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A bi-objective Markov decision process approach to explore retrofit design pathways for maritime decarbonization

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Abstract. Retrofits to alternative fuels like methanol represent a strong candidate for complying with current and upcoming environmental regulations. The decision to retrofit to methanol power, propulsion and energy systems introduces uncertainties linked to technology integration, conversion costs, and environmental performance. This paper proposes a bi-objective Markov decision process as the foundation of a design tool aimed to support retrofit decisions within a vessel's lifecycle. This approach aims to quantify the trade-off between the conflicting objectives of (a) emissions reduction and (b) retrofit costs minimization. The bi-objective formulation is evaluated against the equivalent single-objective formulations of the problem to assess the effect on the feasible design pathways. Depending on the initial vessel preparation level for a retrofit, this paper quantifies the uncertainty in the retrofit pathways during the lifecycle through the metrics of optimal state and optimal action. A case study has been applied to a notional short-sea vessel. Results indicate differing solutions when comparing the bi-objective to two individual single-objective scenarios. Preparation for a retrofit and the selection and usage of a methanol dual fuel configuration indicate a promising strategy to satisfy both objectives for the vessel's lifecycle timespan.

Key words: Retrofit, Ship Design, alternative fuels, Markov Decision Processes, bi-objective optimisation

1. Introduction

Decarbonisation brings evolving emissions targets under constant re-evaluation for 2040 and 2050 by the European Union [1] and the International Maritime Organization (IMO) [2] that vessels need to comply with. As a short to medium-term measure, the EU has enforced the Emission Trading System (ETS) [3] by applying pricing for carbon emissions of the vessels as a market-regulated measure, and its pricing remains uncertain [4]. Alternative fuels are one of the predominant options towards emissions reduction [5, 6, 7]. The adoption of alternative fuels is necessary not only for newbuilds but existing vessels as well [7]. Methanol is one of the most popular choices to decarbonize shipping and various energy converters (EC) are available for its application [8]. Aside from the widespread internal combustion engines (ICE), little emphasis has been placed on configurations with fuel cells (FC) or hybrid configurations that can lead to better efficiency rates and emissions reductions [9]. Alarmingly, Dotto et al.,[10] in a conceptual study for cruise ships, highlighted that usage of gray methanol in ICE may be viable only on a short-term horizon, i.e., until 2030, as methanol may not be compliant with energy performance indices (CII, EEXI). Lastly, alternative ECs need to be evaluated, because hybrid and FC configurations can be better suited to vessels with smaller power requirements.[11].

1.1. Holistic approach for ship design towards decarbonization

Papanikolaou et al.,[12] highlighted that the development of ship design towards decarbonization demands a holistic approach. Studies that have evaluated alternative configurations towards decarbonization within a lifecycle scope pointed out the regulations, advancement of available technologies, and market

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conditions as influencing factors [5, 13, 14]. Lifecycle decision-making frameworks, however, have failed to account for all these factors in their evaluation. McKenney,[14] provided insights into current ship design challenges driven by developments in maritime decarbonization. The large number of technologies under development adds a further challenge to an already complex process. When adopting alternative fuels, among others, additional safety measures are necessary (e.g., fuel supply system, the fuel preparation system, ventilation) that link to the engine room space [15, 16, 17]. Uncertainty occurs in the dimensions and sizing of these systems because of the ongoing development of safety regulations and the variety of available EC technologies [18]. The need for a vessel to retrofit to alternative fuels and EC is an established contemporary design challenge [19]. The level of the vessel preparation for a retrofit depends on how well it is prepared for the integration of the necessary future systems [15, 20]. Choosing suitable decarbonization pathways is linked to decision-making frameworks that can model relevant uncertainties [14]. However, works that have dealt with fuel selection under uncertainty [13, 19] have overlooked the influence of retrofit preparations and the alternative ECs (e.g., FC or a methanol-only ICE) on decision-making. Van Houten et al.,[21] demonstrated that gaining more information about the interaction of different disciplines of the design space is necessary to better understand the necessary compromises for an acceptable vessel design. Bi-objective formulations are an effective choice to perform decision pathway exploration under conflicting requirements [22]. This paper identifies the need to evaluate the interaction of conflicting requirements using a bi-objective formulation of a decision-making framework under uncertainty.

