluation is the solutions of each separate system and connection model. As such, the output of each model dictates the output of the whole system architecture. For example, in the diesel generator and electric propulsion graph shown in Figure 4.4b, emissions are calculated as part of the diesel generator system model, while the total required electrical power is output by the switchboard as a function of all electric demand from other systems.

4.2 System network output

The primary goal of the system network is to provide a comprehensive description of all onboard system architecture components and to assess the extent to which the addition or modification of emission reduction measures affects these systems. The impact of object uncertainty can be investigated by evaluating the system architecture graph. Additionally, alternative system architectures with different emission reduction measures need to be compared to an initial system architecture to be able to understand which components and connections of the system architecture evolve and how the initial architecture can be prepared. Consequently, the comparison of system architectures with alternative components, uncertainty analysis and changeability are discussed below.

4.2.1 Qualitative and quantitative comparison

The methods are further extended using set theory to identify the relationship between different system architectures. Because the graph representation provides a set of nodes and edges for each of the system architectures, set theory can be used to qualitatively compare nodes and edges. This information is valuable for investigating the ability to change between systems, but the real power of the evaluated graphs lies in quantitatively comparing system model variables. Both the qualitative and quantitative are shown in Figure 4.7. The left of figure 4.7 shows the set containing all systems and edges given by

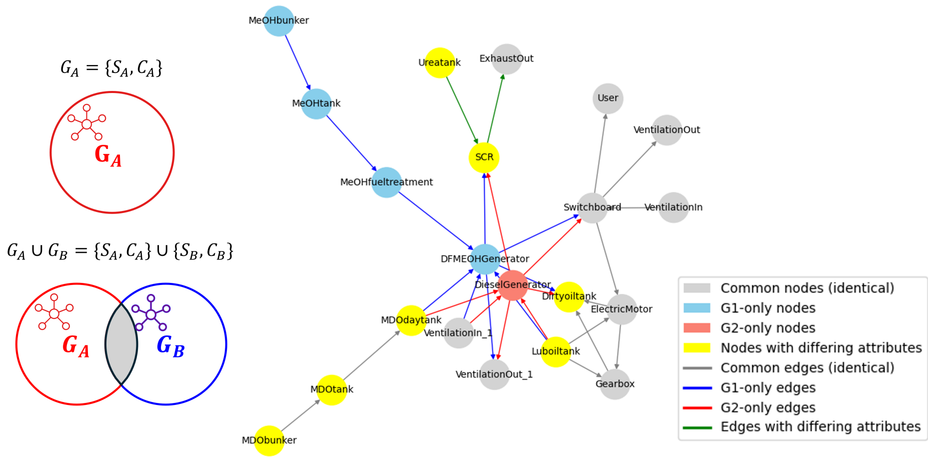


Figure 4.7: Qualitative (left) and quantitative (right) comparison of two system architectures

the union, while overlapping systems are given by taking the intersection of both sets and the unique systems and connections are found by taking the difference. The right of figure 4.7 visualises the intersection (grey) and set difference for two system architecture graphs, but also compares the internal variables (attributes) for each system model. The result is an overview of systems that need to be added and changed in capacity (yellow) when changing from one system architecture to the next.

4.2.2 Sensitivity analysis

Besides comparing system architectures and investigating relationships between systems, object uncertainty is a significant challenge due to the novelty of emission reduction measures. The design space exploration for each system already enables the ability to investigate the local sensitivity of results to uncertainties, but this is impractical when aiming to investigate the full system architecture, especially because relationships between systems would not be included. Therefore, the graph evaluation is extended with a sampling algorithm where uncertain variable ranges are defined globally. This sampling combines different variables into a sample run. Dependent on the number of variables and discrete steps, the sampling can cover the full design space or use Latin hypercube sampling for a uniformly distributed set of sample runs. To avoid recomputation of the whole system architecture, the local system model solver is extended to save previous runs and check whether the surrogate function needs to be rebuilt (when different variables are known between sample runs) and if re-computation is actually necessary (global or throughput variables changing).

The results of the whole system network are saved for each sample run and can be used for global sensitivity analysis. A global sensitivity analysis is performed that measures the percentage change of each system model variable. The decision maker can select variable ranges and steps, and the runs used to visualise sensitivity in a dynamic visualisation tool shown in Figure 4.8.

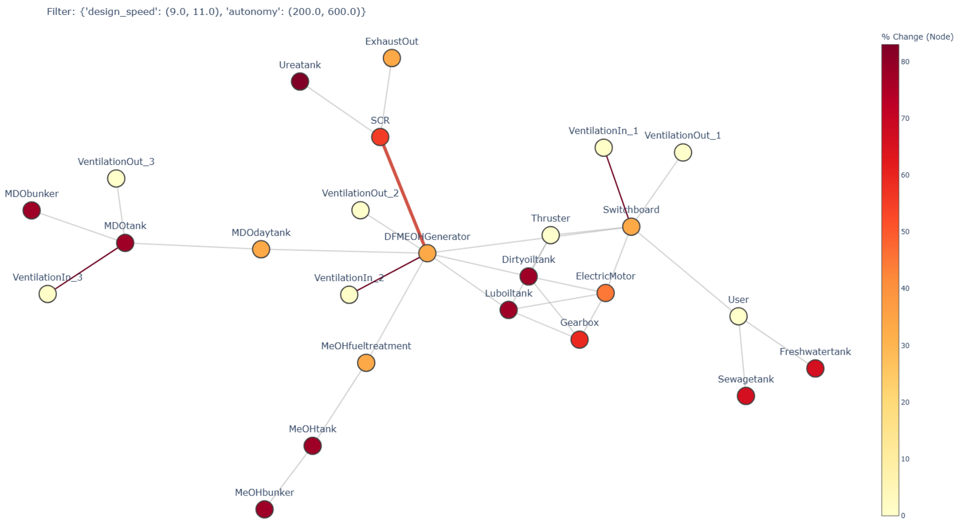


Figure 4.8: Network plot showing the sensitivity of systems and connections for variable input range regarding design speed and autonomy.

The figure shows the percentage sensitivity of both systems and connections in a dual-fuel generator system architecture to changing design speed and autonomy input when compared to a reference system architecture. The color of each node and edge show the maximum deviation of each system to the output in the reference system in percentage. The specific outputs can be investigated when hovering over nodes and edges. It can be used to determine how far each systems outputs deviate from a reference system architecture under alternative design decisions. Besides visualising sensitivity design variables, the results from this analysis can also be used to define uncertainty ranges that are used to account for additional reserved space or increased connection size.

4.2.3 Changeability

Besides comparing graphs visually using set theory, to evaluate changeability, a measure is needed to describe how systems and connections are similar and how much of the graph needs to change to reach the next system architecture. This is a common but challenging problem in graph theory called graph similarity or distance between two graphs [173]. There are different ways to describe similarity, but the most general way is to model similarity as a pairwise metric distance between information [478]. Methods used to search the metric similarity between graphs differ depending on the graph type and search algorithm used, which influence the number of dimensions to compare over [393].

However, the system architecture graphs differs from most graphs mentioned in this literature as these typically describe large sets of data, where nodes have same dimensions (e.g. locations with coordinates or personal data with columned information). Meanwhile, the system models can have different attributes, that are difficult to capture in a metric distance. As such, a selection of cases that are created using set theory is considered to assign metric distance:

- An edge or node is common in both graphs: there is no distance between the pair
- An edge or node is unique to a graph: the distance is 1 to add a node or edge
- A node has different attributes: the distance is calculated based on the type of node and the attribute that differs.
  - For a system with mostly similar attributes, but an increase in number (discrete systems such as engines) or size (systems such as tanks) the distance is taken as the percentage increase divided by hundred.
  - For a system where physical attributes change the distance is 1 to add a new node.
- An edge had different attributes: when attributes have increased, the distance is 1 to add a new edge, else the

Using this distance definition for each node and edge, the next step is to calculate the full distance between two graphs. To do this graph edit distance is used, which augments an initial graph by using edits that are selected based on minimal cost until the target graph is reached [191]. Figure 4.9 visualizes this principle to measure the changes between the diesel generator and a dual fuel generator system architecture graphs. The output provides intermediate graphs and the remaining nodes and edges that need to be added. Using the intermediate and target graphs with the relative changeability metric, preparations can be systematically evaluated. Furthermore, the edit distance could be further extended by weighting graph edit operations with representative connection and system costs. Enabling the decision maker to evaluate the cost of changeability without considering the physical placement.

Furthermore, intermediate graphs with a higher changeability across multiple system architectures can be identified by computing the graph edit distance from an initial system architure to multiple alternative architectures. By investigating what intermediate graphs overlap through both qualitative and quantitative graph comparison. This provides a bottom up approach to changeability assessment, that can be used to gain insight into what system level preparations enable changing between system architectures.

Lastly, when the graph edit distance is combined with the tradespace evaluation, changeability can be explicitly incorporated into early-stage design decisions. By understanding what system attributes occur in multiple system architectures, a system architecture could be adjusted proactively, by installing additional capacity or adding connecions to reduce the graph edit distance distance.

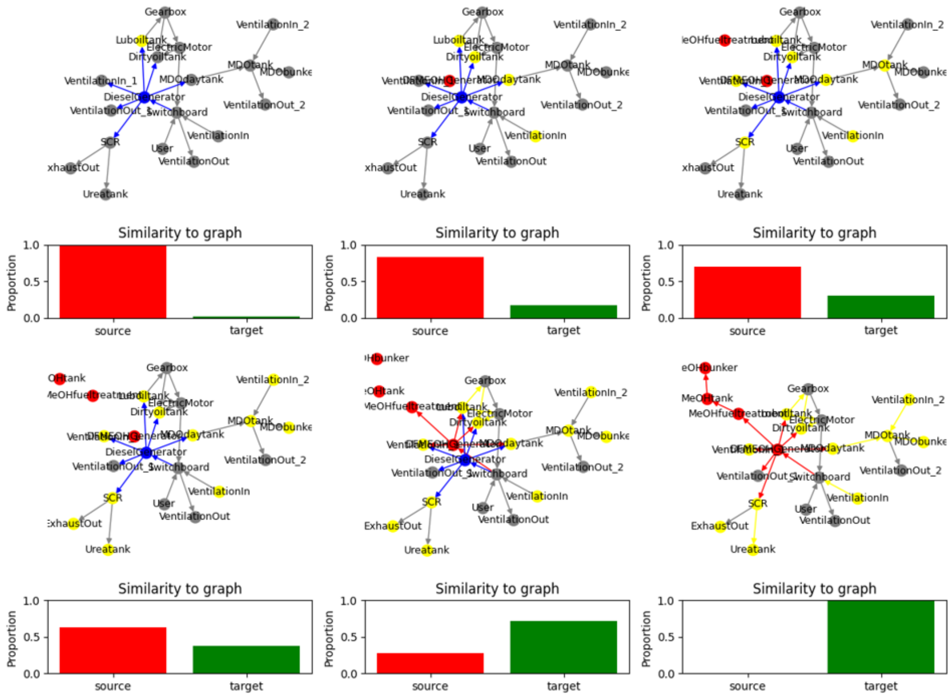


Figure 4.9: Graph edit distance augmentation moving from a source (top left) to a target system architecture (bottom right), including the progress of the metric similarity between the source and the target system architecture.

4.3 Conclusion

To deal with behavioural complexity, object uncertainty and temporal effect challenges at the system level, graph theory has been combined with multi-disciplinary modelling to answer the following research question:

> *How can the evolution of the ship system architecture be described and quantified?*

The methodology was shown to be able to describe system architecture components and their connections using graph theory. Furthermore, the system architecture was quantified using both individual system models and a network of system models. Additionally, set theory was used to qualitatively describe the evolution of a system architecture to include additional or changed systems, while graph edit distance was used to investigate the difference between quantified components. Combined, the What component of the FEAR provides necessary insight into interrelations between components and the impact of decisions and uncertainty. More importantly, it also outputs useful data for further research into the integration of different system architectures in the next component of the FEAR.

5

Ship integration model development

When designing a ship, integrating energy system components is complicated by the limited available space due to the hull form and the need for operational spaces (e.g., cargo hold, pump rooms, or freshwater tanks). Emission regulations or safety measures further limit available space and require structural additions, such as cofferdams, additional ventilation, or fire insulation [358]. Furthermore, weight distribution for stability and structural strength further complicates the integration of a system architecture. These constraints reflect that the evaluation of evolving system architectures cannot be separated from vessel-level considerations that define ship design complexity [115].

This chapter develops a methodology to examine the integration of system architectures within a vessel and how the decision-maker can prepare the ship design to enhance changeability. In contrast to approaches that focus on vessel-level design while using a fixed system architecture, the methodology combines vessel-level constraints with the assessment of system architecture evolution.

The method forms the basis for the how component of the FEAR framework, enabling the vessel's system architecture to adapt and ensure a timely response to developments in the maritime energy transition. This leads to the following research question:

How can ships be prepared to accommodate future system architecture developments?

To address complexity in ship design, the design process is decomposed into several phases with increasing levels of detail, evaluated iteratively to ensure that all requirements are met. However, because both time and financial resources constrain this process, design iterations cannot continue indefinitely. Furthermore, significant changes are preferably implemented during early design phases, when committed costs are low, and design freedom is still high [275]. Therefore, preparations to improve changeability should be considered during the early design phase, when it can still be included at low cost.

Ship design is an effort to define a combination that satisfies the complete set of requirements within a vast and complex design space [128]. Consequently, the integration of new emission reduction measures in an existing system architecture further increases structural complexity, especially when design preparations are included as well. However, while research on emission reduction measure performance has gained traction, limited attention has been paid to how the ship design can accommodate the evolution of its system architecture.

To investigate and compare system architectures in combination with their impact on the vessel by incorporating systems engineering approaches in maritime engineering [155], the inclusion of physical integration is key. This is especially the case when novel emission reduction measures are considered, where information is still incomplete. Furthermore, besides emissions, for many alternative fuels, issues such as toxicity, fire safety, and explosion risks are of particular concern. Therefore, novel emission-reduction measures often require preventive measures to safeguard human and environmental health, as well as the vessel's safety [358]. However, while regulation has a significant influence on integration, much of the information necessary for the placement of system architecture components is still uncertain, further complicating decision-making and preparation in particular.

The methodology is used in the how component of the FEAR to investigate the relationship between system architecture development and vessel-level decisions. Similar to the other components, the how component is treated as a decision problem, and the theoretical decision-making framework introduced in Chapter 2 is used to structure the methodology, as shown in Figure 5.1. The system architectures that can be integrated are

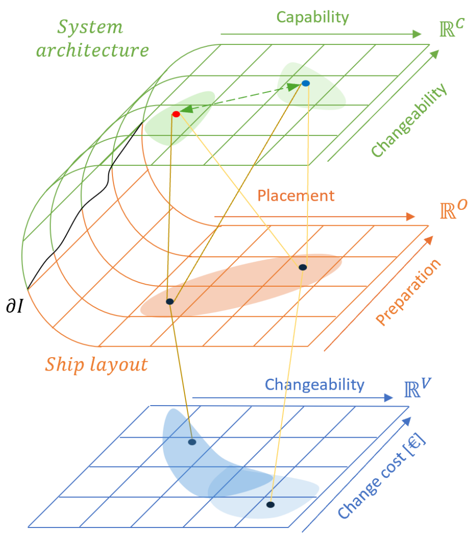


Figure 5.1: Decision space structure for the how component, including the system architecture to place in the context space, and their integration in the ship layout in the object space. The value space reflects the integration of different system architectures inside the ship.

located in the context space. Below, the object space includes vessel preparations and the placement and connections of these system architecture components inside the ship. The value space then reflects the cost and time invested to integrate the system architecture and change components. The mapping model is used to connect each of the three spaces by relating and measuring the initial and retrofit system architecture placement.

To assess the ability to change components in a system architecture during the lifecycle, it is crucial to be able to investigate the physical placement and preparations within the ship. Now that the principles have been defined, the main challenges are defined below:

- Object of choice:
  - Structural complexity: The growth in alternative placements and preparations to accommodate system architectures on board increases the dimensionality of the object space, complicating the evaluation of integration and changeability of the system architectures.
- Mapping:
  - Behavioural complexity: many physical and technological relations are needed to describe the size of system architecture components, the hull shape and the placement of additional safety requirements.

The structure that is followed to address this decision-making problem is shown in Figure 5.2.

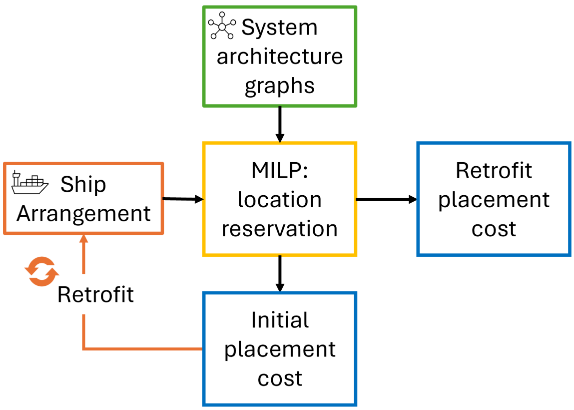


Figure 5.2

The figure shows the context and object inputs, the output to the value space and the methodology developed for mapping in the middle.

5.1 System architecture placement approach

The main goal of the placement algorithm is to evaluate the placement and replacement of different system configurations, while accounting for structural complexity arising from interdependent factors such as stability, weight distribution, and safety requirements.

The output of the placement algorithm should provide insight into the cost to prepare for changes and the value of changeability. Different ways to describe the value of changeability were discussed in the literature review chapter, but typically involve either a top-down or bottom-up approach to reflect the cost and time required to prepare an object with a change enabler and to perform the change [353]. To investigate the value of change, the placement algorithm takes a bottom-up approach, modelling specific modifications to the design and system architecture (change enablers) that can be used to reduce the cost of change relative to the initial investment. To describe the trade-off between investment and lifecycle cost, Fricke and Schulz [148] proposed using two curves to depict the relationship between change cost (the additional investment to improve changeability) and change cost (the cost to change during the lifecycle) at increasing levels of changeability. They also create a combined curve to reflect a theoretical optimal changeability level. By building these curves, the placement algorithm can provide input to the when component of the FEAR. Figure 5.3 shows the approximation of such change curves for a pipe layer vessel, which was created as part of the thesis [287]. The figure shows the investment cost to improve design for

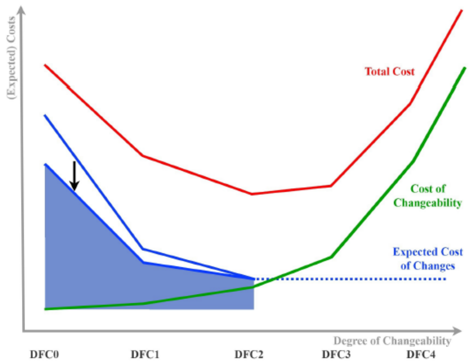


Figure 5.3: Change curves showing the value of design for changeability (DFC) levels [287].

changeability (DFC) levels and the expected cost of changes that were created using a ROA. The total cost curve represents the lifetime cost of changeability and includes categories such as pipe and wall material costs and missed income. However, as shown by the shaded area, the expected cost curve is affected by the object (regarding system size and the timing of the change) and by contextual uncertainty (regarding emission regulations). As such, the optimal total cost will also shift with uncertainty, with higher uncertainty levels requiring greater changeability. Consequently, by reflecting changeability through the total cost curve and incorporating uncertain variables, a surrogate function can be produced that describes the value of different levels of changeability under uncertainty. This curve is used as input to the when component of the FEAR, where exploratory or search methods can be implemented to evaluate the benefit of different levels of changeability under uncertainty.

An earlier version of the placement methodology developed in this thesis was used to create Figure 5.3. It worked independently of the system architecture model and only considered the placement requirements to change energy carriers, including cofferdams and piping to a fixed engine room. However, to evaluate changeability, changing multiple system components and propagating changes to other components in the system architecture were found critical for reflecting the impact on ship stability and operational capability in placement. Consequently, the methodology was re-developed to include input from the system network model as described in section 4.1, as well as different operational profiles and ship shapes.

5.1.1 The placement model setup

To analyse the integration of different system architectures in a vessel, it is essential to also include the material interface and the physical layout of components and connections [238]. In ship design, such spatial layout problems are typically investigated by using methods like automated placement algorithms to explore the design space. Such methods are not only applicable in ship design but are also widely used in design, architecture, and industrial processes. A review describing the use of automatic space layout generation methods for energy-efficient building design found seven different methods and described that the selection of an appropriate method for automated layout generation is a trade-off to either focus on topology (the connections, adjacency and orientation of the layout) or geometry (size of components in the layout) [127]. Nevertheless, these algorithms only consider the physical interface of components. Consequently, to describe both the system interfaces and physical interaction within the vessel, such layout algorithms need to be extended.

When looking at methods used in ship design layout generation and optimisation, similar methods are also found in architectural design, but their application depends on the purpose. For example, the packing approach uses cell assignment and provides insight into the minimum ship size required to fit operational rooms [311], while the network science approach uses graph theory to describe system and room relations to inform pre-processing of layout decisions [166]. Furthermore, several researchers have experimented with physically based methods. For example, the preferred placement and clustering of systems is described using force constants that either pull or push other systems to investigate preferred clustering [79]. Similarly, a recent paper investigated layout clustering based on entropy (temperature) to evaluate the trade-off between reducing distance costs and avoidance [90]. Additionally, the design building block model uses mathematical programming for pre-computed building block placement within a fixed boundary [14].

However, to incorporate changeability in a placement algorithm, both the initial and retrofit placement for different system architectures need to be investigated. Similar to an energy efficiency assessment, changeability requires adding models to evaluate the effectiveness of placement. As such, the assessment itself and the variability of systems result in the design space quickly increasing. Furthermore, when selecting an algorithm for changeability layout generation, a trade-off must be made between topology (the connections between systems and spaces) and geometry (the sizes of systems and spaces), as both are important to include when assessing changeability. Instead, the generation of layouts to investigate the design space is considered to be a secondary goal, as assessment and the creation of the change curves are more important. Consequently, mathematical programming is selected to efficiently search the design space for layouts that are optimised for either the cost of changeability or the cost of changes. When it is used as an automatic layout generation approach, it enables the inclusion of geometry and can also be extended to include several approximations of changeability measures. However, an extension is needed to describe the topology. Therefore, this thesis develops a graph-aided mathematical programming method by extending the system network algorithm's output and modelling the ship shape using graph theory to predefine topological system and placement relations. The topology is then used as an input, while the mathematical programming is used for geometric system and placement sizing.

5.1.2 Ship geometry description

The shape of a vessel can be defined by the operations (e.g. increased stability for heavy lifting or increased hold volume for transport) or influenced by efforts to improve efficiency (e.g. changed aftship for improved propeller inflow or improving the hull shape to reduce resistance). However, when systems are considered for placement, the hull shape also affects the size, shape complexity, and available internal compartment volume. To reflect this in placement algorithms, the hull shape is either pre-defined and sized [336] or folded around the internal systems [311]. This allows for investigating placement while also varying the ship size without being constrained by it. However, when system architecture changeability is included, the design space is already expanded by the presence of variable system sizes. As such, a reference ship shape is used to estimate available internal volume while investigating the changes between system architectures. After evaluating changeability and creating the change curves between system architectures, the ship shape can be resized to investigate the impact of different vessel dimensions.

Discretisation of the geometry

The reference ship shape is described as a triangular mesh using a Python library called trimesh and shown in Figure 5.4. This library allows for calculating attributes such as wet hull area, centre of gravity and volume.

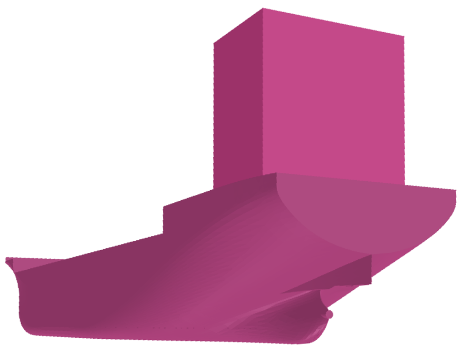


Figure 5.4: Example of a reference ship mesh file

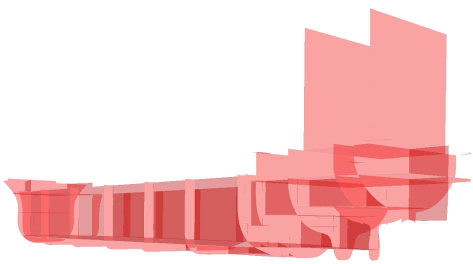
The reference is used to estimate ship-shape parameters to describe the resistance, power and stability. The input from the reference mesh is used in a model as described in [489]. Inputs include the wet hull area, the frontal and side area above water, the point of buoyancy and main dimensions of the ship.

Describing placement relations

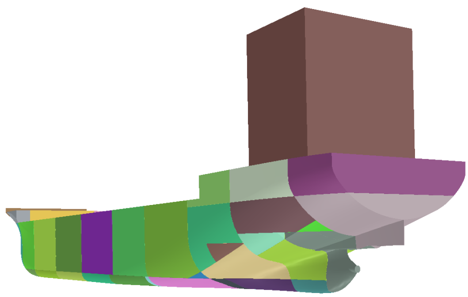
To place rooms or systems, placement algorithms either use coordinates or create a raster of equally sized volumes where systems can be placed. However, because components vary in size and need to be evaluated based on changeability, the physical and functional relations between the ship and systems need to be represented. Therefore, the ship shape is discretised using a grid, where every submesh can be used for (re-)placement of components of the system architecture, while assigning geometric, safety and accessibility attributes to that submesh.

There are several rules that require the placement of specific bulkheads inside the ship. These rules differ depending on ship type, but typical rules prescribe the existence of a double hull and tanktop deck, where a wall or floor is placed next to create additional spacing from the hull. Besides that, ships require a set of watertight bulkheads to be placed based on probabilistic damage stability calculations. Regulation already provides a subdivision of the ship shape, and the remaining space is further divided into equally shaped submeshes.

The mesh is subdivided by wall meshes and is used to cut the hull mesh into multiple complex submeshes. Additionally, to include watertight bulkheads and double hull walls and floors, an additional function re-evaluates if submeshes are small enough and adds walls parallel to the hull shape. This approach avoids slicing the mesh and capping along the slice, splitting the volume along wall locations, as this creates non-water-tight submeshes that can't be used for calculation. An example of the resulting wall-raster is shown in figure 5.5a and the result of the cut is shown in figure 5.5b.



(a) Example of wall mesh raster to cut the hull shape



(b) Example of a set of internal submeshes describing the hull shape

Submesh attributes, adjacency and connections

For each submesh, trimesh is used to calculate the centre of gravity, volume and the area along its faces. However, the topological relations between submeshes, such as the adjacent area to other submeshes and to the outside, still have to be defined. Grids are commonly used to investigate temporal physical behaviour, such as fluid dynamics (CFD) or material behaviour (finite elements). These methods describe their objects of interest using multiple elements that are connected using equations that describe attributes of each element and the transport of mass and energy at their edge. A similar approach is usedto describe the adjacent edges between submeshes and the outside.

To define the nearest intersection of a submesh face with other submeshes and the outside, Ray-tracing is used [283]. Ray tracing is often used in computer graphics for modelling light transport, but it also allows for identifying what submeshes intersect. It is especially useful because the cut submeshes are no longer touching, while face-sharing or mesh overlap approaches need submeshes to be touching. Each submesh is built out of triangular faces with a specific orientation (face normal). For each of these faces, ray tracing "shoots" a ray in the normal direction and checks if the ray hits a face from another submesh. If it does, the direction and the hit submesh are added to the submesh that the ray was shot from. The distance between these meshes is used to determine if submeshes are further away than the cut-wall thickness. When no submesh is within the cut-wall thickness threshold, the face is on the outside of the hull shape and depending on the direction, the face is added to a list that collects what faces are located on the outside along the three principal axes (x,y,z) or if it has an angled orientation (curved plating is more complex to manufacture).

System architecture components placement within the submesh

To determine how much of a component can fit inside a submesh, the placement algorithm cannot only rely on volumes. To approximate the number of components that fit within a submesh, a cell assignment approach is used. The submesh is divided into multiple cells or voxels, and a greedy algorithm is used to test how many voxelized components fit in each submesh to provide an upper bound for the number of systems that fit in a submesh U_{sv}. In other placement algorithms, object dimensions are used to identify how many cells of a fixed size are used for a system. However, the bounds of a submesh cannot be used for component selection, because these are cut from the ship shape, which results in complex and irregular shapes (e.g. L- or convex shapes).

5.2 Mathematical formulation of the initial system architecture

To connect the information from the system architecture and the ship shape description, the MILP is structured using functions that separately add constraints and objectives to the problem. This way, each part can independently be developed and verified. In the same manner, the main functions are described below.

System placement variables and constraints

Equations (5.1)–(5.7) ensure that all systems are allocated to feasible volumes with correct capacity and activation rules.

Sets. Systems $\mathcal{S}$ are placed into candidate submesh volumes $\mathcal{V}$. Subsets of systems are created that describe different placement rules. There are systems where an integer number can be placed, denoted by $\mathcal{S}^{\mathcal{I}}$, such as engines or switchboards. Alternatively, there are systems that are integrated into a volume, where a continuous volume can be placed $\mathcal{S}^{\mathcal{C}}$ that is a fraction of the submesh volume, like tanks. Additionally, some systems from the system architecture represent a connection to the outside or merely the presence of a system without required capacity, denoted $\mathcal{S}^{\mathcal{B}}$. For each system s, a set $\mathcal{H}_s$ defines what volume attributes should be avoided, for example, due to functional constraints or safety requirements.

$$
\begin{aligned}
\mathcal{S} &:= \text{set of systems (index } s), \\
\mathcal{V} &:= \text{set of candidate volumes (index } v), \\
\mathcal{S}^I &:= \{\, s \in \mathcal{S} \;:\; \texttt{type}(s) = \text{Integer} \,\}, \\
\mathcal{S}^C &:= \{\, s \in \mathcal{S} \;:\; \texttt{type}(s) = \text{Continuous} \,\}, \\
\mathcal{S}^B &:= \{\, s \in \mathcal{S} \;:\; \texttt{type}(s) = \text{Binary } and \texttt{Out}(s) = \text{True}, \}, \\
\mathcal{H}_s &:= \{ v \in \mathcal{V} \;:\; \text{volume } v \text{ must be avoided by system } s \}.
\end{aligned}
$$

Decision variables. Because a similar system can still be placed in multiple volumes, the placed capacity of each system in a volume is tracked using variables that depend on the system type: F^I_{sv} and F^C_{sv}. Additionally, the presence of any system type inside a volume is tracked using a binary variable X_{sv}. These are the decision variables,

$$
\begin{aligned}
&F^I_{sv} \geq 0 && \text{count of integer system } s \text{ in volume } v, \\
&F^C_{sv} \geq 0 && \text{volume of continuous system } s \text{ in volume } v, \\
&X_{sv} \in \{0, 1\} && \text{binary activation of system } s \text{ in volume } v.
\end{aligned}
$$

For $s \in \mathcal{S}_I$, the variable F^I_{sv} is integer; for $s \in \mathcal{S}_C$, F^C_{sv} is continuous.

Constraints. For systems in avoidance sets, placement is forbidden:

$$
F^I_{sv} = 0, \quad F^C_{sv} = 0, \qquad \forall s \in \mathcal{S},\ \forall v \in \mathcal{H}_s,\ \forall s \in \mathcal{H}_s. \tag{5.1}
$$

The continuous and integer placement variables are bounded above by the available capacity U_{sv} for system s in volume v:

$$
0 \leq F^I_{sv} \leq U_{sv} X_{sv}, \qquad \forall s \in \mathcal{S}_I,\ \forall v \notin \mathcal{H}_s, \tag{5.2}
$$

$$
0 \leq F^C_{sv} \leq U_{sv} X_{sv}, \qquad \forall s \in \mathcal{S}_C,\ \forall v \notin \mathcal{H}_s. \tag{5.3}
$$

To prevent degenerate activations where $X_{sv} = 1$ but the actual placement is zero, a strictly positive lower bound is imposed when a system is active:

$$
F^I_{sv} \geq X_{sv}, \qquad \forall s \in \mathcal{S}_I,\ \forall v \notin \mathcal{H}_s, \tag{5.4}
$$

$$
F^C_{sv} \geq \varepsilon_C X_{sv}, \qquad \forall s \in \mathcal{S}_C,\ \forall v \notin \mathcal{H}_s. \tag{5.5}
$$

where $\varepsilon_C = \frac{U_{sv}}{20}$ is a small positive constant.

Finally, the overall system requirements are enforced. For integer-type systems, the total number of units placed across all volumes must equal the required total count c_s:

$$
\sum_{v \in \mathcal{V}} F^I_{sv} = c_s, \qquad \forall s \in \mathcal{S}_I. \tag{5.6}
$$

For continuous-type systems, the sum of placements across all volumes must meet or exceed the required total capacity r_s:

$$\sum_{v \in \mathcal{V}} F^C_{sv} \geq r_s, \qquad \forall s \in \mathcal{S}_C. \tag{5.7}$$

A part of the $\mathcal{S}_B$ subset includes interfaces to the ship environment, such as ventilation outlets. These systems are modelled as binary nodes that connect the internal system architecture to the externalities. These are not assigned placement variables F^I_{sv} or F^C_{sv}, but are handled in the routing part of the model. As a result, outlet systems are excluded from the placement activation constraints and do not contribute to the totals in (5.6)–(5.7). This separation ensures that outlets are only created when required by the routing logic, avoiding unnecessary duplication in the placement formulation.

Routing constraints

An important aspect that reflects the relationship between systems inside a vessel is the way in which systems are connected. A literature survey describing the use of automatic pipe routing was used as a basis to investigate pipe routing methods that could be included in the mathematical programming setup [53]. The survey mostly considers detailed in-room routing with known system locations, including obstacles, while the placement algorithm considers unknown placement and global routing between submeshes. Therefore, operational flow constraints are used as these can be added as part of the mathematical programming used for placement. The graph defined network of nodes and edges describe the mapping relations of submeshes and their connections for each system, specifically the system-to-system connections. The graph representation also allows the use of branching and minimum spanning tree methods for pipe routing, but these proved to be too inflexible to combine with the placement setup (requiring solving a two-level optimisation). For each connection $c \in \mathcal{C}$, a flow is supplied from the location of a source system $c_{s^{\mathrm{src}}}$ to where a target system is located $c_{s^{\mathrm{tgt}}}$. The connection flows past intermediate submeshes, while making sure to take into account the set of rooms that the connection flow has to avoid by label $\mathcal{H}^V_c \subseteq \mathcal{V}$ (such as connections that are prohibited from placement in front of collision bulkheads or the double bottom) or by system $\mathcal{H}^S_c \subseteq \mathcal{S}$ (such as connections avoiding tank placement).

The flow is balanced and moves between the locations where the source and target systems are placed. The placement of systems provides the supply and demand locations. Equations (5.8)–(5.24) are used to reflect this in the routing constraints. Initially, the adjacent faces of each submesh were used to carry flow toward neighbouring submeshes. However, when many systems have to be connected together, it was found that only using access faces results in an overestimate of the connection distance. This is because each face-face connection is independent and internal overlapping sections are included multiple times. Furthermore, continuous systems like tanks are typically connected at the edge of a volume, so their flow can be represented by injecting/withdrawing at *access* faces of a submesh, while integer systems like engines are located inside a volume.

Sets. To enable the re-use of sections and reflect the behaviour of different systems, the input for the routing constraints was further extended to also include several internal *hub* nodes besides access nodes, as shown in Figure 5.6. The hub node (called helper in the right figure) is created using intermediate Steiner points that form edge routes based on Steiner trees by connecting faces (access nodes) and other hub nodes using Manhattan distance [83]. Consequently, the sets used in the routing constraints include;

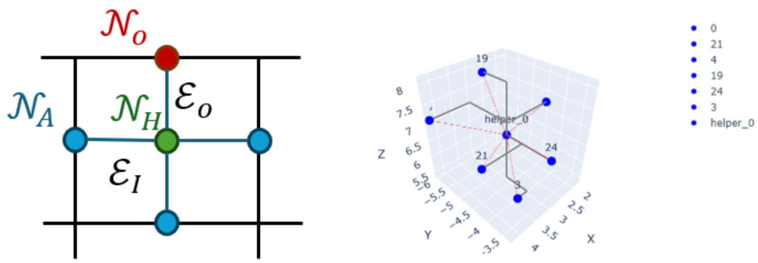


Figure 5.6: Intermediate Steiner point and tree to build hub and access nodes

$\mathcal{C}$:= set of connections c,

$\mathcal{N}_O(i)$:= set of outside nodes (access to OUT) from volume i,

$\mathcal{N}_A(i)$:= set of access nodes to adjacent neighbours j of volume i (adjacent faces),

$\mathcal{N}_H(i)$:= set of hub nodes in volume i,

$\mathcal{E}_I(i)$:= set of ordered internal edges (u,v) available within volume i,

$\mathcal{E}_A := \left\{\{(i,j),(j,i)\} : i \in \mathcal{V},\ j \in \mathcal{N}(i)\right\}$ (unordered access edges between neighbouring volumes).

Decision variables. For each connection, $c \in \mathcal{C}$ we build a signed flow on every internal edge $g^I_{c,i,(u,v)}$ and a signed flow per access edge $g^A_{c,\{(i,j),(j,i)\}}$. To avoid fake source/sink pairs, *signed injections* are used at access and hub nodes. The flow injection at a node is defined by placement (see (5.11)–(5.12)). Binary variables z are used to reflect pay-once edge and access choices.

$z^I_{c,i,(u,v)} \in \{0,1\}$	open internal stub $(u,v) \in \mathcal{E}_I(i)$ in room i,
$g^I_{c,i,(u,v)} \in [-M^{\text{flow}}_c, M^{\text{flow}}_c]$	signed internal flow on $(u,v) \in \mathcal{E}_I(i)$,
$g^A_{c,\{(i,j),(j,i)\}} \in [-M^{\text{flow}}_c, M^{\text{flow}}_c]$	signed access flow on $\{(i,j),(j,i)\} \in \mathcal{E}_A$,
$z^A_{c,\{(i,j),(j,i)\}} \in \{0,1\}$	access-open binary,
$z^O_{c,i} \in \{0,1\}$	open-to-outside binary for volume i if $\texttt{exit}_c = 1$,
$a_{c,i,j} \in [-M^{\text{gate}}_c, M^{\text{gate}}_c]$	signed access injection at node (i,j) with $j \in \mathcal{N}(i)$,
$h_{c,i,p} \in [-M^{\text{gate}}_c, M^{\text{gate}}_c]$	signed hub-node injection at $p \in \mathcal{N}_H(i)$,
$z^{\text{hub}}_{c,(i,j)} \in \{0,1\}$	(anchor mode) hub selection at access (i,j).

Section and access cost variables Binary variables are coupled to the signed flow variables using big-M gates. Internal flows are gated by their open binaries; access flows are gated by either an access-open binary or an outside-open binary:

$$+g^{\mathrm{I}}_{c,i,(u,v)} \le M^{\mathrm{gate}}_c\, z^{\mathrm{I}}_{c,i,(u,v)}, \qquad -g^{\mathrm{I}}_{c,i,(u,v)} \le M^{\mathrm{gate}}_c\, z^{\mathrm{I}}_{c,i,(u,v)}, \tag{5.8}$$

$$+g^{\mathrm{A}}_{c,\{(i,j),(j,i)\}} \le M^{\mathrm{gate}}_c\, z^{\mathrm{A}}_{c,\{(i,j),(j,i)\}}, \quad -g^{\mathrm{A}}_{c,\{(i,j),(j,i)\}} \le M^{\mathrm{gate}}_c\, z^{\mathrm{A}}_{c,\{(i,j),(j,i)\}}, \quad \text{if } \mathrm{N_O} \notin \{i,j\}, \tag{5.9}$$

$$+g^{\mathrm{A}}_{c,\{(i,\mathrm{N_O}),(\mathrm{N_O},i)\}} \le M^{\mathrm{gate}}_c\, z^{\mathrm{O}}_{c,i}, \quad -g^{\mathrm{A}}_{c,\{(i,\mathrm{N_O}),(\mathrm{N_O},i)\}} \le M^{\mathrm{gate}}_c\, z^{\mathrm{O}}_{c,i}, \quad \text{if } \mathtt{exit}_c = 1. \tag{5.10}$$

Flow constraint routing behaviour The flow constraint aims to satisfy the demanded flow at each target, while minimising connection cost. Because of this, if the flow constraint is used as is, the routing will only connect the number of systems that are necessary to provide the demand flow. As shown in Figure 5.7, when multiple source and target systems exist, this per-pair routing behaviour results in pairs of systems being connected. However, when all systems need to be connected, this underestimates the connection length. As such, an anchor routing mode is also developed where the total demand is assigned to one selected hub node that is located in the same room as the system placement.

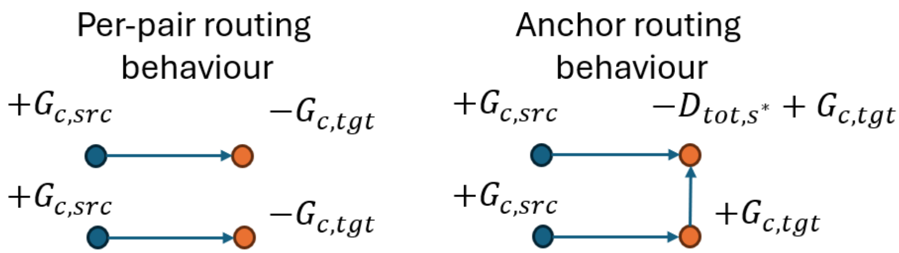


Figure 5.7: Per pair routing behaviour and adding an anchor

Per-pair mode. For continuous systems, supply/demand is added at access nodes; for integer systems, supply/demand is added at hub nodes. We use *signed* injections and gate their sign by placement presence:

$$+a_{c,i,j} \le M^{\mathrm{gate}}_c\, X_{s^{\mathrm{tgt}},i}, \qquad -a_{c,i,j} \le M^{\mathrm{gate}}_c\, X_{s^{\mathrm{src}},i}, \tag{5.11}$$

$$+h_{c,i,p} \le M^{\mathrm{gate}}_c\, X_{s^{\mathrm{tgt}},i}, \qquad -h_{c,i,p} \le M^{\mathrm{gate}}_c\, X_{s^{\mathrm{src}},i}. \tag{5.12}$$

The net access injection plus the net hub-node injection must equal the total room flow. To make sure the flow between systems is defined using their placed volume. The total demand/supply flow is normalised with scaling factors α^{s}_c and α^{t}_c to improve solvability of the model:

$$q_c(i) := \alpha^{\mathrm{t}}_c F_{s^{\mathrm{tgt}},i} - \alpha^{\mathrm{s}}_c F_{s^{\mathrm{src}},i}. \tag{5.13}$$

For each room $i \notin \mathcal{H}_c$,

$$\sum_{\substack{j \in \mathcal{N}(i) \\ (\mathrm{N_O} \notin \{i,j\} \vee \mathtt{exit}_c = 1)}} a_{c,i,j} + \sum_{p \in \mathcal{N}_H(i)} h_{c,i,p} = q_c(i). \tag{5.14}$$

Anchor mode. Introduces a unique anchor selection at an access node and allocates a supply to match the total volume of source and target systems placed in the ship:

$$\sum_{\substack{j\in\mathcal{N}(i)\\ i\notin\mathcal{H}_c,\ (N_O\notin\{i,j\}\vee\texttt{exit}_c=1)}} z^{\text{hub}}_{c,(i,j)} \le F_{s^\star,i}, \quad \text{(anchor gating)}, \qquad \sum_{(i,j)} z^{\text{hub}}_{c,(i,j)} = 1, \tag{5.15}$$

$$h_{c,i} \le M^{\text{gate}}_c \sum_{j\in\mathcal{N}(i)} z^{\text{hub}}_{c,(i,j)}, \qquad \sum_{i\in\mathcal{V}\setminus\mathcal{H}_c} h_{c,i} = D^{\text{tot}}_c. \tag{5.16}$$

Here $s^\star$ is the anchor system, and D^{tot}_c is the sum of system volume defined by placement:

$$D^{\text{C}}_{c,i} = \alpha^{\text{t}}_c F_{s^{\text{tgt}},i} + \alpha^{\text{s}}_c F_{s^{\text{src}},i}, \tag{5.17}$$

$$D^{\text{I}}_{c,i} = \alpha^{\text{t}}_c F_{s^{\text{tgt}},i} + \alpha^{\text{s}}_c F_{s^{\text{src}},i}, \tag{5.18}$$

$$D^{\text{tot}}_{c,i} = D^{\text{C}}_{c,i} + D^{\text{I}}_{c,i}, \qquad D^{\text{tot}}_c = \sum_i D^{\text{tot}}_{c,i}. \tag{5.19}$$

Access demand is split across accesses, but *not* at the selected anchor:

$$\sum_{j\in\mathcal{N}(i)} a^+_{c,i,j} = D^{\text{C}}_{c,i}, \qquad a^+_{c,i,j} \le M^{\text{gate}}_c \left(1 - z^{\text{hub}}_{c,(i,j)}\right). \tag{5.20}$$

Hub demand is split across hub nodes and gated by integer system presence:

$$\sum_{p\in\mathcal{N}_H(i)} h^+_{c,i,p} = D^{\text{I}}_{c,i}, \qquad h^+_{c,i,p} \le M^{\text{gate}}_c X_{s^{\text{tgt}}_c,i}. \tag{5.21}$$

Hub supply is pushed out only via the selected access at each room:

$$\sum_{j\in\mathcal{N}(i)} a^-_{c,i,j} = h_{c,i}, \qquad a^-_{c,i,j} \le M^{\text{gate}}_c z^{\text{hub}}_{c,(i,j)}. \tag{5.22}$$

Here a^+, a^-, h^+ are nonnegative split variables used only in anchor mode; their signed counterparts are $a = a^+ - a^-$ and $h = h^+$ (hub emits demand only).