1.2. Uncertainties influential to retrofit decision-making

Decision-making can be affected by policies and market costs [23] as well as the technological properties of the ECs integrated into the vessel design [18]. When investigating the design of vessels that have a lifecycle of 20 - 30 years, it is likely that they will need to retrofit and reconfigure their systems to comply with changing emission standards [7]. [24, 13] have presented a categorization of key uncertainties when dealing with the design of marine systems. The identified uncertainties have been summarized in Table 1.. The uncertainties within the scope of this research exist on three levels: the policy, the market, and the technology.

Table 1.: Categories and modelling parameters that can be uncertain.

Category of Uncertainty	**Modelling Parameters of Uncertainty**	**Reference**
Policy	Emission pricing, emission restrictions	[14, 23]
Market	Cost of technology, Cost of fuel, Conversion costs	[24]
Technology	Dimensions of components, specific power and energy density of components, efficiency rate of components, preferred technology (FC vs ICE), considerations for safe integration	[18, 25]

- Policy: captures the uncertainty arising from the constantly evolving emissions regulations. This has led to the EU-ETS, which has introduced carbon pricing. These regulations generate uncertainty regarding the extent of the necessary decarbonization of the vessel throughout its lifecycle.

- Market: refers to the uncertainty in prices to adopt the ECs, as well as their operational costs affected by fuel pricing. Conversions to methanol dual fuelled vessels can prove costly [26]. Borghuis,[27] found that conversion costs to methanol across different types of vessels can vary from 100 €/kW up to 900 €/kW, without accounting for the different levels of retrofit preparation measures that may be applied to a diesel vessel.

- Technology: refers to the uncertainties because of the power and energy systems that lead to change in the size and are dependent primarily on the technology development and system operation [18]. This uncertainty type reflects the impact of the new systems for methanol fuel handling and EC conversion

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on the vessel size. The impact on vessel size is quantified based on the 2D layout generation. [18, 19].

The uncertainties presented in Table 1. can interact with each other and have an effect on the decision pathway to retrofit for vessel decarbonization. Therefore, a bi-objective decision-making framework that accounts for financial and emissions rewards is a promising option. Minderhoud,[20] accounted for possible preparation measures and the perceived impact of the design change when converting to a dual-fuel methanol vessel.

1.3. Shaping of the research gap

Based on the identified uncertainties, studies that evaluate the alternative fuel and EC selection were evaluated in Table 2.. Most of the studies have overlooked the influence of retrofit preparation on decision-making and have failed to deal with all the set requirements. The retrofit preparation has been tackled by [15] that evaluated its impact to conversion costs. Minderhoud,[20] focused on evaluating alternative configurations for the storage of methanol within the vessel and possible measures to take when future-proofing a vessel. However, these approaches did not include the retrofit preparation in a bi-objective decision-making framework and did not account for alternative ECs.

Table 2.: Overview of aspects considered for retrofit frameworks (adapted from [28]).

Financial objective	**Emissions objective**	**Components performance uncertainties**	**Retrofit preparation**	**Required space**	**Uncertainty modelling**	**Reference**
✓	✓	✗	✗	✗	✗	[8]
✗	✗	✓	✓	✓	✓	[15]
✗	✗	✓	✓	✓	✓	[20]
✓	✗	✓	✗	✓	✓	[28]
✓	✓	✗	✗	●	✓	[13, 19]
✓	✓	✗	✗	●	✓	[29]
✗	✗	✗	✗	✓	✗	[30]
✓	✓	✗	✗	✓	✗	[31]
✓	✗	✗	✗	✓	✗	[32]
✓	✓	✗	✗	✗	✓	[33]
✗	✗	✓	✗	✓	✓	[34]