Flow conservation (signed divergence). To make sure the system placement forces flow, for any internal node N (an access node or a hub node inside i), define the internal divergence

$$\operatorname{div}^{\text{int}}_{c,i}(n) := \sum_{(u,v)\in\mathcal{E}_I(i)} \big([v=n]-[u=n]\big)\, g^{\text{I}}_{c,i,(u,v)}.$$

Then for:

(a) Access nodes. For every access node (i,j) with $i\notin\mathcal{H}_c$ and $j\in\mathcal{N}(i)$, let the access flow $g^{\text{A}}_{c,\{(i,j),(j,i)\}}$ be oriented from $(\min\{i,j\},\max\{i,j\})$ to its counterpart; its contribution at (i,j) is $+g$ if (i,j) is the head and $-g$ otherwise. Flow balance is

$$\operatorname{div}^{\text{int}}_{c,i}\big((i,j)\big) \;+\; \operatorname{div}^{\text{acc}}_c\big((i,j)\big) \;=\; a_{c,i,j}. \tag{5.23}$$

(b) Hub nodes. For each $p\in\mathcal{N}_H(i)$,

$$\operatorname{div}^{\text{int}}_{c,i}(p) \;=\; h_{c,i,p}. \tag{5.24}$$

Co-location of integer systems So far, the routing constraint only considers routing between submeshes. However, when systems connected by c are placed within the same volume, a connection should also be included. The binary $y^{\text{same}}_{c,v}$ captures integer co-location at the room level via a standard three-inequality AND constraints. It is defined only for integer–integer connections $\mathcal{C}_{\text{I}}$. Equations (5.25)–(5.27) define a binary indicator that is one exactly when the source and target systems of a connection are placed in the same room.

Sets.

$$\begin{aligned} \mathcal{C} &:= \text{set of connections (index } c\text{)}, \\ s_c^{\text{src}}, s_c^{\text{tgt}} &:= \text{source and target system of connection } c, \\ \mathcal{C}_{\text{I}} &:= \{\, c \in \mathcal{C} : \ s^{\text{src}} \in \mathcal{S}_I \cap \mathcal{S},\ s^{\text{tgt}} \in \mathcal{S}_I \cap \mathcal{S} \,\}. \end{aligned}$$

Decision variable.

$$y^{\text{same}}_{c,v} \in \{0,1\} \qquad \text{for } c \in \mathcal{C}_{\text{I}},\ v \in \mathcal{V},$$

5

which is intended to be 1 if both source and target systems of the connection c are present in room v.

Constraints. Let $X_{sv} \in \{0,1\}$ be the placement activation of system s in room v (from the placement section). The logical AND is enforced by:

$$y^{\text{same}}_{c,v} \le X_{s_c^{\text{src}},v}, \qquad \forall c \in \mathcal{C}_{\text{eng}},\ \forall v \in \mathcal{V}, \tag{5.25}$$

$$y^{\text{same}}_{c,v} \le X_{s_c^{\text{tgt}},v}, \qquad \forall c \in \mathcal{C}_{\text{eng}},\ \forall v \in \mathcal{V}, \tag{5.26}$$

$$y^{\text{same}}_{c,v} \ge X_{s_c^{\text{src}},v} + X_{s_c^{\text{tgt}},v} - 1, \qquad \forall c \in \mathcal{C}_{\text{eng}},\ \forall v \in \mathcal{V}. \tag{5.27}$$

If either activation variable is structurally undefined for a given (s,v) (i.e. the system cannot be placed in the room v), it is treated as identically zero so that (5.25)–(5.27) remain valid.

WALL AND PARTITION CONSTRAINTS

Equations (5.28)–(5.46) enforce wall logic: (i) room–outside interfaces add an extra exterior layer only when required and with the correct cavity depth, (ii) in-room separations cover continuous–integer coexistence, single- and double-pair rules, and the partial-continuous rule, and (iii) room–room interfaces default to a single layer, with an optional second layer triggered by specific system pairs. Exterior faces add exactly one extra layer when demanded by present systems and size the cavity to the maximum required depth among active triggers (Eqs. (5.28)–(5.31)). Inside rooms, the baseline counter W_v^{base} covers continuous–integer coexistence (5.34), single pairs (5.35), and the base part of double pairs (5.37); W_v^{extra} records additional layers for double pairs. The partial-continuous rule (5.38)–(5.42) ensures that any partially filled continuous system forces at least one baseline partition. Between rooms, faces are single by default and become doubled only when cross-room pairs are active; any required clearance depth is captured by (5.46). The cavity volumes $V^{\text{air}}_{\text{cav},v}$ and $V^{\text{sea}}_{\text{cav},v}$ can be subtracted in the room balances.

Sets.

$$
\begin{aligned}
\mathcal{H}_W^S &:= \text{single separation wall required for } s \text{ when co-existing in a volume with a system or label},\\
\mathcal{H}_W^D &:= \text{double separation wall required for } s \text{ when co-existing in a volume with a system or label},\\
\mathcal{H}_O^A &:= \text{additional wall required for } s \text{ when co-existing in a volume with outside wall to air},\\
\mathcal{H}_O^S &:= \text{additional wall required for } s \text{ when co-existing in a volume with outside wall to seawater},\\
\mathcal{F} &:= \{\{i,j\} : \text{unordered adjacent room pairs (faces)},\ i,j \in \mathcal{V},\ i \neq j\}.
\end{aligned}
$$

Parameters.

$$
\begin{aligned}
A_v^{\text{air}} &:= \text{dry (outside-air) face area of room } v,\\
A_v^{\text{sea}} &:= \text{wet (seawater) face area of room } v,\\
d_s^{\text{air}} &:= \text{required AIR cavity depth for system } s \in \mathcal{H}_O^A,\\
d_s^{\text{sea}} &:= \text{required SEAWATER cavity depth for system } s \in \mathcal{H}_O^S,\\
d_{s_1 s_2}^{\text{edge}} &:= \text{required clearance depth across a room–room face for pair } (s_1, s_2) \in \mathcal{H}_W^D,\\
\tau &:= 0.02 \text{ (tolerance for “full” fill)}.
\end{aligned}
$$

Define big-M bounds for exterior cavity depths:

$$
M_{\text{air}} := \max_{s \in \mathcal{H}_O^A} d_s^{\text{air}}, \qquad M_{\text{sea}} := \max_{s \in \mathcal{H}_O^S} d_s^{\text{sea}}.
$$

Decision variables.

$W_v^{\text{base}} \in \mathbb{Z}_{\geq 0}$	number of baseline (single) internal partitions in room v,
$W_v^{\text{extra}} \in \mathbb{Z}_{\geq 0}$	number of additional (double) internal partitions in room v,
$W_v^{\text{air}} \in \{0,1\}$	whether room v has an extra exterior AIR layer,
$W_v^{\text{sea}} \in \{0,1\}$	whether room v has an extra exterior SEA layer,
$D_v^{\text{air}} \geq 0$	AIR cavity depth at the exterior face of room v,
$D_v^{\text{sea}} \geq 0$	SEA cavity depth at the exterior face of room v,
$W_{ij}^{\text{dbl}} \in \{0,1\}$	whether the face between adjacent rooms i, j is doubled,
$D_{ij}^{\text{edge}} \geq 0$	clearance depth assigned to the face $\{i,j\} \in \mathcal{F}$.

We reuse the placement flags $X_{sv} \in \{0,1\}$ and placements F_{sv}^C, F_{sv}^I from the previous subsections.

Room–outside faces: on/off logic with depths. If a system that requires an AIR or SEA double is present in a room exposed to AIR or SEA, the extra exterior layer must be active, and the cavity depth must not be smaller than the system's requirement:

$$
D_v^{\text{air}} \geq d_s^{\text{air}} X_{sv}, \quad W_v^{\text{air}} \geq X_{sv}, \qquad \forall v,\ \forall s \in \mathcal{H}_O^A \text{ with } A_v^{\text{air}} > 0, \tag{5.28}
$$

Symmetrically for seawater:

$$D_v^{\text{sea}} \geq d_s^{\text{sea}} X_{sv}, \quad W_v^{\text{sea}} \geq X_{sv}, \qquad \forall v,\ \forall s \in \mathcal{H}_O^S \text{ with } A_v^{\text{sea}} > 0. \tag{5.29}$$

If no such systems are present, the extra layer must be off and the depth zero; big-M bounds implement this cleanly:

$$W_v^{\text{air}} \leq \sum_{s \in \mathcal{H}_O^A} X_{sv}, \qquad D_v^{\text{air}} \leq M_{\text{air}} W_v^{\text{air}}, \qquad \forall v \text{ with } A_v^{\text{air}} > 0, \tag{5.30}$$

$$W_v^{\text{sea}} \leq \sum_{s \in \mathcal{H}_O^S} X_{sv}, \qquad D_v^{\text{sea}} \leq M_{\text{sea}} W_v^{\text{sea}}, \qquad \forall v \text{ with } A_v^{\text{sea}} > 0. \tag{5.31}$$

For later volume balances, the resulting exterior cavity volumes are

$$V_{\text{cav},v}^{\text{air}} := A_v^{\text{air}} D_v^{\text{air}}, \qquad V_{\text{cav},v}^{\text{sea}} := A_v^{\text{sea}} D_v^{\text{sea}}.$$

5

In-room partitions: tanks, pairs, and partial-tank rule. First, when tanks and engines co-exist, baseline partitions must separate them and also separate multiple tanks if present. Using an “any-engine” indicator $Y_v^E \in \{0, 1\}$,

$$W_v^I \geq X_{sv} \qquad \forall v,\ \forall s \in \mathcal{S}^I, \tag{5.32}$$

$$W_v^I \leq \sum_{s \in \mathcal{S}^I} X_{sv} \qquad \forall v, \tag{5.33}$$

$$W_v^{\text{base}} \geq \sum_{s \in \mathcal{S}^C} X_{sv} + W_v^I - 1 \qquad \forall v. \tag{5.34}$$

Second, single separation pairs add at least one baseline partition whenever both systems are present in the same room:

$$W_v^{\text{base}} \ \geq\ X_{s_1 v} + X_{s_2 v} - 1, \qquad \forall v,\ \forall (s_1, s_2) \in \mathcal{H}_W^S. \tag{5.35}$$

Third, double separation pairs require both a baseline and an extra partition. Introduce $Y_{s_1 s_2 v}^D \in \{0, 1\}$ to implement an AND:

$$W_{s_1 s_2 v}^D \leq X_{s_1 v}, \quad W_{s_1 s_2 v}^D \leq X_{s_2 v}, \quad W_{s_1 s_2 v}^D \geq X_{s_1 v} + X_{s_2 v} - 1, \qquad \forall v,\ (s_1, s_2) \in \mathcal{H}_W^D, \tag{5.36}$$

$$W_v^{\text{base}} \geq W_{s_1 s_2 v}^D, \qquad W_v^{\text{extra}} \geq W_{s_1 s_2 v}^D, \qquad \forall v,\ (s_1, s_2) \in \mathcal{H}_W^D. \tag{5.37}$$

Finally, enforce the partial-tank rule: if a tank in room v is *not* filled to (at least) a $(1 - \tau)$ fraction of room capacity, then at least one baseline partition is required. Let

$$F_{sv}^C \geq (1 - \tau)\, \text{cap}_v F_{sv}^{\text{full}}, \qquad \forall v,\ \forall s \in \mathcal{S}^C, \tag{5.38}$$

$$F_{sv}^{\text{full}} \leq X_{sv}, \qquad \forall v,\ \forall s \in \mathcal{S}^C, \tag{5.39}$$

$$F_{sv}^{\text{part}} \geq X_{sv} - F_{sv}^{\text{full}}, \quad F_{sv}^{\text{part}} \leq X_{sv}, \quad F_{sv}^{\text{part}} \leq 1 - F_{sv}^{\text{full}}, \qquad \forall v,\ \forall s \in \mathcal{S}^C, \tag{5.40}$$

$$F_v^{\text{part}} \geq F_{sv}^{\text{part}}, \qquad \forall v,\ \forall s \in \mathcal{S}^C, \tag{5.41}$$

$$W_v^{\text{base}} \geq F_v^{\text{part}}, \qquad \forall v. \tag{5.42}$$

Room–room faces: baseline single, optional double and depth. Every room–room interface defaults to a single layer; the binary x_{ij}^{dbl} adds the second layer when required by cross-room system pairs. For each adjacent face $\{i,j\} \in \mathcal{E}$ and each double pair $(s_1, s_2) \in \mathcal{P}^D$, the trigger is active if s_1 is present in one room and s_2 in the other (either direction). Using two AND indicators $Y^{12}_{s_1 s_2, ij}, Y^{21}_{s_1 s_2, ij} \in \{0,1\}$,

$$F^{12}_{s_1 s_2, ij} \le X_{s_1 i}, \quad F^{12}_{s_1 s_2, ij} \le X_{s_2 j}, \quad F^{12}_{s_1 s_2, ij} \ge X_{s_1 i} + X_{s_2 j} - 1, \tag{5.43}$$

$$F^{21}_{s_1 s_2, ij} \le X_{s_1 j}, \quad F^{21}_{s_1 s_2, ij} \le X_{s_2 i}, \quad F^{21}_{s_1 s_2, ij} \ge X_{s_1 j} + X_{s_2 i} - 1, \tag{5.44}$$

$$W_{ij}^{\text{dbl}} \ge F^{12}_{s_1 s_2, ij}, \qquad W_{ij}^{\text{dbl}} \ge F^{21}_{s_1 s_2, ij}, \qquad \forall \{i,j\} \in \mathcal{F},\ (s_1, s_2) \in \mathcal{H}^D_W. \tag{5.45}$$

If a depth requirement applies across the face, accumulate it with big-M-free lower bounds:

$$D_{ij}^{\text{edge}} \ \ge\ d^{\text{edge}}_{s_1 s_2} F^{12}_{s_1 s_2, ij}, \qquad D_{ij}^{\text{edge}} \ \ge\ d^{\text{edge}}_{s_1 s_2} F^{21}_{s_1 s_2, ij}, \quad \forall \{i,j\} \in \mathcal{F},\ (s_1, s_2) \in \mathcal{H}^D_W. \tag{5.46}$$

Stability and capacity constraints

The stability block balances longitudinal moments caused by the distributed system masses and, when active, adjusts with ballast according to standard MCT and TPC conventions (Eqs. (5.50)–(5.54)) [34, 73]. Furthermore, transverse balance (5.55) constrains the mass moment about the centreline as a small fraction of the beam. Equations (5.49)–(5.57) ensure global longitudinal/vertical stability and transverse balance while (5.59) enforces that volume in a room is not exceeded, including systems, connections, and cofferdams.

Multiple parameters that are dictated by the ship shape or that have been calculated using the hull shape mesh are needed for weight and stability equations [34].

$$
\begin{aligned}
L, B &:= \text{ship length and beam},\\
\text{LCB} &:= \text{longitudinal centre of buoyancy},\\
\text{MCT} &:= \text{moment to change trim by 1 cm},\\
\text{TPC} &:= \text{tons per cm immersion},\\
\text{Displ} &:= \text{displacement limit},\\
\text{LWT} &:= \text{lightship weight},\\
\text{KG}_{\text{max}} &:= \text{maximum admissible vertical KG},\\
\text{KG}_{\text{LWT}} &:= \text{lightship KG},\\
\rho &:= \text{seawater density (default 1.025 t/m}^3\text{)},\\
\alpha_t &:= \text{ Maximum tank filling factor},\\
C_i &:= \text{geometric capacity of room } i \text{ (volume minus reserves)},\\
(x_i, y_i, z_i) &:= \text{centroid of room } i,\\
w_s &:= \text{weight per unit (integer) or per m}^3 \text{ (continuous) for system } s,\\
v_s^{\text{I}} &:= \text{volume per integer system unit .}
\end{aligned}
$$

Global weight (displacement) constraint. Let s^{bal} denote the ballast tank system. The (effective) ballast mass per room is

$$M_v^{\text{bal}} \ :=\ \alpha_b\, \rho\, F^C_{s^{\text{bal}} v}, \tag{5.47}$$

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and the mass of all *other* placed systems per room is

$$M_v^{\text{sys}} := \sum_{s \in \mathcal{S}_E} w_s F_{sv}^I + \sum_{\substack{s \in \mathcal{S}_T \\ s \neq s^{\text{bal}}}} w_s F_{sv}^C. \tag{5.48}$$

With total system mass $\sum_v M_v^{\text{sys}}$ and lightship LWT, the displacement limit reads

$$\sum_{v \in \mathcal{V}} M_v^{\text{sys}} + \text{LWT} \leq \text{Displ}. \tag{5.49}$$

System-only longitudinal trim. Define the longitudinal moment of the system masses about LCB and translate it into aft and forward draft changes (T_a, T_f) using the standard MCT scaling (cm) and the longitudinal lever arms:

$$T_a := \frac{1}{100} \sum_{v \in \mathcal{V}} \frac{-\text{LCB}}{L} \frac{M_v^{\text{sys}} (x_v - \text{LCB})}{\text{MCT}}, \qquad T_f := \frac{1}{100} \sum_{v \in \mathcal{V}} \frac{L - \text{LCB}}{L} \frac{M_v^{\text{sys}} (x_v - \text{LCB})}{\text{MCT}}, \tag{5.50}$$

and bound the trim difference according to [73]:

$$-\frac{3L}{100} \leq T_f - T_a \leq \frac{1.5L}{100}. \tag{5.51}$$

Ballast-assisted longitudinal trim. Including ballast and a TPC immersion correction term, define

$$T_a^{\text{bal}} := \frac{1}{100} \sum_v \left[\frac{-\text{LCB}}{L} \frac{\left(M_v^{\text{bal}} - M_v^{\text{sys}}\right)(x_v - \text{LCB})}{\text{MCT}} - \frac{M_v^{\text{bal}} - M_v^{\text{sys}}}{\text{TPC}} \right], \tag{5.52}$$

$$T_f^{\text{bal}} := \frac{1}{100} \sum_v \left[\frac{L - \text{LCB}}{L} \frac{\left(M_v^{\text{bal}} - M_v^{\text{sys}}\right)(x_v - \text{LCB})}{\text{MCT}} - \frac{M_v^{\text{bal}} - M_v^{\text{sys}}}{\text{TPC}} \right], \tag{5.53}$$

and impose the same bounds:

$$-\frac{3L}{100} \leq T_f^{\text{bal}} - T_a^{\text{bal}} \leq \frac{1.5L}{100}. \tag{5.54}$$

Transverse balance (roll/list). The transverse mass moment about the centreline is constrained as a small fraction $\varepsilon_{trans} = 0.005$ of the beam:

$$-\varepsilon_{trans} B \sum_v \left(M_v^{\text{f}} + M_v^{\text{bal}}\right) \leq \sum_v \left(M_v^{\text{f}} + M_v^{\text{bal}}\right) y_v \leq \varepsilon_{trans} B \sum_v \left(M_v^{\text{f}} + M_v^{\text{bal}}\right). \tag{5.55}$$

Vertical KG stability. The vertical KG condition (5.57) caps the combined KG of lightship and placed systems. Let the vertical mass moment of all placed systems be

$$\text{KG}^{\text{sys}} := \sum_{s \in \mathcal{S}_E} \sum_v w_s F_{sv}^I \, \text{VCG}_s(v) + \sum_{s \in \mathcal{S}_T} \sum_v w_s F_{sv}^C \, \text{VCG}_s(v), \tag{5.56}$$

where $\mathrm{VCG}_s(v)$ equals the system's given VCG when available, otherwise the room height $\frac{z_i}{2}$. With total system mass $M^{\mathrm{tot}}_{\mathrm{sys}} := \sum_v M^{\mathrm{sys}}_v$, the global KG limit reads

$$\mathrm{KG}^{\mathrm{sys}} + \mathrm{LWT}\,\mathrm{KG}_{\mathrm{LWT}} \leq \mathrm{KG}_{\max}\left(M^{\mathrm{tot}}_{\mathrm{sys}} + \mathrm{LWT}\right). \tag{5.57}$$

Room capacity accounting. For each room i, let the integer system volume be $V^{\mathrm{I}}_{sv} := v^{\mathrm{I}}_s F^{I}_{sv}$ (for $s \in \mathcal{S}_E$), the continuous system volume be $V^{\mathrm{C}}_{sv} := F^{C}_{sv}$, and V^{conn}_v collect connection/tunnel volumes (internal openings) computed from the connection decisions.

We also reuse the cofferdam volumes from the wall section,

$$V^{\mathrm{cav}}_v := V^{\mathrm{air}}_{\mathrm{cav},v} + V^{\mathrm{sea}}_{\mathrm{cav},v}. \tag{5.58}$$

Finally, per-room capacity (5.59) ensures that engine volumes, tanks, connections, and cofferdams fit within the net available space. Let R_v be the freed space from removals (legacy systems/tanks taken out). Then the per-room capacity constraint is

$$\sum_{s \in \mathcal{S}_I} V^{\mathrm{I}}_{sv} + \sum_{s \in \mathcal{S}_C} V^{\mathrm{C}}_{sv} + V^{\mathrm{conn}}_v + V^{\mathrm{cav}}_v \leq C_v + R_v, \qquad \forall v \in \mathcal{V}. \tag{5.59}$$

5

Objective function

The objective function is used to guide placement. It combines all additional material costs and hours to integrate systems S and connections C into the ship shape. As such, it can use all decision variables created in the constraint functions and can be extended with cost estimates from a shipyard or design bureau. As a start, multiple objective functions are added that mirror the constraint functions. Equations (5.60)–(5.69) define cost functions that aggregate walls and partitions, piping (hours and materials), access/opening work, co-location penalties, and tank conservation.

Parameters.

$$\begin{aligned}
A^{\mathrm{cut}}_v &:= \text{minimum full internal cut area in room } v,\\
A^{\mathrm{air}}_v,\ A^{\mathrm{sea}}_v &:= \text{outside face areas (dry/wet) of room } v,\\
A_{ij},\ K_{ij} &:= \text{area and complexity factor of the shared face between rooms } i \text{ and } j,\\
c^{\mathrm{wall}} &:= \text{unit wall cost (currency per m}^2),\\
c^{\mathrm{hr}} &:= \text{hourly labour rate}, \quad k_c := \text{connection complexity multiplier } (\texttt{cost}),\\
c^{\mathrm{mat}} &:= \text{pipe material cost per inch}\cdot\text{m},\\
L^{\mathrm{out}}_i &:= \text{outside pipe clearance height from room } i \text{ to OUT (if present)},\\
\Delta_v &:= C_v^{1/3} \quad \text{(room characteristic length for co-location)},\\
c^{\mathrm{paint}} &:= \text{tank conservation (painting) cost per m}^3.
\end{aligned}$$

As pipe costs are typically described using inch·m, the connection diameter is transformed to inches. We reuse the wall variables and routing variables from previous subsections. Additionally, when penalising integer system co-location, we use $y^{\mathrm{same}}_{c,v} \in \{0,1\}$ which is set to one if both source and target engines of connection c are placed in the same room v (see the co-location logic).

Wall costs. *Internal partitions.* Each full internal cut (baseline plus extra) in the room v carries a cost proportional to the added wall area A_v^{cut}:

$$C^{\text{wall-int}} = c^{\text{wall}} \sum_{v\in\mathcal{V}} \left(W_v^{\text{base}} + W_v^{\text{extra}} \right) A_v^{\text{cut}}. \tag{5.60}$$

Exterior extra layers. Added AIR/SEA layers are charged by outside area:

$$C^{\text{wall-ext}} = c^{\text{wall}} \sum_{v\in\mathcal{V}} \left(W_v^{\text{air}} A_v^{\text{air}} + W_v^{\text{sea}} A_v^{\text{sea}} \right). \tag{5.61}$$

Room–room extra layer. The second layer on a shared face $\{i,j\}$ is charged once and scaled by a complexity factor:

$$C^{\text{edge}} = c^{\text{wall}} \sum_{\{i,j\}} W_{ij}^{\text{dbl}} A_{ij} K_{ij}. \tag{5.62}$$

Piping and openings. *Pipe labour (hours).* For each connection c, internal runs are charged by length; if a system is connected to the externality, it should include an additional length to ensure clearance:

$$C^{\text{pipe-hr}} = c^{\text{hr}} \sum_c k_c \sum_i \sum_{(u,v)\in\mathcal{E}_I(i)} z^I_{c,i,(u,v)} \left(\mathbf{1}_{\{u=\text{OUT}\vee v=\text{OUT}\}} L_i^{\text{out}} \right). \tag{5.63}$$

Pipe materials. Only for pipe-type connections $c \in \mathcal{C}_{\text{pipe}}$:

$$C^{\text{pipe-mat}} = c^{\text{mat}} \sum_{c\in\mathcal{C}_{\text{pipe}}} d_c^{\text{inch}} \sum_i \sum_{(u,v)\in\mathcal{E}_I(i)} z^I_{c,i,(u,v)} \left(\mathbf{1}_{\{u=\text{OUT}\vee v=\text{OUT}\}} L_i^{\text{out}} \right). \tag{5.64}$$

Wall openings to OUT and access. Per-room outside openings and (if used) access openings are charged as fixed hours:

$$C^{\text{open}} = c^{\text{hr}} \sum_c k_c \left(3 \sum_i z^O_{c,i} + 3 \sum_{\{(i,j),(j,i)\}\in\mathcal{E}_A} z^A_{c,\{(i,j),(j,i)\}} \right). \tag{5.65}$$

Here $\mathcal{A}_c$ is the (optional) set of access openings for connection c with binaries $y_{c,a}^{\text{acc}}$.

co-location penalty (engines in the same room). Let $\mathcal{C}_{\text{eng}}$ be the set of connections whose source and target are integer-type engines. The penalty scales with a room length $\Delta_v = C_v^{1/3}$:

$$C^{\text{same-hr}} = c^{\text{hr}} \sum_{c\in\mathcal{C}_{\text{eng}}} k_c \sum_{v\in\mathcal{V}} \Delta_v \, y_{c,v}^{\text{same}}, \tag{5.66}$$

$$C^{\text{same-mat}} = c^{\text{mat}} \sum_{c\in\mathcal{C}_{\text{eng}}\cap\mathcal{C}_{\text{pipe}}} d_c^{\text{inch}} \sum_{v\in\mathcal{V}} \Delta_v \, y_{c,v}^{\text{same}}. \tag{5.67}$$

Tank conservation (painting).

$$C^{\text{paint}} = c^{\text{paint}} \sum_{s \in \mathcal{S}_T} \sum_{v \in \mathcal{V}} F^C_{sv}. \tag{5.68}$$

Total objective. The model minimises the sum of all active components:

$$\min\ C = C^{\text{wall-int}} + C^{\text{wall-ext}} + C^{\text{edge}} + C^{\text{pipe-hr}} + C^{\text{pipe-mat}} + C^{\text{open}} + C^{\text{same-hr}} + C^{\text{same-mat}} + C^{\text{paint}}. \tag{5.69}$$

If some components are not present in a given instance, the corresponding sums vanish, and the objective reduces accordingly.

5.2.1 Example output

The placement algorithm receives a list of system architecture components and connections from the what module. Besides system components and connecting pipes and cables, an additional table of safety requirements is input to constrain the placement of systems and add the required number of walls to separate systems from the marine environment or other systems. Pipe and cable material and labour costs are calculated using the distance between systems and the number of walls crossed. The wall surface inside a compartment is used to estimate conservation paint cost, and additional separation surfaces are used for wall material and labour cost. These cost penalties, with the constraints described above, force placement that is compliant while minimising system architecture location and connection cost. Figure 5.8 shows an example of a conventional diesel electric system architecture placed inside a reference bulk carrier ship shape. The output from the placement algorithm provides system locations, volume and connections within and between compartments. Besides guiding placement, the different cost categories provide insight into the main contributors to initial cost.

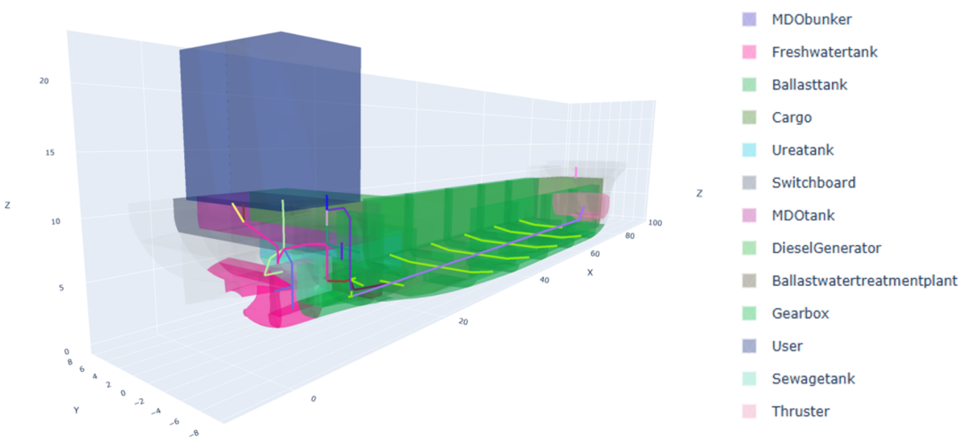

Figure 5.8: Example of systems and connections placed inside a reference ship.

5.3 Mathematical formulation of a retrofit

So far, the setup only considers the initial placement of any system architecture. However, to investigate how ships can be prepared to accommodate changes, the algorithm needs to be extended to prepare the initial placement and compare it with future placements. To describe system retrofits, the graph-aided MILP is extended to consider two stages. Both the initial and target system architectures are loaded from the system network algorithm, including every node (system) and edge (connection). For the initial system architecture placement, most of the MILP code is reused, but parts are extended to enable taking future system changes into account. Below, the changes and additions to each constraint are discussed. It covers adding new systems and removal variables for the initial placement variables. The new system architecture largely uses the same constraint functions as before, like stability, routing and wall constraints that still need to be satisfied in the retrofit placement. However, as some systems might be removed or remain from the initial system architecture, we need to include them in the second stage constraints as well.

5.3.1 Two-stage system placement

5

The placement formulation is extended to a two-stage setting in order to distinguish between (i) an *initial placement* of systems and (ii) the *final placement* after possible removals and additions of systems. This extension allows the optimisation to represent refit scenarios or incremental design updates while ensuring that initial allocations remain feasible.

Stage 1: Initial placement. For each system in the first stage, systems in the first stage system architecture $s \in \mathcal{S}^{\nmid}$ and candidate volume $v \in \mathcal{V}$, we define initial placement variables that describe placement and preplacement by using the total system set at stage 1 $S^{T,1} \subseteq S^1 \cup S^2$:

$$
\begin{aligned}
F_{sv}^{I,\mathrm{T},1} &\geq 0 && \text{integer units of system } s \text{ initially placed in } v, \\
F_{sv}^{C,\mathrm{T},1} &\geq 0 && \text{continuous volume of system } s \text{ initially placed in } v, \\
X_{sv}^{\mathrm{T},1} &\in \{0,1\} && \text{initial activation of system } s \text{ in } v.
\end{aligned}
$$

These are governed by the same avoidance and capacity bounds as in Eqs. (5.1)–(5.5). The system totals for the first stage system architecture are enforced per system:

$$\sum_{v \in \mathcal{V}} F_{sv}^{I,1} = c_s^1, \qquad \forall s \in \mathcal{S}^I, \tag{5.70}$$

$$\sum_{v \in \mathcal{V}} F_{sv}^{C,1} \geq r_s^1, \qquad \forall s \in \mathcal{S}^C. \tag{5.71}$$

Stage 2: Additions and removals. Relative to the initial state, the second stage introduces add/remove variables:

$$
\begin{aligned}
Fa_{sv}^{I}, Fr_{sv}^{I} &\geq 0 && \text{integer units of system } s \text{ added/removed in } v, \\
Fa_{sv}^{C}, Fr_{sv}^{C} &\geq 0 && \text{continuous volume of system } s \text{ added/removed in } v.
\end{aligned}
$$

The total systems that are placed or remain in stage 2 are described using the system set $S^{T,2} \subseteq S^1 \cup S^2$. Consistency is enforced by:

$$F^{I,\mathrm{T},2}_{sv} = F^{I,\mathrm{T},1}_{sv} - Fr^I_{sv} + Fa^I_{sv}, \qquad \forall s \in \mathcal{S}^I,\ v \in \mathcal{V}, \tag{5.72}$$

$$F^{C,\mathrm{T},2}_{sv} = F^{C,\mathrm{T},1}_{sv} - Fr^C_{sv} + Fa^C_{sv}, \qquad \forall s \in \mathcal{S}^C,\ v \in \mathcal{V}, \tag{5.73}$$

with the restriction that removals cannot exceed what was initially placed in stage 1,

$$Fr^I_{sv} \le F^{I,\mathrm{T},1}_{sv}, \qquad Fr^C_{sv} \le F^{C,\mathrm{T},1}_{sv}. \tag{5.74}$$

Final stage activation variables X^2_{sv} are linked as in the single-stage formulation, using $F^{I,2}_{sv}$ and $F^{C,2}_{sv}$ with bounds $U_{sv}X^2_{sv}$ and small positive lower thresholds ($\varepsilon_C = \frac{U_{sv}}{20}$).

Stage 2 totals. The total system requirements now apply to the systems that are required for the second-stage system architecture:

$$\sum_{v \in \mathcal{V}} F^{I,2}_{sv} = c^2_s, \qquad \forall s \in \mathcal{S}^I, \tag{5.75}$$

$$\sum_{v \in \mathcal{V}} F^{C,2}_{sv} \ge r^2_s, \qquad \forall s \in \mathcal{S}^C. \tag{5.76}$$

Outlets and binary systems $\mathcal{S}^B$ remain excluded from both stages. The two-stage formulation ensures that fixed (non-replaceable) systems are preserved, while others may shift through removal and addition. The rest of the model (routing, walls, stability, etc.) uses either the 1st or 2nd stage placements as inputs, so that all downstream constraints reflect the updated system layout.

5.3.2 Two-stage routing constraints

To extend the routing constraints, we distinguish between the required (i) initial connections C^1 and (ii) final connections after removals and additions C^2. To reflect pre-placement and remaining connections in a stage, the total connection sets $C^{T,1} \subseteq C^1 \cup C^2$ and $C^{T,2} \subseteq C^1 \cup C^2$ represent, respectively, all active connections in stage 1 and stage 2. The stage 1 formulation guarantees the feasibility of the initial routing, while stage 2 ensures that additions/removals yield a feasible updated layout. Only C^1 and C^2 carry stage-specific requirements; $C^{T,1}$ and $C^{T,2}$ ensure consistency across stages. The same compact signed-flow structure (internal edges, access edges, hub injections) is preserved in both stages.

Stage 1 (initial routing). The routing constraint is separated into binary variables that describe the installation of a connection $c \in C^{T,1}$ on an edge in a room i that we define

$z^{\mathrm{int},1}_{c,i,(u,v)} \in \{0,1\}$	pay once binary to install connection on internal edge (u,v)
$z^{\mathrm{acc},1}_{c,(i,j)} \in \{0,1\}$,	pay once binary to install connection on access edge (i,j)
$z^{\mathrm{out},1}_{c,i} \in \{0,1\}$,	pay once binary to install connection on outside access

For each required connection in a stage $c \in C^1$ in a room i, we define flow variables

$$g^{\text{int},1}_{c,i,(u,v)} \in [-M, M] \qquad \text{signed flow on internal edge } (u,v),$$
$$g^{\text{acc},1}_{c,(i,j)} \in [-M, M] \qquad \text{signed flow on access edges } (i,j),$$
$$g^{\text{out},1}_{c,i} \in [-M, M] \qquad \text{signed flow on outside access.}$$

In *pair mode*, Integer systems inject/withdraw flow via hub variables

$$h^1_{c,i,p} \in [-M, M], \qquad (i,p) \in \text{hub nodes},$$

and continuous systems inject/withdraw via access variables

$$a^1_{c,i,j} \in [-M, M], \qquad (i,j) \in \text{access nodes}.$$

Gate constraints enforce $|g| \leq Mz$ on every edge, restricting at most one active access or hub per room. Node conservation is enforced by:

$$\sum_{(u,v)} \pm g^{\text{int},1}_{c,i,(u,v)} + \sum_{(i,j)} \pm g^{\text{acc},1}_{c,(i,j)} = a^1_{c,i,j}, \qquad \forall (i,j), \tag{5.77}$$

$$\sum_{(u,v)} \pm g^{\text{int},1}_{c,i,(u,v)} = h^1_{c,i,p}, \qquad \forall (i,p). \tag{5.78}$$

5

Injection balances tie back to system placements in stage 1.

In *anchor mode* both integer and continuous system types demand flow and a supply anchor is allocated at a hub to match the total demand.

Stage 2 (additions and removals). Stage two variables mirror the previously described setup, but also introduces removal and addition binaries for the total connection set in stage two $C^{T,2}$:

$$z^{\text{int,rem}}_{c,i,(u,v)},\ z^{\text{int,add}}_{c,i,(u,v)} \in \{0,1\},$$
$$z^{\text{acc,rem}}_{c,(i,j)},\ z^{\text{acc,add}}_{c,(i,j)} \in \{0,1\},$$
$$z^{\text{out,rem}}_{c,i},\ z^{\text{out,add}}_{c,i} \in \{0,1\}.$$

Consistency is enforced by

$$z^{\text{int},2}_{c,i,(u,v)} = z^{\text{int},1}_{c,i,(u,v)} - z^{\text{int,rem}}_{c,i,(u,v)} + z^{\text{int,add}}_{c,i,(u,v)}, \tag{5.79}$$

$$z^{\text{acc},2}_{c,(i,j)} = z^{\text{acc},1}_{c,(i,j)} - z^{\text{acc,rem}}_{c,(i,j)} + z^{\text{acc,add}}_{c,(i,j)}, \tag{5.80}$$

$$z^{\text{out},2}_{c,i} = z^{\text{out},1}_{c,i} - z^{\text{out,rem}}_{c,i} + z^{\text{out,add}}_{c,i}, \tag{5.81}$$

with restrictions $z^{\text{rem}} \leq z^1$ so that only existing connections may be removed. Flows and injections in stage 2 are defined analogously to stage 1 and only reflect connections that are required in stage two C^2

$$g^{\text{int},2}_{c,i,(u,v)} \in [-M, M], \qquad g^{\text{acc},2}_{c,(i,j)} \in [-M, M],$$
$$h^2_{c,i,p} \in [-M, M], \qquad a^2_{c,i,j} \in [-M, M].$$

The gate and conservation constraints are identical to Eqs. (5.77)–(5.78), but defined over C^2. Injection terms now reference stage 2 system placements.

5.3.3 Two-stage wall and partition constraints

Similar to the other constraint extensions, the stage 1 wall constraints determine the initial number of partitions and exterior layers, while stage 2 allows removals and additions relative to the initial state. The sets, parameters, and placement flags are similar to those defined in Sec. 5.2.

Stage 1 (initial). Initial variables follow Eqs. (5.28)–(5.46):

$$W_v^{\text{base},1},\, W_v^{\text{extra},1} \in \mathbb{Z}_{\geq 0}, \qquad W_v^{\text{air},1},\, W_v^{\text{sea},1} \in \{0,1\}, \qquad W_{ij}^{\text{dbl},1} \in \{0,1\},$$
$$D_v^{\text{air},1},\, D_v^{\text{sea},1} \geq 0, \qquad D_{ij}^{\text{edge},1} \geq 0.$$

These satisfy the same coexistence, pair, and partial-continuous rules as in the single-stage case, but now evaluated for the total system set in stage 1 $\mathcal{S}^{T,1}$ and rooms $\mathcal{V}$.

Stage 2 (updates). Stage 2 introduces add/remove variables for each wall type:

$$W_v^{\text{base,add}},\, W_v^{\text{base,rem}} \in \mathbb{Z}_{\geq 0}, \qquad W_v^{\text{extra,add}},\, W_v^{\text{extra,rem}} \in \mathbb{Z}_{\geq 0},$$
$$W_v^{\text{air,add}},\, W_v^{\text{air,rem}} \in \{0,1\}, \qquad W_v^{\text{sea,add}},\, W_v^{\text{sea,rem}} \in \{0,1\},$$
$$W_{ij}^{\text{dbl,add}},\, W_{ij}^{\text{dbl,rem}} \in \{0,1\}.$$

Consistency is enforced by

$$W_v^{\text{base},2} = W_v^{\text{base},1} + W_v^{\text{base,add}} - W_v^{\text{base,rem}}, \tag{5.82}$$
$$W_v^{\text{extra},2} = W_v^{\text{extra},1} + W_v^{\text{extra,add}} - W_v^{\text{extra,rem}}, \tag{5.83}$$
$$W_v^{\text{air},2} = W_v^{\text{air},1} + W_v^{\text{air,add}} - W_v^{\text{air,rem}}, \tag{5.84}$$
$$W_v^{\text{sea},2} = W_v^{\text{sea},1} + W_v^{\text{sea,add}} - W_v^{\text{sea,rem}}, \tag{5.85}$$
$$W_{ij}^{\text{dbl},2} = W_{ij}^{\text{dbl},1} + W_{ij}^{\text{dbl,add}} - W_{ij}^{\text{dbl,rem}}. \tag{5.86}$$

Restrictions $W^{\text{rem}} \leq W^1$ prevent the removal of non-existent partitions, exterior layers, or doubled faces. The feasibility rules (5.34)–(5.46) are re-applied in stage 2 using the updated placements $X_{sv}^{\text{T},2}$. The resulting cavity depths $D^{\cdot,2}$ define stage 2 cavity volumes for use in the room capacity balances.

5.3.4 Two–stage stability and capacity constraints

The stability formulation is extended to both placement stages. As before, the equations ensure that global displacement, longitudinal trim, transverse balance, and vertical stability (KG) remain within admissible limits. Both stages follow the same structure as in Eqs. (5.49)–(5.57), but account for all placed systems S^T in that stage.

Stage 1 (initial placement). Stage 1 constraints guarantee the feasibility of the baseline configuration. System and ballast masses are computed from the initial placements $F_{sv}^{I,\text{T}}, F_{sv}^{C,\text{T}}$.

Let $M_v^{\text{sys},1}$ denote the system mass in the room v, excluding ballast, and $M_v^{\text{bal},1}$ the effective ballast mass at stage 1. Constraints enforce:

$$\sum_{v\in\mathcal{V}} M_v^{\text{sys},1} + \text{LWT} \le \text{Displ}, \tag{5.87}$$

$$-\tfrac{3L}{100} \le T_f^1 - T_a^1 \le \tfrac{1.5L}{100}, \tag{5.88}$$

$$-\tfrac{3L}{100} \le T_f^{\text{bal},1} - T_a^{\text{bal},1} \le \tfrac{1.5L}{100}, \tag{5.89}$$

$$-\varepsilon_{trans} B \sum_v (M_v^{\text{sys},1} + M_v^{\text{bal},1}) \le \sum_v (M_v^{\text{sys},1} + M_v^{\text{bal},1}) y_v \le \varepsilon_{trans} B \sum_v (M_v^{\text{sys},1} + M_v^{\text{bal},1}), \tag{5.90}$$

$$\text{KG}^1 + \text{LWT} \cdot \text{KG}_{\text{LWT}} \le \text{KG}_{\max} \Big(\sum_v M_v^{\text{sys},1} + \text{LWT} \Big). \tag{5.91}$$

Stage 2 (final placement). Stage 2 constraints ensure that modifications through additions/removals remain within the same hydrostatic limits. Analogous constraints are imposed using the updated placements $F_{sv}^{I,2}, F_{sv}^{C,2}$. Denote by $M_v^{\text{sys},2}$ the new system mass in room v, and $M_v^{\text{bal},2}$ the effective ballast mass at stage 2. The governing equations read:

$$\sum_{v\in\mathcal{V}} M_v^{\text{sys},2} + \text{LWT} \le \text{Displ}, \tag{5.92}$$

$$-\tfrac{3L}{100} \le T_f^2 - T_a^2 \le \tfrac{1.5L}{100}, \tag{5.93}$$

$$-\tfrac{3L}{100} \le T_f^{\text{bal},2} - T_a^{\text{bal},2} \le \tfrac{1.5L}{100}, \tag{5.94}$$

$$-\varepsilon_{trans} B \sum_v (M_v^{\text{sys},2} + M_v^{\text{bal},2}) \le \sum_v (M_v^{\text{sys},2} + M_v^{\text{bal},2}) y_v \le \varepsilon_{trans} B \sum_v (M_v^{\text{sys},2} + M_v^{\text{bal},2}), \tag{5.95}$$

$$\text{KG}^2 + \text{LWT} \cdot \text{KG}_{\text{LWT}} \le \text{KG}_{\max} \Big(\sum_v M_v^{\text{sys},2} + \text{LWT} \Big). \tag{5.96}$$

Two-stage capacity constraints Room capacity limits are enforced separately for both the first-stage and second-stage placements. As in Eq. (5.59), the occupied volume in each room must not exceed the available net capacity, including allowances for connections and cofferdams.

Stage 1 (initial placement). For each room $v \in \mathcal{V}$, the occupied volume consists of:

$$\begin{aligned} V_v^{\text{I},1} &:= \sum_{s\in\mathcal{S}^I} v_s^I F_{sv}^{I,\text{T},1}, \\ V_v^{\text{C},1} &:= \sum_{s\in\mathcal{S}^C} F_{sv}^{C,\text{T},1}, \\ V_v^{\text{conn},1} &:= \text{connection volume in } v, \\ V_v^{\text{cav},1} &:= \text{cofferdam volume in } v. \end{aligned}$$

The total must respect the reduced room capacity C_v:

$$V_v^{\text{I},1} + V_v^{\text{C},1} + V_v^{\text{conn},1} + V_v^{\text{cav},1} \le C_v, \qquad \forall v \in \mathcal{V}. \tag{5.97}$$

Stage 2 (final placement). Analogous constraints are enforced for the updated placements $F_{sv}^{I,\mathrm{T},2}, F_{sv}^{C,\mathrm{T},2}$. Denote

$$\begin{aligned}
V_v^{\mathrm{I},2} &:= \sum_{s\in\mathcal{S}^I} v_s^I F_{sv}^{I,\mathrm{T},2},\\
V_v^{\mathrm{C},2} &:= \sum_{s\in\mathcal{S}^C} F_{sv}^{C,\mathrm{T},2},\\
V_v^{\mathrm{conn},2} &:= \text{connection volume in } v,\\
V_v^{\mathrm{cav},2} &:= \text{cofferdam volume in } v.
\end{aligned}$$

The per-room capacity constraint is

$$V_v^{\mathrm{I},2} + V_v^{\mathrm{C},2} + V_v^{\mathrm{conn},2} + V_v^{\mathrm{cav},2} \;\leq\; C_v, \qquad \forall v \in \mathcal{V}. \tag{5.98}$$

Both stages include connection and cofferdam volumes whenever present.

5

5.3.5 Changeability constraints

In addition to placement, routing, stability, capacity, and wall rules, stage 2 introduces *changeability constraints* to model the physical feasibility of removing or adding system architecture components. The transport and accessibility constraints guarantee that every large integer system unit (such as engines) removed or added in stage 2 noted with S^{ch} can be transported through openings in the ship's structure. The openings are cut once and sized consistently, to make sure no system exceeds the geometric limits of an opening.

Transport and accessibility. For each physical wall (undirected edge) $\hat{e} = \{i, j\}$ we define a continuous opening area

$$A_{\hat{e}}^{\mathrm{open}} \;\in\; [0, \bar{A}_{\hat{e}}],$$

where $\bar{A}_{\hat{e}}$ is the available face area. Each opening incurs a penalty proportional to the plate thickness, complexity, and the existence of plate stiffeners along a wall encoded in a parameter $k_{\hat{e}}$. The opening must be large enough to accommodate the maximum cross-section of any system that passes through it.

For every candidate directed arc (i, j) and every changeable system $s \in \mathcal{S}^{\mathrm{ch}}$ we define a flow

$$f_{s,(i,j)}^{\mathrm{acc}} \geq 0, \qquad u_{s,(i,j)} \in \{0, 1\},$$

where $f_{s,(i,j)}^{\mathrm{acc}}$ is the transported volume of s along arc (i, j) and $u_{s,(i,j)}$ indicates whether the system s uses the arc (i, j) to calculate the transport distance of a system. Tight big-M constraints couple flow and usage:

$$f_{s,(i,j)}^{\mathrm{acc}} \;\leq\; M_s\, u_{s,(i,j)}, \qquad A_{\hat{e}}^{\mathrm{open}} \;\geq\; a_{s,\hat{e}}\, u_{s,(i,j)},$$

where M_s is the maximum movable volume, and $a_{s,\hat{e}}$ the minimum cross-sectional area required for system s to pass through the opening $\hat{e} = \{i, j\}$.

Flow balance. For each node i and each changeable system s, the conservation law is

$$\sum_{j:(i,j)} f^{\text{acc}}_{s,(i,j)} - \sum_{j:(j,i)} f^{\text{acc}}_{s,(j,i)} = b_{s,i},$$

where the supply $b_{s,i}$ encodes removals and additions:

$$b_{s,i} = \begin{cases} +Fr^I_{s,i}\, v_s & \text{if units of } s \text{ are removed from room } i, \\ +Fa^I_{s,i}\, v_s & \text{if units of } s \text{ are added into room } i, \\ -\sum_v Fr^I_{s,v}\, v_s & \text{if units of } s \text{ are removed by using exterior access in room } i, \\ -\sum_v Fa^I_{s,v}\, v_s & \text{if units of } s \text{ are removed by using exterior access in room } i, \\ 0 & \text{otherwise.} \end{cases}$$

Here $Fr^I_{s,i}$ and $Fa^I_{s,i}$ are the removal and addition variables from Sec. 5.3.4, and v_s is the unit volume of system s.

5.3.6 Two-stage Objective function

The cost model distinguishes between stage 1 (initial build) and stage 2 (refit/change). Each stage accumulates multiple contributions k.

Stage 1 costs. The initial objective aggregates

$$C^1_{\text{intwall}}, \quad C^1_{\text{outwall}}, \quad C^1_{\text{dblwall}}, \quad C^1_{\text{pipe}}, \quad C^1_{\text{conserv}},$$

corresponding to internal and external wall partitions, doubled walled partitions, pipe cost (including material cost and labour hours), and tank conservation cost. The total is

$$C^1_{\text{tot}} = \sum_k C^1_k.$$

Stage 2 costs. The refit stage includes analogous wall and pipe costs plus explicit changeability terms:

$$C^2_{\text{access}}, \quad C^2_{\text{clean}}, \quad C^2_{\text{intwall}}, \quad C^2_{\text{outwall}}, \quad C^2_{\text{dblwall}}, \quad C^2_{\text{pipe}}.$$

Here C^2access accounts for labour to cut wall openings and transport of system components. It is calculated using accessibility flows weighted by distance, system volume, and system weight. C^2clean charges cleaning costs for removed tanks. The total is

$$C^2_{\text{tot}} = \sum_k C^2_k.$$

Multi-objective handling. To explore trade-offs, we use an ε−constraint approach [284]. The model can be solved in different modes:

$$\begin{aligned}
&\min C^1_{\text{tot}} \quad \text{s.t. } C^2_{\text{tot}} \le \varepsilon,\\
&\min C^2_{\text{tot}},\\
&\min(C^1_{\text{tot}} + C^2_{\text{tot}}),\\
&\min C^1_{\text{tot}} \quad (\text{without } \varepsilon \text{ cap}).
\end{aligned}$$

This allows explicit analysis of the Pareto frontier between stage 1 build cost and stage 2 changeability cost. Furthermore, to investigate the true extremes, the stage 1 variables can be fixed after optimising the first stage. The stage 2 variables are then used to optimise the second-stage cost. This output reflects the general case, where the ship design has been developed to support the conventional system architecture, without taking into account any retrofit.

5.4 Discussion

In the introduction of this chapter, we defined several requirements for the placement algorithm. The requirements are discussed below to investigate in what way the How component of the FEAR can be used to answer the subquestion:

How can ships be prepared to accommodate future system architecture developments?

The first requirement is the ability to integrate a system architecture into a ship while taking into account safety requirements. The graph-aided mixed integer linear formulation can be used to integrate systems and their connections, while avoidance constraints make sure systems and connections avoid parts of the ship and other systems that have to be avoided due to safety reasons. In Figure 5.8, a generated layout is shown that follows safety requirements and places additional cofferdams while minimising the cost of materials and hours for plates, piping and conservation. Integer systems like engines were not included except for their connection and avoidance of hazardous locations and systems. The additional materials for safety and the pipe cost reflect the trade-off between distance and routing, which is a driving factor for placement [90].

The second requirement is to identify differences and similarities between different system architecture integrations. In Figure 5.9, the initial system placement was performed for two different architectures. The placement locations are saved, and just like the system network model, the differences and similarities can be reflected using set theory. Below is the initial system architecture on the top left side and the retrofit system architecture on the top right. The systems that overlap between the system architectures and remain are visualised in grey, while systems that remain but have to change in size are shown in yellow. Systems that only occur in the system architecture B are shown in blue.

After having built the initial placement algorithm, the code was extended to a two-stage setup to be able to reflect changeability. In each stage, a different system architecture is integrated. Additionally, in the first stage, connections and systems that are required for the second-stage system architecture can be preplaced. In the second stage, connections and systems that are no longer required may be removed. Figure 5.10 shows a typical

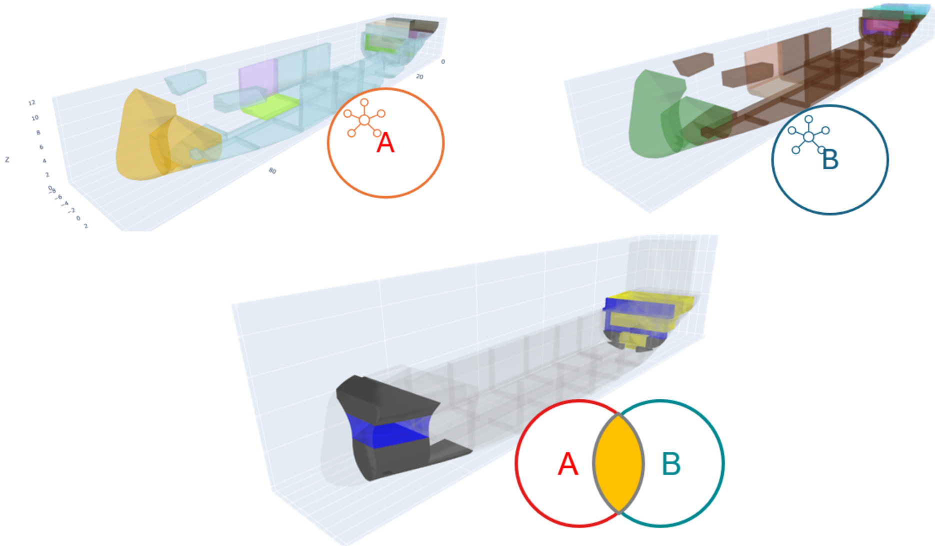

Figure 5.9: Example of initial placement (left) and retrofit placement (right) inside a reference ship. The bottom figure shows the overlapping set of systems placed in both system architectures.

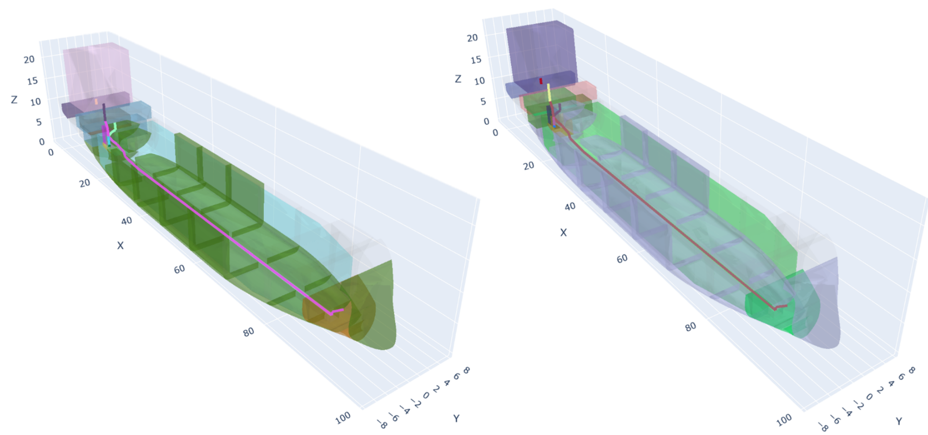

Figure 5.10: Example of initial placement (left) and retrofit placement (right) inside a reference ship.

output from the two-stage retrofit placement model. The left figure shows an exemplary placement of an initial system architecture and its connections. The right figure shows what systems remain in the reference vessel and also accounts for removed systems in red. Lastly, the placement model should provide insight into the benefit of changeability, defining the additional cost in the first stage and the second stage cost reduction. To do this, the graph-aided two-stage mixed-integer linear model is extended to handle multi-objectives. This allows us to investigate the trade-off between first and second stage costs. This is typically represented using a Pareto front as shown in Figure 5.11 below.

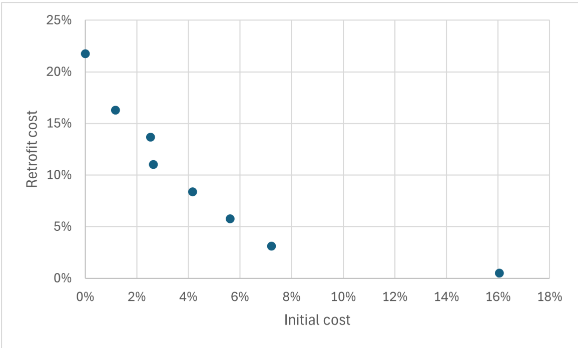

Figure 5.11: Pareto front showing the gradual increase in initial costs to reduce retrofit costs.

By rewriting the Pareto front to show the additional cost required to reduce retrofit costs (improved changeability), the same data can be used to visualise the change curves as defined by Fricke below.

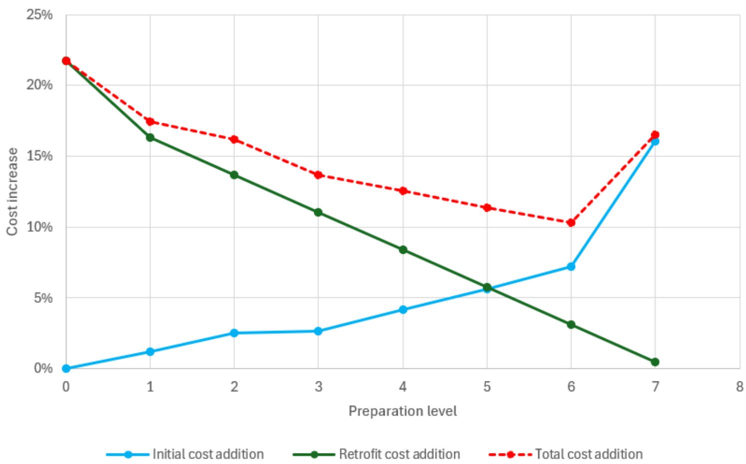

Figure 5.12: Change curve representation based on data from the placement model.

The figure reflects the increased cost due to preparations in the first stage to reduce the second stage cost.

5.5 Conclusion

The methodology developed for the how component is found to be able to place different system architectures. While also being able to create the change curves to compare the changeability between system architectures. These curves allow a decision-maker to investigate the placement of a system architecture and preparations to accommodate future system architectures to answer the subquestion.

Additionally, similar to exploration methods described in chapter 3, the model can already be sampled over with different system architectures and ship integration variables to reflect the impact of uncertainty on the change cost curve. Further research could investigate the inclusion of stochastic variables or uncertainty sets, as discussed for the search methods. Additionally, the combination of placement and routing presents a computationally heavy optimisation problem. This is mainly because routing presents a problem that is difficult to prove to be optimal. However, because the placement and routing model is at the compartment level, the estimates of global pipe and cable placement are assumed satisfactory for now. Nevertheless, for more detailed placement and improvements in computational speed, further research could investigate combining the placement with heuristic approaches.

6
Application in design

6.1 Connecting the modules of the framework

Having built the How, What and When components of the FEAR, the full framework can be connected. An overview of the modules, their connections, and the inputs (object and context of choice), outputs (value) and the mapping functions is shown in Figure 6.1.

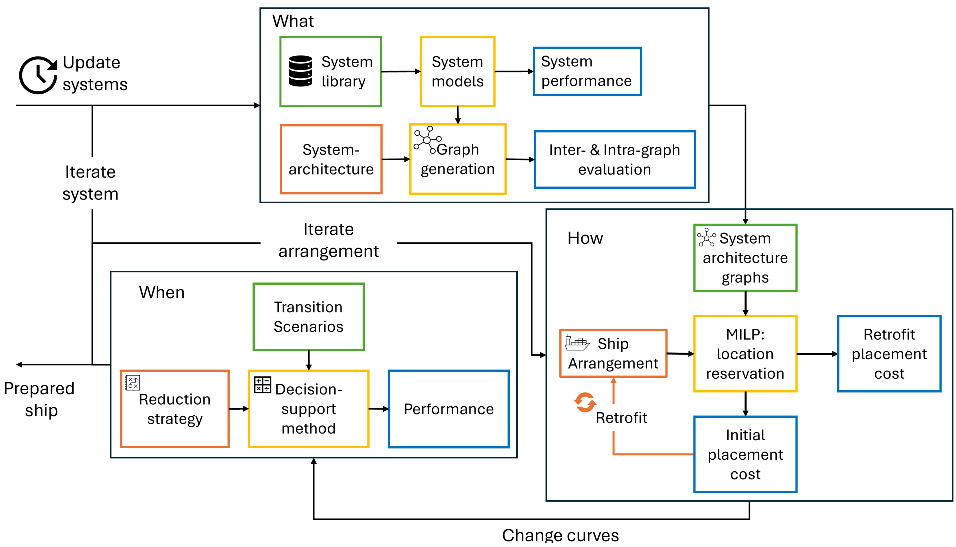

Figure 6.1: Representation of the connected modules in the FEAR

The FEAR is an iterative framework that can be used throughout the design phase and lifecycle. It starts at the what module, where system architectures are defined from a library of system models. The generated graphs can be used to evaluate: 1) the impact of design decisions on system performance, 2) interrelations within alternative system architectures, and 3) relations and changeability between system architectures.

In the how module, the system architecture results provide the context for the ship arrangement selection. The methodology is used to optimise the initial placement for each system architecture. These initial placements are used to determine the extremes for the change curves. Next, an epsilon constraint on the retrofit cost is used to force the two-stage optimisation to reduce the second-stage cost by leveraging initial placement and system architecture preparations. The initial and target system architecture placement costs serve as upper and lower bounds. The placement can be used to explore: 1) the initial placement, 2) the comparison between system architecture placements and 3) the initial placement and system architecture preparations that can be used for different system architectures.

The change curves are used in the when module mapping function to quantify the changeability during the lifecycle. Different energy transition scenarios serve as the context of choice, and the ship arrangement and system architecture selection as the object of choice. The selection is evaluated for both lifecycle emission and total cost of ownership, while including fuel and carbon cost uncertainty. As explained in Chapter 3, different decision support methods can be used in the when module as long as the developed mapping function and the approaches used by decision support method suit the decision problem.

ARO was selected as it is suitable to deal with uncertain variables and multiple objectives, while also including multiple temporal stages for multiple objects of choice.The output from the when module can be used to visualise: 1) different initial designs and change pathways during the lifecycle, 2) the impact of uncertainty on the pathways, and 3) the impact of improved changeability on the cost and emission performance.

After one iteration, the framework can be used to select an initial ship design and system architecture, including change enablers. This selection can be iterated further by adding new systems to the system library or selecting different system architectures. Additionally, the ship shape and design requirements can be modified to investigate ship-level improvements. Because of this, the FEAR offers a unique framework for the assessment of changeability during the early design phase. Furthermore, during the lifecycle, the ship arrangement in the how module is fixed, but the system library in the what module can be updated to track the development of system architectures and the change cost from the initial placement.

6.2 Application of the FEAR

The next step is to investigate how the FEAR can be applied in practice using a case study. The main goal of the case study is to verify the developed modules and investigate how it can enable using changeability as a strategy during the conceptual ship design phase. Consequently, this chapter aims to answer the following research question:

To what extent can system developments be included in design in a practical case study?

To show that system developments can be included, system characteristics that could impact the ship design, including additional connections, size and weight, and safety requirements, are incorporated in the case study. Additionally, ship level requirements, such as the required addition of fire insulation, increased ventilation, cofferdams and avoiding placing certain systems together or close to other functional spaces such as crew quarters, are also included. The case study is performed with Conoship, a ship design bureau, to investigate whether system and ship aspects can be properly taken into account in the ship design phase using the how and what components of the FEAR. Besides a description of the case study and its inputs, this chapter discusses results and the perceived applicability of the FEAR by expert designers.

6.3 Case study setup

The case study considers how initial placement and preparations can improve changeability to a future-fuel. The study is performed on a 6300 ton general cargo vessel as shown in Figure 6.2.

Figure 6.2: The case study vessel CIP6300, a future-fuel-ready general cargo vessel.

The vessel is already classified to be a future-fuel-ready vessel and, as such, offers the opportunity to see how the framework can support decision-making regarding preparations. The case study investigates changing from a conventional initial system architecture toward a system architecture using methanol. Methanol is chosen because, when compared to conventional systems, it needs multiple system developments and necessary additions on board, presenting both system and ship characteristics that the FEAR should be able to incorporate.

Regarding system characteristics, depending on its production pathway, methanol emits relatively low GHG emisions when combusted, making it an interesting alternative for the maritime industry. However, the application and integration of a methanol system architecture in a ship design is more complex, especially when compared to a conventional diesel system architecture. A list of aspects that make application and integration challenging is provided below.

- Substance hazards: Methanol is highly flammable, burns invisibly, is corrosive to systems and structures if not properly protected, and is toxic when ingested or inhaled. Due to these hazards it should be handled with care and requires certain safety measures to limit exposure, detect and extinghuish fires, but also treatment of surfaces that are in direct contact.
- Low energy density: When stored in liquid form, the energy density of methanol is almost half that of conventional Diesel, requiring nearly twice the fuel capacity for the same autonomy.
- Supporting systems for combustion and emission reduction support: Even though methanol is highly flammable, it is difficult to use in conventional compression

ignition engines due to its low cetane number and high latent heat of combustion. As such, engines still require it to be mixed with other fuels such as diesel to function as a pilot fuel [483]. While it reduces GHG emissions, methanol still emits NOx, requiring Selective Catalytic Reduction (SCR) systems before emission, to comply with Emission Control Area (ECA) regulation. Besides that, the corrosiveness requires changes to conventional engines.
- Supporting systems to ensure safety: areas where methanol is used require proper ventilation, which is also separated from ventilation inlets that supply air to accomodation. Additionally, to manage fire risk, stored fuel needs to be blanketed with nitrogen to reduce the oxygen ratio inside the tank.
- Hazardous placement precautions: depending on the adjacency to other areas on board and the outside hull plating above the waterline, methanol tanks and pipes require double walls when close to accomodation, cargo and outside air to act as a buffer. However, as it rapidly decomposes in water and is not toxic to the marine environment, it can be placed next to water. Additionally, it requires specialized fire safety precautions, including fire insulation and specialized extinghuishing systems.

The main focus of the case study is to investigate the models from the framework and determine if they can be used to assess system and ship level preparations. The system preparations include the impact that reducing the operational characteristics, such as speed and autonomy have on different systems. Besides the specific methanol requirements, there are several generic design requirements such as stability and displacement, but also design knowledge that are implicitly included in the case study. In this section, the input to the what and how components of the FEAR are further defined to enable investigation of a methanol system architecture and the change when compared to a conventional diesel electric setup. The main output of the case study is the investigation of the effectiveness of different system and ship level change enablers that were defined with expert designers.

- Component pre-placement, re-use or oversizing: This is a system level change enabler, where overlapping systems are oversized to ensure the systems can directly be re-used without changing.
- Connection pre-placement, re-use or oversizing: similar to component re-use, connections can be re-used if they occur in both system architectures. However, when connections differ in size, the designer might have to oversize the connections. Additionally, if a connection is costly to place during the lifecycle, because of limited room or accessibility, space can be reserved for future connections or even pre-placed.
- Improved accessibility: To ensure system components can be more easily retrofit or replaced without having to remove numerous connections or systems, a designer can include access routes in the design.
- Space reservation: This is a ship level change enabler, where space inside the vessel is reserved for the placement of expected future system architecture components without additional outfitting.
- Room outfitting: On top of space reservation, a room can already be prepared for the placement of future system architecture components. This can happen in different levels, by either already placing material such as cofferdams and additional piping, and upgrading ventilation and fire insulation.

A change enabler is the addition or change to an initial design to support change during the lifecycle. Currently, several change enablers such as additional piping or reserving space are already used in ship designs for alternative fuels and in defense applications (under the description "provisions for"). However, besides preparations, to the knowledge of the author and the design bureau involved in this case study no method currently exists outside the FEAR framework to investigate the impact of these change enablers during the design phase and their effectiveness in supporting changes.

6.3.1 What: component, investigating system changes

The first step is to define system components for the conventional and methanol system architecture. The system components included in the system library for the case study is shown in Table 6.1 below. To reflect the safety requirements, the avoidance constraints were further developed and added to the system library. The constraints consist of two parts, avoiding specific locations on board and avoiding specific systems. From current regulation and data sheets on hazardous materials, the generic categories shown in Table 2 in Appendix B were defined to be able to include multiple precautions regarding fire safety, ventilation, cofferdam placement and avoidance in the placement algorithm.

For each system, the table shows specific attributes and the system type (continuous or integer) that impacts the placement. Furthermore, the additional information regarding system temperature, apparatus group, category and system mediums is added to an avoid column that automatically avoids placement in the same room with other systems. Additionally, the "hard avoid" column is used to define rooms to be avoided based on colision bulkheads, double bottom or side shell regulation.

The "separate from" column represents soft constraints, where systems can be in a discretized submesh, but need to be separated from another system or the outside by a cofferdam. The cofferdam distance is given as well. Lastly, fire insulation and ventilation requirements are also included.

The same is done for specific connections. As explained in the system network chapter, each connection type is defined in a similar manner to systems. Table 6.2 is used to store avoidance constraints for connections. Besides this, it also includes the volume flow speed V_{medium} and density ρ_{medium} to estimate pipe diameter.

6.3.2 How: integrating components

The main additions to the placement algorithm are the definition of costs driving placement. Below an overview including the material cost and hours that are separated into Stage 1 (initial design/placement optimization) and Stage 2 (retrofit/removal). The following categories are considered, for several costs public references where used, but not all costs are included due to confidentiality.

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Table 6.1: Overview of system components added to the system library for the case study

System name	Type of node	Inputs	Outputs
DieselGenerator	Separated	MDO_flow, air, luboil, water_cool	Electricity, dirtyoil, exhaust, water_hot, air_ventilated
SCR	Separated	exhaust, Urea	exhaust_cleaned
Ureatank	Distributing		Urea
Luboiltank	Distributing		luboil
Switchboard	Distributing	Electricity, air	Electricity_net, air_ventilated
Dirtyoiltank	Distributing	dirtyoil	
ElectricMotor	Separated	Electricity_net, luboil	Power, dirtyoil
Gearbox	Separated	Power, luboil	Power, dirtyoil
Thruster	Separated	Electricity_net, luboil	dirtyoil
User	Distributing	Electricity_net, water_fresh, water_sewage	
MDObunker	Distributing		MDO_Bunker_station
MDOtank	Distributing	MDO_Bunker_station, air	MDO_bunker, air_ventilated
MDOdaytank	Distributing	MDO_bunker	MDO_flow
MeOHbunker	Distributing		MeOH_Bunker_station
MeOHtank	Distributing	MeOH_Bunker_station	MeOH_stored
MeOHfueltreatment	Distributing	MeOH_stored	MeOH_flow
DFMEOHGenerator	Separated	MDO_flow, MeOH_flow, air, luboil, water_cool	Electricity, dirtyoil, exhaust, water_hot, air_ventilated
Ballasttank	Distributing		water_ballast
Ballastwatertreatmentplant	Distributing	water_ballast, Electricity_net	
Freshwatertank	Distributing		water_fresh
Sewagetank	Distributing		water_sewage
Cargo	Distributing	air	air_ventilated
VentilationIn	Separated		air
VentilationOut	Separated	air_ventilated	
ExhaustOut	Separated	exhaust_cleaned	exhaust_outside

Table 6.2: Connection medium safety and attribute definitions

Medium	Attributes	Connection type	V_{medium}	ρ_{medium}	Avoid
MDO	Diameter	Pipe	3	880	cargo, accommodation, freshwater, ballastwater, sewage
MeOH	Diameter	Pipe	3	792	cargo, accommodation, freshwater, ballastwater, sewage
electricity	Area	Cable			cargo, MDO, freshwater, ballastwater, sewage, MeOH
urea	Diameter	Pipe	3	1100	cargo
exhaust	Diameter	Duct	20	0.6168	cargo, accommodation, freshwater, ballastwater
air_ventilated	Diameter	Duct	5	1.168	
air	Diameter	Duct	10	1.168	
dirtyoil	Diameter	Pipe	3	980	cargo
luboil	Diameter	Pipe	3	1100	cargo
water	Diameter	Pipe	3	1000	cargo

- Steelworking (submesh walls): Material costs for placing single or double walls, either internal, external, or adjacent to submeshes. In Stage 2 this includes both material and additional removal/cleaning hours.
- Fire insulation: A-60 insulation at a fixed rate per square meter including hours.
- Connections (pipes, cables, ducts): Hour costs for creating openings and placing components; material costs defined per inchmeter dependent on connection required to be cable, duct or pipe and defined as single-walled or double-walled for methanol.
- Tank conservation: Defined per paint type; includes both material and hours, addition of complexity in Stage 2 due to access difficulty. Paint hours are defined to be 0.1 hours per coat per m^2 [74].
- Tank removal and addition (Stage 2 only): Includes cleaning and preparation of tanks depending on cubic meters, surface area, and substance [74].
- Access and transport (Stage 2 only): Based on [96], the hours for access creation and transportation for removal or addition of system architecture components is calculated.
- Staging hours: Scaffold work inside the vessel, dependent on added systems and complexity [74].

The placement model only considers additional cost due to changes to the initial placement. This results in standard cost estimate categories like hull material, labour and capital costs [1]. In the case study, the cost only considers additional material and labour costs necessary to prepare or retrofit the ship toward methanol. Additionally, discussions with expert designers identified several characteristics that influence component placement. These include the venting of tanks and onboard spaces through ventilation ducts, as well as the inclusion of manhole covers to allow access to tanks, void spaces, and compartments between cofferdams. However, even though ventilation was incorporated in the placement model, manhole covers were excluded from the case study due to the high computational effort required to generate access routes to each manhole cover.

6.4 Case study results

6.4.1 What: System architecture comparison

Several design decisions that influence the system architecture selection are defined to be included in the "what component". These primarily include operational characteristics, such as the autonomy and design speed, that are often used as a separate key performance indicator for owners. Additionally, it is currently common practice to oversize the diesel storage to provide more flexibility to sail multiple trips, while bunkering at the lowest price along the journey. Furthermore, for methanol, the reduced energy density impacts tank size, which could result in a decreased autonomy to ensure that all systems fit on board.

Additionally, the dual fuel mix ratio of methanol positively impacts autonomy, but a higher ratio of diesel also increases GHG and NOX emissions. This provides decision makers with an additional change-enabler while balancing emission reduction, autonomy, and the ability to accommodate the mass and size of system architecture components.

Consequently, the system architectures are built for the system library components below. The three decision variables are then quantified using the system model network to generate potential system sizes. Figure 6.3 shows a quantification of different diesel to methanol mix ratios (MDO ratio) going from 5 to 75 percent. The Figure is an extension of

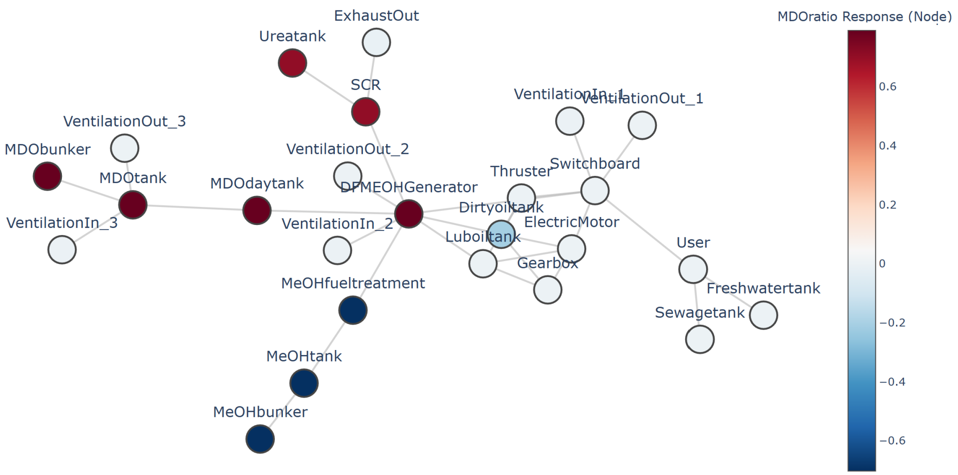

Figure 6.3: Sensitivity of dual fuel methanol system architecture to different fuel ratios at 400 hours autonomy and 10kts design speed. Negative elasticity (blue) represents system node decreasing attribute values for higher MDO ratio and positive (red) represents increasing attribute values.

Figure 4.8, using a logarithmic sensitivity metric [167] to evaluate relative changes between variables while avoidsing the instability of percentage-based metrics when reference values approach zero. The figure reflects how fuel ratios, while keeping the same autonomy and design speed, impacts the required fuel storage, luboil and SCR system. In the reference vessel at a speed of 10 kts and 400 hours of autonomy, a 5% vs 75% MDO ratio would result in a fuel tank variability of (17-150 m^3 MDO versus 370-55 MeOH m^3 for minimally 200 to maximally 400 m^3 fuel capacity). This information could be used to establish what dual fuel storage to apply and to oversize SCR and urea capacity to support increased MDO ratios over the lifecycle without changing components. However, to investigate whether the autonomy and design speed have to be reduced, the integration of these system architectures inside the ship is researched in the how module.

6.4.2 How: System architecture integration

To investigate the different change enablers, the two-stage graph-aided mixed-integer linear programming model is allowed to use any preparation, as long as it satisfies the constraints. The model starts with the placement of the initial diesel and methanol system architecture as extreme cases. Figure 6.4 shows the overlap in placement and connections between the two system architectures, when the model does not consider the second stage. The figure shows the overlap between both initial placements and the connections and

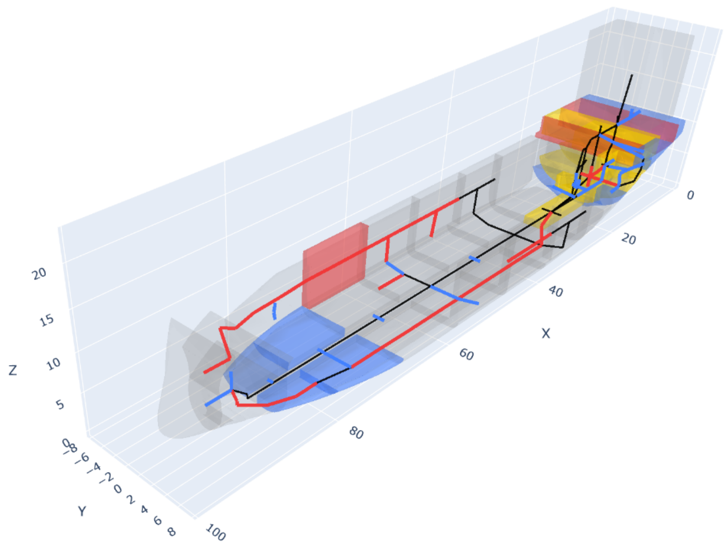

Figure 6.4: Placement overlap and differences for diesel versus methanol system architecture placement. Grey and black are systems and connections that are common for both placements, blue is only diesel, and red is only methanol, yellow represents compartments with different systems.

rooms that are unique (red or blue) or differ in either placement (yellow). To increase overlap and reduce retrofit cost, the model is extended to consider two stages. The first extreme case uses the initial placement of a conventional diesel-electric system, without any preparation for future retrofits, as a starting point, and then fixes the first-stage decisions while optimising the retrofit placement to methanol dual-fuel. The second case is allowed to change first-stage decisions to minimise the methanol dual fuel retrofit costs. An epsilon constraint sweep is used to identify the Pareto front between the two extreme cases. The results, including the impact of different cost categories, are shown in Figure 6.5 below. For each epsilon constraint step (00 – 05), three bars are shown representing the first stage,

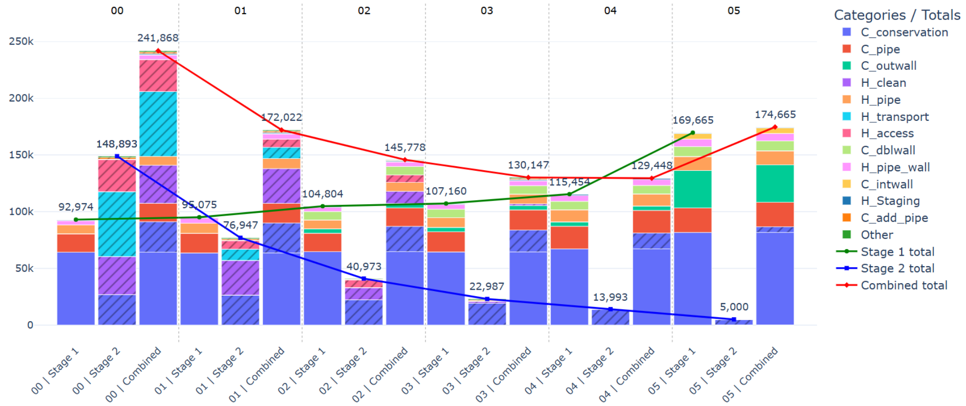

Figure 6.5: Change curves showing the benefit of design preparation and the categories where change preparation was done for 400 hours of autonomy.

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second stage and combined cost. The legend shows the cost categories, which consider material and labour costs, excluding the cost of system components. Because of this, the costs are not representative of the real retrofit costs toward methanol, but serve as an indication of the use of the how module to evaluate changeability. The epsilon constraint was limited to a value of 5000, because $\varepsilon \rightarrow 0$ forced the optimisation into long computation times against little first-stage cost improvements. In Figure 6.5, the first extreme case shows that the second stage requires a lot of additional transport and access cost (removing or adding system components in the ship), adding pipes (also includes additional cable and duct material and hours) and placing cofferdams. When the optimisation focuses more on reducing the second stage cost, the first stage includes more pipe, wall and tank placement, while the second stage cost becomes limited to only conservation cost. To understand how placement is impacted by different autonomy, Figure 6.6 investigates how a halved autonomy of 200 hours would affect the cost curves.

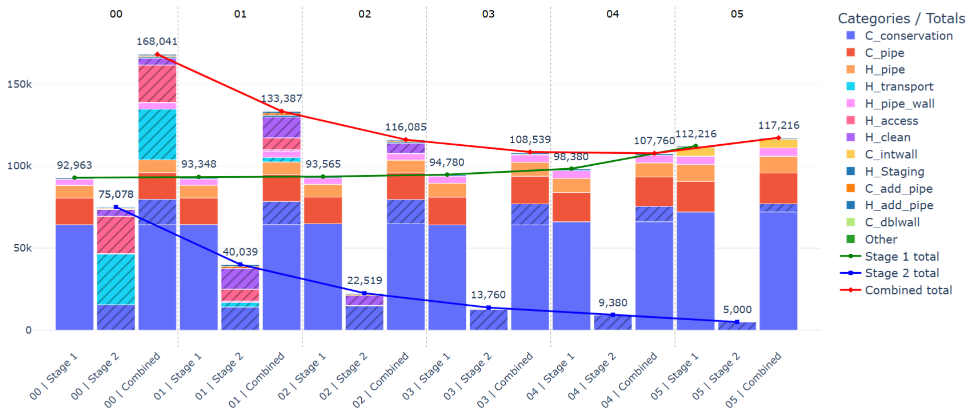

Figure 6.6: Change curves showing the benefit of design preparation and the categories where change preparation was done for an autonomy of 200 hours with methanol.

The figure shows that the cleaning cost significantly decreases compared to the higher autonomy figure, because the methanol storage can be placed without removing diesel capacity. The transport labour also significantly reduces as fewer systems are relocated to create room for methanol storage. The model starts preparing full methanol storage by building internal walls and adding conservation. In contrast, the higher autonomy methanol-extreme case in Figure 6.5 also requires double walls and walls to the outside. This can be explained by the required addition of future system architecture components beside original components in the first stage, which increases the filling grade and structural complexity of the vessel. To find low-cost space, the methanol tanks are placed further from the engine room, which requires more pipe costs. Consequently, placement of systems with more safety requirements such as methanol storage, is a trade-off between selecting compliant compartments and limiting the length of piping. Lastly, the change curve optimum for the lower autonomy seems to flatline earlier, while the change cost for higher autonomy rises due to the impracticality of full preparation. Overall, changeability be used to reduce relative material and labour costs by 28-46% for a retrofit toward methanol dual fuel with 400 hours of autonomy and 20-35% for 200 hours of autonomy. However, these values are indicative and will be influenced by shifts in wages, material cost, system cost and timing of the retrofit.

6.5 Discussion of the case study results

It is found that for higher autonomy, the diesel tanks are forced to be replaced, which results in a relatively high share of cleaning and conservation costs in the total additional cost. Consequently, the ability to reuse a compartment without high cleaning and conservation costs is a significant change enabler. The reference vessel can be retrofit to a maximum of around 300 m^3 methanol before it is limited by cargo and ballast weight requirements. This number impacts the maximum autonomy (<400 hr), fuel ratio (> 10 % MDO) or design speed (<10kts). Furthermore, the placement of the full dual fuel system architecture is further impacted by stability constraints. This highlights a trade-off between autonomy and speed and cargo capacity, which can be investigated in further research.

Furthermore, for higher levels of changeability, preplacement of connections and oversizing of overlapping support systems are low-cost change enablers applied by the model. However, placing systems together in a first stage significantly increases the second-stage cost due to increased transport and access costs. Especially for ships with excess volume, the preparation of access and transport routes during the first stage can result in a large reduction of cost.

6.6 Case study interview

Two expert designers were asked to reflect on the outputs of the framework modules. They were provided with interactive versions of the Figures presented in the dissertation in the order that the framework outputs them. For each figure, stakeholders were asked to describe the figure and discuss insights. After this, any questions they had on the contents were answered, and the interviewees were asked their views on applying the tools in practice. Below, the findings from the interview are summarised to investigate if the three questions for the research objective were met:

- Support the exploration and comparison of emission reduction strategies.
- Provide quantitative insight into the feasibility of changing strategies.
- Inform the decision-maker what preparations enable changes and how these actions influence lifecycle costs.

6.6.1 Stakeholder view of the what module output

The first figures shown are the Methanol dual fuel and diesel electric system architecture representations as shown in Figure 4.4. The stakeholders found the network representation difficult to understand at first, but explained that this could be due to the substantial difference between the networks and standard diagrams that are currently used to describe functional information on sizes, capacity, and separation of systems within the ship. Nevertheless, these diagrams are used to represent individual systems. Therefore, the network representation was found to provide a novel insight and overview of the interaction between systems, but the use of system network representations would not improve or change results in the current process.

The second figure was an interactive system model tradespace visualization diagram from Figure 4.6, which allowed stakeholders to investigate the performance of different system designs. Similar to the system architecture network, the designers found that the number of variables to investigate was too large, preferring a limited selection of variables to improve understandability and insight.

Next, the comparison of both system architectures as shown in Figure 4.7 was found to provide insight into what system architecture components and connections will have to be replaced or reused during a retrofit to methanol. The network comparison was found to allow the visualization of changeability considerations during the design phase. One designer even noted how this specifically adds value when selecting systems, placement and design preparations while considering the alternative system architectures.

The sensitivity graph from Figure 6.6 was noted to be especially useful, also without current design projects. The colour gradients made the figure clear to understand, and the interactive figure allowed for exploration of the impact of design decisions on system size and performance. The figure was found to grant the ability to clarify and discuss the connections between vessel-level requirements and system-level decisions.

The graph edit distance Figure 4.9 was the last figure shown. While this representation mainly provides input to the how module, and the figure is deemed to be difficult to understand, the figure was still shown as it provides a different insight into the dimensionality of changing between system architectures. As expected, the figure was found to be mainly theoretical, but the experts did understand its purpose and the ability to investigate what intermediate system architectures.

To conclude the What module, the designers did identify the core purpose that the module was designed for from the results. They explicitly mentioned how parts of the what module support the exploration and comparison of emission reduction strategies. Nevertheless, they also noted that the design space and graph distance needed clarification and further development. For use in decision-making, such representations were found to be complex, warranting a reduction of information. A part of this could be improved by prolonged use, but an important direction for further research is the investigation of what levels of information improve confidence and insight. More importantly, the what module can be used to exploration and comparison of system-level emission reduction strategies. The network representation was found to provide novel tooling that is already valuable to provide insight into interactions of complex systems. Its use for changeability assessment further adds value.

6.6.2 Discussion on the benefit of the how module

The first two figures illustrate the Methanol dual fuel and diesel electric system architecture integration in te ship similar to Figure 5.8. In general, these figures were received with more recognition than the network representation. Nevertheless, the designers observed that the model occasionally generated placement decisions with which they did not fully agree. They indicated that this can be addressed by adding constraints to better reflect design rationale. This observation is consistent with findings reported in other studies, where the formulation of explicit placement rules proved challenging due to the presence of tacit design knowledge [116]. Despite these concerns, the capacity to visualise both spatial placement and inter-compartmental connections was regarded as valuable. The designers suggested that the generated layouts could function as a reference for the design team during the development of the general arrangement and could enhance the early integration of global piping routes. Consequently, the model is considered suitable for use within the design process to explore variations in both system architecture and general arrangement decisions.

The third figure was the comparison of both placements from Figure 6.4. This comparison was found to provide insights relevant to the preparation of piping routes and cofferdam arrangements, including the identification of longer routes and structural boundaries that could be incorporated during the initial design phase to reduce future retrofit costs. However, while the detailed technical considerations are valuable for design team analysis, they require further refinement and discussion for communication with decision-makers.

The change curve figures 6.5 and 6.6 were shown next. The designers expressed particular interest in understanding the preparatory measures proposed by the model and the associated costs along these change curves. However, due to the limited transparency of the assumptions underlying the change–cost relationships, they remained cautious in applying the model in its current form. They emphasised that greater confidence in the results would depend on a clearer understanding of the model structure and its embedded assumptions. Accordingly, now that the conceptual framework has been established, it would primarily benefit from practical development aimed at identifying and managing perceived complexity and uncertainty. Nevertheless, the designers concluded that the change curves provide a quantitative representation of ship- and system-level change enablers, which offer a structured basis for informed decision-making.

Overall, the How module received considerable interest from the designers. At the same time, it was recognised that the model exhibits a challenge common to many software-based decision support tools: perceived uncertainty and complexity of the framework and modelling approach may discourage practical application. To mitigate this, the designers argued that thorough validation is required before the model can be implemented in operational practice. Nevertheless, they agreed that the "how" module enables exploration and comparison of ship-level emission-reduction strategies during the early design phase. In addition, by visualising and quantifying preparatory measures that facilitate future system changes, it supports strategic design considerations.

6.6.3 Discussion on the benefit of the when module

The when module incorporated ARO figures from chapter 3, where the results were slightly modified to reflect the impact of change cost curves. The module could not be applied in its intended form, as the case study focused primarily on the how and what module. To effectively include the when module in the case study, multiple system architectures must be compared to reflect the benefits of change curves. Therefore, the figures were used to reflect on the module's results instead.

Among the presented outputs, the figures associated with the when module were perceived as the most difficult to interpret and required more extensive explanation. Following this clarification, the designers acknowledged that the visualisation enhanced their understanding of the benefits of fuel flexibility under conditions of uncertainty. Nevertheless, although the module provides insight into the potential advantages of preparedness, the energy transition remains a deeply uncertain problem. Ultimately, the decision to invest in preparatory measures rests with the shipowner. The designers observed that many shipowners operate with limited financial margins and are therefore inclined to select vessels with lower initial capital expenditure. As a result, they may be less inclined to invest in changeability or preparatory design measures.

For shipowners who adopt a lifecycle cost perspective, the module offers a valuable visualisation of long-term cost implications. However, the designers did not consider the current representation sufficiently persuasive to convince more sceptical stakeholders. This limitation may in part be attributed to the complexity of the figure itself. Further research could therefore investigate alternative visualisation approaches or expand the underlying economic model to improve the visualization of lifecycle cost developments and risk reduction benefits to shipowners and financiers. Overall, the when module was found to provide quantitative insight into changeability and its influence on lifecycle costs. As such, it's the final step in supporting decision-makers, offering insight into the lifecycle implications of preparatory measures, the selection of emission-reduction strategies, and the impact of cost uncertainty. At the same time, the designers emphasised that additional uncertainties affect decision-making and the applicability of the model as a whole, particularly regarding access to capital. Because of the modular structure of the framework, future research could explore the application of alternative decision-support approaches in the when module, such as Multi-Objective Robust Decision Making (MORDM). This model can be used to assess the robustness of a changeable ship design for different uncertain scenarios, rather than focusing on optimisation. Furthermore, the regulatory scenarios and uncertain variables in the when module as presented in Chapter 3 should be updated to reflect recent developments in regulation and market-based measures, such as the inclusion of maritime transport in the EU Emission Trading Scheme (ETS).

6.6.4 Discussion on the benefit of the full framework

One of the insights from the interviews was the perceived complexity, when asked about the perceived complexity of the model, the designers indicated that this largely depends on the background of the user. For users with prior experience with graph approaches, the framework was considered relatively intuitive and comprehensible.

The designers do not expect the framework to alter how design decisions are made, but will instead improve argumentation underlying those decisions. In their view, the framework would be particularly valuable during the early conceptual design phase. As it would be beneficial to generate additional insight within a relatively short time frame. Current practice often relies on experienced designers and represents systems, placement and piping as processes that are developed separately, this is especially challenging when considering future system architectures with different requirements. The framework provides insight into preparatory measures at both the system and ship levels and enables the explicit representation of these interdependencies.

Furthermore, the designers noted that it could reduce uncertainty surrounding the energy transition for ship-level decision-makers, but this is strongly influenced by the attitude and strategic orientation of the decision-maker. By incorporating change curves, the framework offers a structured assessment of preparatory investments. However, the designers concluded that improved changeability alone could be also presented as "future-proof" or environmentally progressive, even if no immediate emission reductions are achieved. To ensure that environmental impact is evaluated alongside changeability, future work should emphasise emission reduction performance from the what module as part of the placement model output as well.

When asked about reasons for not adopting the framework, the main concerns regarded usability and a lack of confidence in the model outputs. Additionally the designers emphasised that the framework should function as a decision-support tool rather than a replacement for the design and decision-making process itself. Lastly, a dedicated interface should be developed to ensure clarity and usability. In addition, building greater confidence in the reliability and robustness of the results was identified as a key prerequisite for practical implementation. With the interview in mind, this will require the right balance of improved model transparency and reducing perceived complexity.

6.7 Reflection and conclusion on the application of the FEAR

The case study, which evaluated two system architectures for a single ship type, demonstrated that the framework is capable of addressing the three research objectives: the exploration of system architectures, the quantification of changeability, and the investigation of lifecycle changes. However, the broader scientific value of the framework lies in enabling the systematic investigation of changeability across a multiple system architectures for different ship types. Exploring these combinations remains an important direction for future research.

Furthermore, to be able to apply the framework in practice, expert designers indicated that additional development is required. As expected for frameworks composed of multiple underlying models, the current framework is perceived to be complex. Consequently, to support application, decision-makers need to develop familiarity with, and trust in, the underlying assumptions, inputs, and outputs. Furthermore, future research should focus on reducing the amount of information presented to the essential elements required for decision-support, while also assessing whether the overall scope and complexity of the framework are proportional to the benefits it delivers in practice. Nevertheless, the interviews indicated that the system architecture comparison and sensitivity analysis, the ship integration comparison and change curves, and the reduction pathway analysis provide valuable tools for strengthening decision argumentation.

During the interviews, the influence of uncertainty and complexity in regulatory developments, financing conditions, and infrastructure support on decision-making in the maritime energy transition became clear once again. Within the framework, regulatory and market uncertainty are addressed in the context space of the when module; uncertainties and complexities related to system architectures are embedded in the what module; and ship-level spatial and technical complexity is incorporated in the how module. The framework primarily focuses on the vessel and its systems, enabling the evaluation and integration of changeability as a ship-level strategy.

However, a more in-depth examination at the fleet level is currently lacking. Such an analysis requires including the influence of power dynamics within the industry, access to capital, and the availability of supporting yard and fuel supply infrastructure. Decisions discussed in the case study, such as reducing autonomy or speed, or selecting an emission reduction strategy, are ultimately part of a broader ecosystem that strongly influences vessel-level decision-making. However, these factors, fall outside the decision space defined for the FEAR. Nevertheless, even though the current framework is intended primarily for decision support at the vessel level, future research could extend the When module and use the system architecture and ship integration models as inputs to investigate the benefits of ship changeability at the fleet level.

Another important observation from the interviews concerned the potential use of the framework for "greenwashing." This raises a more fundamental question regarding the concept of changeability: does the inclusion of future options provide a means of coping with uncertainty, or does it represent a substantive solution? It is essential to clarify that changeability is not a solution to the energy transition in itself, but rather a supporting strategy. Its value lies in reducing risk and cost exposure in the face of significant future fluctuations. This is particularly relevant for capital-intensive assets with long lifetimes, such as ships, which cannot be built or retrofitted rapidly.

Consequently, the FEAR framework quantifies the changeability of a ship with respect to alternative system architectures and provides insight into the impact of ship- and system-level preparations during early ship design. This enables decision-makers to evaluate strategies for improving changeability. Nevertheless, the effectiveness of investments in changeability ultimately depends on whether the embedded preparatory measures are exercised in the future. Higher upfront investments correspond to greater potential for cost and risk reduction at later stages. In this sense, changeability can be compared to an insurance mechanism: an intentional investment made to reduce perceived uncertainty surrounding the energy transition and to mitigate the risk of decision paralysis.

7 Conclusions

This thesis investigated how vessel-level decision-makers can be supported to meet emission reduction targets through the use of decision-support methods and changeability as a strategy. In the introduction, multiple political, financial, and technological challenges were identified that can explain why most vessels in the current fleet are waiting to implement emission-reduction measures. The maritime energy transition is described as a deep uncertain decision problem. The main question that this thesis aimed to answer is stated to be:

How can decision-making in the maritime energy transition be supported to enable timely ship design and retrofit decisions under deep uncertainty?

Several research directions were defined to support stakeholders involved in design, build, and retrofit decisions. Promising directions include improving changeability to lower barriers to reduce emissions and utilising decision-support methods to address challenges in the maritime energy transition.

This chapter provides an overview of the research presented in this thesis by discussing the answers to each subquestion and restating the respective scientific contribution for each chapter. After answering each subquestion, the answer to the main research question is stated in combination with the scientific and societal contributions of the thesis. Thereafter, it reflects on the framework proposed by this thesis and its application to answer the main research question. Lastly, the limitations and avenues for future research are discussed.

7.1 Research questions

In this section, each research sub-question is answered using the insights gained in its respective chapter.

1. *What makes decision-making under deep uncertainty, such as in the maritime energy transition, particularly challenging, and how can these challenges be systematically characterised and addressed?*
   Decision-making challenges such as complexity and uncertainty have been widely

studied across multiple fields, resulting in the development of numerous decision-support methods. Chapter 2 proposes a theoretical framework to investigate decision-making problems, the challenges that affect them, approaches to address these challenges, and applicable decision-support methods. The decision-space is structured into four elements: the context space, the object-of-choice space, the reflected-value space, and a mapping function that connects these spaces. Within each of these elements, two main categories of challenges can complicate decision-making: complexity and uncertainty. The impact of these challenges depends on their source and level, as well as additional characteristics such as temporal effects, risk and power dynamics. The theoretical framework provides a method overview comprising 193 decision-support methods that address these challenge categories across the different spaces and the mapping function. The approaches used by these methods are categorised into five groups: reduction, exploration, extension, structuring, and transformation. The contribution of this chapter is the development of a theoretical framework that structures decision-making challenges and approaches, including a systematic mapping of decision-support methods and their applicability to specific decision-making challenges.

2. *How to facilitate decision-making under deep uncertainty in the maritime energy transition?*
   A multi-disciplinary framework is proposed to enable the investigation of separate levels of detail with challenge-appropriate methods. The development of the framework and additional methods was further guided by three additional research questions, as discussed below.

3. *Which existing methods can support decision-making in the maritime energy transition, and what are their limitations?*
   According to the theoretical framework, to support maritime energy transition decision-making, methods must handle temporal effects and high levels of object uncertainty. An approach that was identified to enable dynamic decisions in response to uncertainty is the application of an adaptive strategy. Consequently, three existing methods from different fields that use this approach in combination with exploration to address uncertainty were selected: Dynamic adaptive policy pathways, Robust decision-making, and responsive systems comparison. These decision support methods offer various tools to investigate decision-making under deep uncertainty, but require additional detail to descripe the system- and ship-level functions needed to evaluate and explore the maritime decision problem. Furthermore, exploration requires complex visualisation and produces large datasets, especially in large design spaces. Additionally, two existing methods that use the transformation approach to search (optimise) the object space were selected to investigate the benefit of reducing the design space to optimum decisions while incorporating uncertainty. The two selected methods were stochastic programming, which extends the context space with stochastic variables, and robust optimisation, which uses uncertainty sets. It was found that either can benefit decision-making, especially compared to optimisation that does not consider uncertainty, and that both can handle multiple temporal intervals, while addressing input uncertainty. However, when multiple uncertain variables

are included, optimisation becomes more complex and limited by non-convexity. Consequently, the investigated methods can support decision-making by providing insight into the relationships among uncertain variables, scenarios, and decisions, or by providing an optimal decision while considering uncertainty. The contribution of this chapter is the investigation of the benefits of search and exploration methods to support emission reduction measure selection under temporal effects and high levels of object uncertainty, using an adaptive strategy. The methods were found to be limited to context-level decisions and challenges, requiring additional information to properly reflect the ability to adapt a ship to emission reduction measures.

4. *How can the evolution of ship system architectures be described and quantified?* System architecture components and their connections were described using graph theory. It was further extended with set theory to qualitatively compare system architectures, enabling the description of a system architecture's evolution through the addition or modification of components. The system architecture was quantified using system models to explore individual system performance and using multi-disciplinary modelling to structure connected systems and address behavioural complexity. The sensitivity of a system architecture to object uncertainty and design decisions was investigated using local solvers that allow discrete or continuous variable ranges to be included in each system model. Additionally, the evolution of a quantified system architecture over time was described using graph edit distance. The contribution of this chapter is the development of a novel network algorithm to hierarchically connect components within a system architecture. The creation of dynamic system architecture representations can be used to evaluate and compare system architectures under uncertainty during the ship design and retrofit phases. However, as physical interrelations between the system architecture and the vessel also significantly affect the ability to add or modify system components, the graph representation requires the incorporation of ship-level information.

5. *How can ships be prepared to accommodate future system architecture developments?* To investigate the integration of different system architectures in the ship, a graph-aided mixed-integer linear programming model was developed. It is used to place systems and their connections inside a discretised ship shape, while using avoidance constraints to ensure safety requirements. The optimisation minimises the cost of materials and hours for placement, piping and conservation. Solutions are compared using set theory to identify differences and similarities between different system architecture integrations. To reflect changeability, the initial placement algorithm was extended to include a second stage where a future system architecture is integrated. This allows the model to retrofit for second-stage system architecture components, while first-stage components can be removed. The graph-aided two-stage mixed-integer linear model is extended to handle first-stage and second-stage costs as bi-objectives, allowing for the investigation of trade-offs using a Pareto front and the visualisation of initial, retrofit and combined change cost curves. As such, the chapter contribution is the development of a placement algorithm specifically designed to evaluate changeability and accommodate future system architecture

developments during the design phase, bridging the gap between changeable system architecture and ship design.

6. *To what extent can system developments be included in design in a practical case study?* The what and how components were applied to and validated with a practical case study. Several challenges related to system and ship-level decisions were defined in collaboration with expert ship designers. These include vessel-level improvement of access for system removal and placement and compartment preparations such as wall and pipe placement, conservation and system-level connections and oversizing of supporting systems. The case study further examined the impact of preparation during ship design, including trade-offs between additional performance indicators such as autonomy and sailing speed. Several change enablers were defined and investigated, including space preparation, system oversizing, pre-installing pipes and cofferdams and improving accessibility for the addition and removal of system architecture components. The case study insights showed that FEAR can be used to investigate multiple system-level developments, whose integration can then be further researched within a reference ship design. The framework supported designers by providing insights into what specific change enablers offer cost reductions during retrofit and how these preparations can be incorporated in the initial ship design. Additionally, due to its generic setup, novel systems can be added to the system library, and both system architecture and ship design decisions can be varied. To investigate the application during practice, the FEAR should be further applied and developed during a real design process. The general-cargo vessel case study has been used to validate that the FEAR can be used to explore how change enablers improve the value of changeability, preparing a conventional vessel for alternative fuels such as methanol.

7

7.2 Conclusion

To answer the main research question and support stakeholders involved in vessel decisions for the maritime energy transition, this dissertation developed the Framework for Exploration of Adaptive Robustness in vessels (FEAR). The modules and their connections in the fully developed FEAR are shown in Figure 6.1 and explained in detail in Chapter 6.7.

The What component can be used to investigate which potential emission-reduction measures to adopt and what changes or additions to the system architecture are necessary for their implementation. In the How component, the system architecture graphs and the multi-disciplinary model description can be used to investigate the impact of integrating emission-reduction measure components and changeability within the ship. The When component can be used to assess the value of changeability and alternative emission reduction pathways under uncertainty. The final step then allows the FEAR to be re-iterated to investigate differen emission reduction measures or arrangements. During the early design phase, the FEAR enables investigation of the implementation of emission-reduction strategies, including the system architecture and change enablers incorporated into the initial vessel design.

The FEAR was applied in a case study to investigate its practical applicability and to assess whether the research goals and objectives established in the introduction were achieved. By analysing two alternative system architectures for one ship, the framework showed how these systems can be integrated and what system- and vessel-level preparations can facilitate future transitions. Based on an initial case study, the reduction of material and labour costs was evaluated to be 20-46% compared to the case without any consideration for the future. Consequently, the results from the case study indicate that implementing change enablers during the design phase, such as reserving space and the pre-installion of piping can significantly reduce both material and labour costs compared to a design that does not account for future modifications. These benefits become even more pronounced when additional lifecycle factors are considered in the when module, such as yard cost, lost revenue and the timing of retrofits. In an interview with expert designers, the tools developed for the FEAR were found to provide novel insights in the early design stages that can support system and ship level decision argumentation. Consequently, the case study demonstrated that the framework is capable of addressing the three research objectives: exploring system architectures, quantifying changeability, and analysing lifecycle transitions. As such, it highlights the value of incorporating changeability into ship design to support the maritime energy transition. FEAR provides a theoretically substantiated and practically applied approach to support decision-making under deep uncertainty in the maritime energy transition. It offers decision-support tools that provide insight into system architecture evolution and the integration and preparation required to implement reduction measures, and the benefit of changeable strategy under uncertainty. Consequently, for stakeholders who are involved in vessel design, build and retrofit decisions, the framework supports robust investment and emission reduction decisions today, despite uncertainty about which technologies, regulations, economic or infrastructure conditions will dominate tomorrow.

7.3 Recommendations and future research

Looking ahead, three directions for future research are recognized: the validation of the proposed framework, further extension of the framework and the development of its modules.

A first direction for further research concerns improving the practical applicability of the FEAR. Feedback from stakeholders during the case study indicated that the perceived complexity of the framework may complicate its adoption. Future research should therefore focus on simplifying model interaction and validating the framework through its application in practice. Furthermore, the case study conducted in this thesis primarily served as a proof of concept and only considered two system architectures for a single vessel. To improve generalisability, the framework should be applied to a wider range of system architectures and vessel types. In addition, the current framework does not capture fleet-level dynamics such as access to capital, social dynamics, or the availability of supporting yard and fuel supply infrastructure. Extending the When module to incorporate fleet-level analysis could therefore enable investigation of how ship-level changeability influences transition strategies at the fleet level.

To extend the FEAR, further research is required to expand the number of modelled change enablers. In the case study it was found that first-stage change enablers, such as piping preparation and room reservation can significantly reduce second-stage retrofit costs while remaining relatively inexpensive. However, more extensive change enablers should also be considered, including the integration of pre-built modular system architecture components or vessel sections. An initial step in this direction was taken in a conference paper [382], where the system network algorithm was extended with graph-theory clustering to identify clustered modules. Additionally, the system model library and placement model could be extended to include ESTs. The integration of these technologies depends on their point of interaction with the vessel. EST that influence hydrodynamic characteristics could be incorporated by adjusting the resistance and load profiles used in the system models, while technologies that require additional components could be directly represented within the system model library.

Another extension is to investigate changeability as operational decision. The dissertation mainly focused on long-term strategic design and retrofit decisions, while it can also be applied to shorter-term operational system architecture decision-making. Given the maritime industry's delayed cyclical response to market, regulatory and technological changes, further research could investigate operational decision-making with strategic changeability decisions. In collaboration with the READINESS project's first work package, the semantic description of the system algorithm was already linked to investigate connecting software-based control decisions to hardware system architecture decisions [239]. For example, on-board control algorithms could trigger iterations of the FEAR framework using an online system library to evaluate system architecture modifications that improve operational performance or ensure compliance with new regulations.

Regarding development of the What module, the current system models in the system library primarily function as proof-of-concept representations. The development of an online version of the FEAR framework and a corresponding extension of the system model library is required to enable operational decision support. Furthermore, a significant extension of the system library requires the further development of the branch search algorithm. The current algorithm explores the design space by generating all potential system architectures, which performs adequately for relatively small libraries. However, structural and behavioural complexity increases with larger numbers of systems and connections. Therefore, methods from computer science that utilise classification and categorisation techniques for large datasets can be used to improve search efficiency. For example, tree-based methods classify subsets of data and apply pruning techniques to remove redundant sections, thereby reducing the size of the search space while preserving its structure [298]. Precomputing such trees from the system library could enable the analysis of significantly larger system sets.

Finally, the How module currently supports two-stage placement optimisation and the identification of system- and vessel-level preparations that reduce second-stage costs. However, change cost curves were generated for only two system architectures. Expanding the number of system architectures would enable investigation of interactions between system architecture placement and preparation strategies. This would also allow fuller utilisation of the When module, as change curves provide an additional object-space variable that can be evaluated under uncertainty. Such research could help determine appropriate levels of changeability for different levels of uncertainty. In addition, although the How module MILP can already be sampled across different system architectures and integration variables, the model could be further extended to incorporate stochastic variables or uncertainty sets, enabling more robust analysis of changeability decisions under uncertainty.

Appendix

A Method overview

				Context of choice				Object of choice					Value of choice				Mapping			
No	Method	Short	References	Reduction	Exploration	Extension	Transformation	Reduction	Exploration	Extension	Structuring	Transformation	Reduction	Exploration	Extension	Transformation	Reduction	Extension	Structuring	Transformation
1	Axiomatic design approach	ADA	[209, 355, 419]	X	X					X	X	X			X			X		
2	Probabilistic design	PD	[411]	X	X					X		X			X			X		
3	Robust design/ taguchi method	RD	[60, 330, 379, 439?]	X	X					X		X			X			X		
4	Design spiral/ point based design	PBD	[78]		X						X									
5	Concurrent design	CD	[75, 78]		X						X				X					
6	Set based design	SBD	[401]	O	X						X				X					
7	Systems engineering	SE	[139, 484]		X						X				X					
8	model based systems engineering	MBSE	[268]		X				O		X						X	O	X	
9	Design space / tradespace exploration	DSE	[78]		X				X		X									
10	Knowledge based engineering	KBE	[362]			X					X								X	
11	Decision analysis	DA	[192]	X	O	X		O				X	X					X		
12	Real options analysis	ROA	[2, 181, 182, 234, 235, 297, 335]	X	O	X		O		X	O	X	X					X		
13	Design of Experiments	DOE	[300, 337, 466]		X				X					O		O		X		X
14	Monte Carlo sampling	MCS	[129, 334, 432, 474]		X				X	X				O		O		X		X
15	Latin hypercube sampling	LHS	[6, 156, 348]		X				X					O		O		X		X

16	Factorial sampling	FA	[6, 156]		X				X					O		O		X		X
17	Forecasting	FO	[99, 140, 280, 429]	X		X								X				X		X
18	Geometric Brownian motion	GBM	[138, 181]		X	X								X		X		X		
19	(Geometric) Brownian bridge	GBB	[285]		X	X								X		X		X		
20	Jump diffusion	JD	[138, 269]		X	X								X		X		X		
21	Autoregressive motion	AM	[138, 257]		X	X								X		X		X		
22	Mean reversion (+Ornstein uhlenbeck)	MROS	[408]		X	X								X		X		X		
23	Sensitivity analysis	SA	[29, 145, 201, 458]	X	X	X	X	X	X	O		X		X		X		X	O	X
24	Fourier amplitude sensitivity test	FAST	[145, 241, 267]	X	X	X	X	X				X		X	X	X		X		X
25	Mutual information index	MII	[145]		X	X	O	X		X		X			X	X		X		X
26	Nominal range	NR	[145]	X	X	X	X	X				X			X	X		X		X
27	Technology foresight	TFO	[103, 157, 164]	X	O	X				X		X	X					X		
28	Multi attribute tradespace exploration	MATE	[361, 367, 368]		X		O		X							X		X		
29	Epoch era analysis	EEA	[101, 141, 155, 228, 332, 333, 350]		X	X		X	X				X	X		X	X			
30	Responsive systems comparison	RSC	[154, 333, 359, 369, 381]		X	X			X			O	X	X		X	X			
31	Scenario discovery	SD	[104, 169]	X	X	O	X	X					X	X				X		X
32	Scenario analysis	SCA	[291, 340]	X		O		X						X		X		X		
33	Open exploration/ Scatter plots	OE	[145, 290]	X	X		O		X					X		O		X		X
34	PRIM	PRIM	[104, 298]		X	O	O		O				O			X		X	X	X
35	CART	CART	[298]		X	O	O		O				O			X		X	X	

36	Random forest	RF	[19, 48, 298]		X	O	O		O							X		X	X	
37	Iterative dichotomizer	IDE	[298, 344]		X	O	O		O							X		X	X	
38	Gradient boosting method	GBOM	[298]		X	O	O		O							X		X	X	
39	Regularized class association rules algorithm	RCAR	[298]		X	O	O		O							X		X	X	
40	Associative classification	AC	[298]		X	O	O		O							X		X	X	
41	Rough sets	RS	[6, 441]	X	O	X	O					X						O	X	
42	Exploratory modelling and analysis	EMA	[6, 243, 290]		X	O	X	X						X		X		X		X
43	Robust decision making	RDM	[35, 185, 226, 254, 273, 290, 403]	X	X	O	X	X	O			O		X		X		O		
44	Info-gap method	IG	[39, 130, 190, 273]	X	X	O	X	X		X		X		X	X	X	X	X		
45	Robustness discrepancy model	RDiM	[255]	X	X		X	X				X		X	X	X	O	X		
46	Mode pursuing sampling	MPS	[255]	O									X	O				X		X
47	Dynamic adaptive policy pathways	DAPP	[175, 176, 385, 436]	X	X	X				X		X		X	X	X	O	X		
48	Adaptation planning	APM	[457]	X	O	X				X		X					O	X		
49	Assumption based planning	ABP	[457]	X		X				X		X				X	O	O		
50	Multi-objective optimisation	MOO	[218, 262, 272, 375, 403, 469, 476]	X	O				X				X	X		X		X		
51	Collaboration method/ Collaborative optimisation	CM	[187, 255]	X	O				X			X	X	O				X		
52	Concurrent subspace optimisation	CSO	[187]	X	O		O		X				X	O				X		
53	bilevel integrated system synthesis	BLISS	[187]	X	O				X				X	O				X		
54	Analytical target cascading	ATC	[187]	X	O				X				X	O				X		

55	Genetic algorithm	GA	[106, 126, 301, 366]	X		O			X				X					X		
56	Evolutionary algorithms	EA	[348, 375]	X		O			X				X					X		
57	Swarm optimisation algorithm	PSO	[87, 262]	X		O			X				X					X		
58	Metaheuristics	MH	[218, 262]	X		O	O		X				X	O				X		
59	Multi objective GA	MOGA	[52, 476]	X		O			X				X	X		X		X		
60	Strength pareto evolutionary algorithm	SPEA	[348, 476]	X		O			X				X	X		X		X		
61	Pareto archived evolution strategy	PAES	[476]	X		O			X				X	X		X		X		
62	Many objective evolutionary algorithm	MOEA	[348]	X		O			X				X	X		X		X		
63	auto-adaptive multi operator MOEA	Borg-MOEA	[180, 348, 404]	X		O			X				X	X		X		X		
64	Multiobjective PSO	OMOPSO	[348, 395]	X		O			X				X	X		X		X		
65	Indicator based evolutionary algorithm	IBEA	[348, 487]	X		O			X				X	X		X		X		
66	Generalized differential evolution 3	GDE3	[242, 348]	X		O			X				X	X		X		X		
67	a multi algorithm genetically adaptive method	AMAL -GAM	[348, 454]	X		O			X				X	X		X		X		
68	Epsilon constraint	EC	[272, 472]	X	X				X				X	X		O		X		
69	Pareto front	PF	[128]	X	X				X				O	X		X		X		
70	Robust optimisation	RO	[150, 480]	X	X			X	X			X	X	O	X	O		X		
71	Adaptive robust optimisation	ARO	[46, 185, 488]	X	X	O			X			X	X	X	X	O		X		
72	Stochastic programming	SP	[231, 247, 309, 325, 482]	X	X	X		X	X	X		X	X	O	X	O		X		

73	Distributionally Robust Optimisation	DRO	[40, 345]	X	X	X		X	X	X		X	X	O	X	O		X		
74	Approximate linear programming	ALP	[373]	X		O														X
75	Mixed-integer (non)-linear programming	MINLP	[27, 76, 212, 453]	X					X				X				X			X
76	Agent based model	ABM	[194, 224, 446]	X	O	O		X	X					X	X	X	X	O		
77	Discrete event modelling/ simulation	DEM	[302, 309, 484]	X	O	X		X	X		O			X		X	X	X		
78	Simulation/ Physical model	SIM	[8, 95, 294]		O	X								X		X	X	X		
79	System dynamics	SDY	[224, 340]	X		X			X		X	O	O	X	O	O	X	X	X	X
80	Multi-disciplinary design optimisation	MDO	[119, 187, 255, 317, 319, 330, 406, 473]	X		O			X		O		X	O	O	X		X		O
81	Multi-fidelity model	MFM	[23, 81, 263, 328]	O	O	X	O		O	O		X		X	O			X		X
82	Meta/ Mixed/ Surrogate modelling	MMSM	[151, 156, 160, 217, 232, 263, 400, 428, 461, 475, 485]	O		X	O		O				O	X		O		X		X
83	Least squares regression	LSR	[156, 187, 232, 319, 400, 411]	X		O	O		X				O	X		O				X
84	Polynomial regression	PR	[156, 217]	X		O	O		X				O	X		O				X
85	Response surface method/ polynomial response surface	RSM	[145, 187, 252, 255, 300, 337, 400, 428]	X	X	O	O		X				O	X		O				X
86	Ridge regression	RR	[279]	X		X	O		O			O	O	X		O		X		X
87	Multi-adaptive regression splines	MARS	[82, 217, 461]	X		X	O		O			O	O	X		O				X
88	Polynomial chaos expansion	PCE	[82, 428]	X	X	X	X		X	O				X	X			X	X	O
89	Kriging	KRIG	[156, 217, 232, 252, 255, 263, 428, 473, 485]	X		X	O		X	O			O	O	X			X		X

90	Gaussian process/ bayesian optimisation	GP	[105, 156, 475]			X	O		X	O				X	X			X		X
91	Bayesian approach/ inference	BYA	[201, 355, 411]			X			O	X				X	X			X	X	
92	Bayesian framework/ networks	BF	[52, 105, 213]			X				X				X	X			X	X	
93	Kernel methods	KER	[400]	X		X	O		X			O		X		O			X	
94	Principal component analysis	PCA	[104, 295]	X		X	O		X			O		X		O			X	
95	Spectral clustering	SC	[215]		O	O			X							X			X	X
96	k-means clustering	KMC	[196]		O	O			X							X			X	X
97	k-nearest neighbours	KNN	[196, 203]		O	O			X							X			X	X
98	Support vector machines	SVM	[82, 156, 461]		O	O			X					O		X		X	X	X
99	Analysis of variance	ANOVA	[6, 145]	X		X	O			X				X	X				X	
100	Neural network/ artificial neural network	ANN	[82, 142, 156, 187, 189, 400, 461]	O		X			X				X	O		X		O		X
101	Radial basis functions	RBF	[82, 217, 252, 461]	O	O	X	O		O			O	O	X		O				X
102	Inductive/ machine learning algorithm	IL	[142, 196, 212, 298, 329, 400, 426, 461]			X							O	O		X		O		X
103	Reinforcement learning/ Q-learning	RL	[189]			X							O	O		X		O		X
104	Uncertainty quantification	UQ	[23, 119, 474]	O		X	X			X		X		X	X			X		X
105	Probability model	PM	[105]	O	O	X	X			X		X		X	X			X		X
106	Probability box model	Pbox	[105]	O	O	X	X			X		X		X	X			X		X
107	Interval model	IM	[105]	X	O	X	X					X		X	X			X		X
108	Dempster Shafer theory, Second order probability/ belief functions	DST	[270, 465]	O	O	X	X			X		X		X	X			X		X

109	Design structure matrix	DSM	[31, 36, 66, 89, 193, 320]	X	X			X	X		X				O		X		X	
110	Engineering system matrix	ESM	[36]	X	X			X	X		X				O		X		X	
111	Domain mapping matrix	DMM	[36]	X	X			X	X		X				O		X		X	
112	Time expanded decision network	TDN	[396]	O	X	X			X		X	X	X	X	X	O	X	X	X	
113	Graph theory/ Networks	GT	[76, 127, 129, 179, 236, 386, 392, 450]	X	X			X	X		X	O	O	X	O		X		X	
114	Decision graphs/ decision tree	DG	[213, 396]	O	X						X			O			X	O	X	
115	Petri net	PN	[319]	X	O	X					X			X	X	X	X	X	X	
116	Flow diagram/ flowchart	FD	[413]	X	O	O					X		O	X			X		X	
117	Dynamic programming	DP	[85, 142, 308, 469]	X	X						O	X	X	O	O	O	O	O		
118	Markov decision processes	MDP	[221–223, 303–305, 418]	X	X	X				X	X	X	X	O		O	X	X	X	
119	Partially observable MDP	POMDP	[213]	X	X	X				X	X	X	X	O	X	O	X	X	X	
120	Markov chain	MC	[64]	X	X	X				X		X			O		X		X	
121	Changeability	CHA	[80, 131, 148, 236, 281, 350, 353, 370, 371]	X		O						X	O	O	X			O		
122	Modularity	MOD	[92, 124, 399, 419]	O							X	X	O	O	X			O	X	
123	Flexibility	FLEX	[32, 63, 108, 138, 315, 350, 376, 381, 408]	O								X	O	O	X			O		
124	Robustness	ROB	[361]	O								X	O	O	X			O		
125	Product platforms	PP	[91–93, 126, 216, 306, 398, 399]	O							X	X	O	O	X			O	X	
126	Margins	MAR	[134, 351]	O				X							X			O		
127	Technology roadmap	TRM	[9, 11]	X	O	X				X		X	X	X	X	X		X	X	
128	Multi criteria analysis/ multi criteria decision making	MCA	[21, 274, 355, 477]	X	O			X					X	O	O		X			

129	Probabilistic discrete choice model	DCM	[86]	X	X				O	O		X		X	X	X		X		O
130	Analytical hierarchy process	AHP	[114, 188, 199, 292]	X	O			X					X	O	X		X			
131	Order Preference by Similarity to Ideal Solution	(T)OPSIS	[274, 355]	X	O			X					X	O	X		X			
132	Analytic network process	ANP	[274, 355]	X	O			X					X	O			X		X	
133	Multi-criteria Optimisation and Compromise Solution	VIKOR	[355]	X	O			X	X				X	O		O	X	X		
134	Decision making trial and evaluation laboratory	DEMATEL	[274, 441]	X	O	O		X					X	X		O	X		X	
135	data envelopment analysis	DEA	[100]		O	X	O		O			X		X		X	X		X	
136	Preference ranking organization method for Enrichment of evaluations	PROME -THEE	[274, 355]	X	O			X					X	O	X		X			
137	Elemination et choix traduisant la realite	ELECTRE	[208, 274, 355]	X	O			X					X	O	X		X			
138	complex proportional assessment	COPRAS	[274]	X	O			X					X	O	X		X			
139	Adittive ratio assessment	ARAS	[274]	X	O			X					X	O	X		X			
140	multi-objective optimization on the basis of ratio analysis	MOORA	[274]	X	O			X					X	O	X			X		
141	WASPAS	WASPAS	[274]	X	O			X					X	O	X		X			
142	Fuzzy MCA	FMCA/ FMCDM	[274]	X	O	O		X				X	X	O	O		X			
143	Shannon entropy technique/information theory entropy	SENT	[208]		O	O									X			X		

144	Simple additive weighting	SAW	[441]	X	O								X		X		X			
145	Weighted product method	WPM	[435]	X	O								X		X		X			
146	Weighted sum method	WSM	[208, 435]	X	O								X		X		X			
147	Normalized attribute values	NAV	[208, 435]	X	O								X		X		X			
148	Gray relational analysis/Gray system theory	GRA	[256, 263, 441]	X	O									X		X		X	X	
149	Grey number theory	GNT	[256, 274, 477]	X	O				X					X	X			X		
150	Reliability block diagram/dependence diagram	RBD	[319]	X				X			X			X	X		X		X	
151	Fault trees/failure tree analysis	FTA	[319, 411]	X							X						X	O	X	
152	Failure mode and effect analysis	FMEA	[355, 411]	X				X	X		X		X	X	X	O	X		X	
153	Quality function development	QFD	[36, 355]	X				X			X		X	X			X		X	
154	Event trees	ET	[16, 319]	X		X					X		X		X		X	O	X	
155	Fuzzy integral/choquet integral	FI	[296, 441]	X		X									X				X	
156	Fuzzy sets	FS	[77]			X									X					
157	Fuzzy pareto front/trace	FPF	[101, 141, 372, 381, 406]			X								X	X	X		X		
158	Fuzzy logic	FL	[77, 172, 323]			X			X						X					
159	Mahalanobis Taguchi system/ Mahalanobis-Taguchi Gram-Schmidt	MTGS	[295, 329, 467, 475]											X		X		X	X	

160	Net present value	NPV	[42, 57, 234, 297, 333–335, 381]										X		O	X		X		
161	Black scholes	BSM	[210]	X				X							X	X				X
162	Capital asset pricing model / Weighted average cost of capital	CAP	[455]										X		X	X		O		
163	Discounted cashflow	DCF	[41, 108, 181, 297]										X		O	X		O		
164	Total cost of ownership	TCO	[30, 304]					X					X					X		
165	Marginal abatement cost/MAC curve	MAC	[229, 474]	X				X					X	X				O		
166	Life cycle value	LCV	[67]										X				X			X
167	Filtered outdegree	FOD	[131, 350, 353, 367, 372]	X								X	X	X					X	
168	Expected value	EV	[108, 182, 331, 332, 350]										X		X	O		X		
169	Environmental measures: EEDI, CO2eq, CO2, GHG	EM	[57, 163, 330]										X	X		O		X		
170	Multi attribute expense	MAE	[333]										X					X		
171	Multi attribute utility	MAU	[333, 355]										X		X			X		
172	Revenue	REV	[334]										X	X				X		
173	Cost	COST	[330, 334]										X	X				X		
174	Risk Theory	RT	[236, 321, 334]										O	X	X			O		
175	Freight rate	RFR	[57, 240, 307, 337]										X	X				X		
176	Environmental accounting/ auditing/ performance evaluation	ENV	[139]								X		X	X				X		
177	Game theory	GAME	[142, 235, 485]	X		X			X			X	X	X	X					
178	Cost benefit analysis	CBA	[22, 32, 188, 258, 264, 266, 455]	X							X		X	X		O		O		
179	Life cycle management	LCM	[139, 354]	X					X		X			X		X	X	X		

180	Life cycle costing	LCC	[139, 264, 437]	X							X		X			O	X	O	O	X
181	Life cycle assessment/analysis	LCA	[49, 70, 174, 214, 271, 289, 364, 389]	X							X		X	X		O	X	O	O	X
182	Environmental product declaration	EPD	[111]	X							X		X	X		O	X			
183	Break even analysis	BEA	[145, 240]	X		O		X				X		X	X	X	O			
184	Utility theory	UT	[144, 153]	X				X	X				X		X					
185	Robustness measures	RM	[192]	X									O		X			X		
186	Maximin	Maxmin	[192]	X									O		X			X		
187	Maximum likelihood	MaxL	[411]	X									O		X			X		
188	Signal to noise ratio	STNR	[137, 244]	X									O		X			X		
189	Mean variance	MV	[192, 244]	X									O		X			X		
190	Undesirable deviations	UNDEV	[244]	X									O		X			X		
191	Proportional, Integral and Derivative controller	PID	[55]	X														X		
192	Model predictive control	MPC	[4]	X														X		
193	Digital twin	DT	[314, 427]			X								X				X		

B System safety table

Table 2: SAdditional requirements for systems from the system library used for the case-study. Attributes M, V, LxWxH, n_s represent mass, volume, dimensions and number of systems. Additional shorthands: FW = freshwater, SW = Seawater, BW = Ballast water, Acc = Accommodation, DB = Double bottom, SS = Sideshell.

System descriptor							Additional systems			Space Additions			Placement rules		
System name	**Attributes**	**System category**	**System temp**	**Apparatus group**	**Category**	**System mediums**	**System**	**Inert gas**	**Ventilation**	**Cofferdam**	**Separate from**	**Material addition**	**Avoid**	**Separated**	**Distance from**
			T1–T6 (450–85 °C)	I or II | A–C	A, 0, 1, 2		FiFi, detection		no/hour	width [m]	not adjacent	Enclose in			
Electric Motor	M, V, LxWxH, n_s	Discrete	T1							0			FW, Acc, Cargo		
Switchboard	M, V, LxWxH, n_s	Integer					yes		30	0		A-60	SS, DB, Cargo, Acc, FW, BW		
User		Binary	T1							0					
Dirty oil tank	M, V	Continuous								0,76	FW, Cargo		FW, Acc, Cargo		
Gearbox	M, V	Discrete								0			FW, BW, Acc, Cargo		
Ureatank	M, V	Continuous								0			FW, Acc, Cargo		
SCR	M, V, LxWxH, n_s	Integer								0			FW, Acc, Cargo		

System descriptor							Additional systems			Space Additions			Placement rules		
System name	**Attributes**	**System category**	**System temp**	**Apparatus group**	**Category**	**System mediums**	**System**	**Inert gas**	**Ventilation**	**Cofferdam**	**Separate from**	**Material addition**	**Avoid**	**Separated**	**Distance from**
MDO bunker	M, V	Continuous					yes		30	0,76	FW, Cargo		FW, SS, Acc, Cargo		
MDO tank	M, V	Continuous				MDO	yes			0,76	SW, FW, Cargo		FW, SS, Acc, Cargo, Cat_A	yes	
MDO daytank	M, V	Continuous				MDO	yes		30	0,76	FW, Cargo		SW, DB, SS, Acc, Cargo		
Luboil-tank	M, V	Continuous					yes			0,76	FW, Cargo		FW, Acc, Cargo		
Diesel Generator	M, V, LxWxH, n_s	Integer	T1		Cat_A	MDO	yes		30	0,76	SW, Acc, Cargo	A-60	FW, Acc, Cargo		
MeOH tank	M, V	Continuous	T2	IIA	Cat_0	MeOH	yes	Nitrogen		0,9	Air, Cat_A, FW, BW, Acc, Cargo		Cat_A, Cat_1, Cat_0, Acc, FW, Cargo	yes	0,8
MeOH fueltreatment	M, V	Continuous	T2	IIA	Cat_1	MeOH	yes		30	0,9	Air, Cat_A, FW, BW, Acc, Cargo		Cat_A, FW, Cargo, Acc		
MeOH bunker	M, V	Continuous	T2	IIA	Cat_1	MeOH	yes		30	0,9	Air, Cat_A, FW, BW, Acc, Cargo		Acc, Cargo		
DFMEOH Generator	M, V, LxWxH, n_s	Integer	T1	IIA	Cat_A	MeOH, MDO	yes		30	0	SW, Acc, Cargo	A-60	SS, DB, Acc		

Curriculum Vitæ

Jesper Jan Zwaginga

Jesper Jan Zwaginga was born in Zeist, the Netherlands, on 30 September 1994. He completed his pre-university education (VWO) at the Herbert Vissers College in Nieuw-Vennep in 2013. In 2017, he obtained his BSc in Marine Technology from Delft University of Technology. He graduated cum laude in 2020 with an MSc in Ship Design from the same university. His MSc thesis was titled "Exploring Market Uncertainty in Early Ship Design."

In November 2020, he started his PhD research at Delft University of Technology within the READINESS project, under the supervision of Hans Hopman and Jeroen Pruyn. His doctoral research, titled "Enabling Ship Changeability: A Lifecycle Approach to the Maritime Energy Transition," focuses on applying changeability principles in the context of the maritime energy transition.

Since January 2026, he has been working as a Specialist in Voyage and Scenario Simulation at MARIN (Maritime Research Institute Netherlands) in Wageningen.

List of Publications

Journal articles:

- **J. Zwaginga**, B. Lagemann, S. O. Erikstad & J. Pruyn (2024). “Optimal ship fuel selection under life cycle uncertainty”. Sustainability, 16(5):1947.

- **J. Zwaginga**, J.J.Hopman & J.F.J.Pruyn (2025). ”Navigating the maritime energy transition: A framework to deal with design and engineering challenges”. Under review in Research in Engineering Design.

Conference papers:

- **J. Zwaginga** & J.F.J. Pruyn (2022) "An evaluation of suitable methods to deal with deep uncertainty caused by the energy transition in ship design." SNAME International Marine Design Conference. SNAME, 2022.

- N. Kougiatsos, **J.Zwaginga**, J.F.J.Pruyn & V.Reppa (2023). ”Semantically enhanced system and automation design of complex marine vessels”, IEEE Symposium Series on Computational Intelligence (SSCI)

- E. Scheffers & **J.Zwaginga** (2025). "From Components to Clusters: Strategies for Smarter Placement of Onboard Energy Systems". 16th International Symposium on Practical Design of Ships and Other Floating Structures (PRADS)

Other publications:

- A. Kana, S. Brans, P. Bronkhorst, N. Charisi, L.Lupoae, C. van Lynden, I.T.Kao, J.le Poole & **J. Zwaginga** (2022). "Development and Lessons Learned of New Modular Ship Design Activities for Graduate Education During COVID". In SNAME International Marine Design Conference

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- C. Karademir, **J.J. Zwaginga**, B. Beirigo, B. Atasoy (2025). "A two-stage stochastic optimization model for synchronized two-echelon routing problems". Operations Research Spectrum.

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