Souflis-Rigas et al.,[28] focused primarily on integrating the information created using the probabilistic layout tool in a Markov decision process (MDP) for decision-making between alternative power and energy converters to better model the potential technology development. This study aims to capture the necessary information for the trade-off between conversion costs and emissions for a set of candidate EC configurations. The conversion impact of these configurations on the vessel is evaluated via 2D layout generation to account for the identified technical uncertainties. Integrating the technical, financial, and environmental uncertainties due to alternative energy converters (EC) configurations in an uncertainty modelling framework can generate valuable information for decision-making in the lifecycle of the vessel, as these uncertainties typically remain disconnected. Studies on alternative systems selection to comply with evolving emissions regulations include Niese et al., Kana et al., Patricksson et al.,[35, 36, 37]; however, these studies used financial rewards as the value indicator and a single objective formulation. Zwaginga et al., Lagemann et al., Terün et al.,[13, 19, 29] presented frameworks for alternative fuels selection under uncertainty in emissions and total cost of ownership (TCO). However, details for the systems configurations to adopt an alternative fuel were overlooked. This is represented with the yellow circle on the table for the required space evaluation, because empirical formulas were used for this evaluation. This paper also applies the objectives of emissions and costs for the problem in MDPs, which can provide critical insights when dealing with retrofit decision-making, like water ballast treatment or LNG fuel conversion [33, 36] and more specifically, analy-

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sis of the changes in decision-making across the lifecycle. The proposed framework incorporates all of the aforementioned aspects.

This paper aims to answer the research question:

How can a bi-objective decision-making framework elucidate retrofit design pathways for alternative fuels and energy converters under uncertainty?

To tackle this research question, the relevant research gaps and method requirements have been aligned with the proposed research contributions in Table 3.. This study attempts to provide insight into the decision-making underlying the expected values for the set objectives. The main focus is on understanding patterns occurring in decision-making. Section 2. analyzes the proposed method and, more specifically, the Bi-objective MDP formulation and the measures for the analysis of decarbonization pathways (Contribution 1,2). Section 3. applies the proposed method to analyze the different retrofit pathways for a diesel vessel that may retrofit to methanol by applying both the Single objective and Bi-Objective MDP (Contribution 3).

Table 3.: Overview of method requirements, corresponding research gaps and contributions (adapted from [18]).

Research Gaps	**Method Requirements**	**Research Contribution**
Lack of understanding of the impact of conflicting requirements (e.g., reducing emissions vs costs for technology adoption) on decision-making.	Establish financially and environmentally viable configurations for methanol adoption	[1] Extending upon the initial work of the authors [28], the MDP is extended to a bi-objective to quantify the trade-off between emissions compliance and costs for conversion.
Lack of understanding the impact of design preparation for a retrofit, when dealing with alternative fuels and ECs.	Propose a problem formulation that accounts for energy converters (ECs) using different fuels and having different levels of preparation for the transition to another technology.	[2] Provide insight on realistic decarbonizing design pathways.
There is limited insight on the underlying decisions of the solution space generated by a bi-objective formulation.	Application of suitable evaluation indices to understand the quantify the underlying patterns for decision-making towards technology selection.	[3] Quantify the probabilities of a retrofit choice being made for the bi-objective solution space.

2. Method

Figure 1. outlines the process flow to integrate the identified uncertainties in the bi-objective MDP and understand decision pathways for decarbonized designs. As shown, the technological uncertainties are used to define the state space of candidate EC solutions, and their design impact is quantified using the layout tool.

- **Lifecycle Uncertainties:** The left column presents the uncertainties identified in Section 1.2. that are taken into account, namely: technology, policy, and market.
- **Bi-objective Markov Decision Process**: The centre column includes the formulation of the MDP [28] that has been adapted to a Bi-objective MDP. Mainly, it presents the parameters that are necessary to define the MDP tuple (see Sections 3.4., 2.3.). The arrows connecting the left column of "Lifecycle uncertainties" with the center column, illustrate the way that each type of uncertainty is accounted for in the MDP Framework. Policy and market are considered in the rewards calculation. Technology affects the defined states, as well the impact on the design change. In comparison to the original formulation of [28]:

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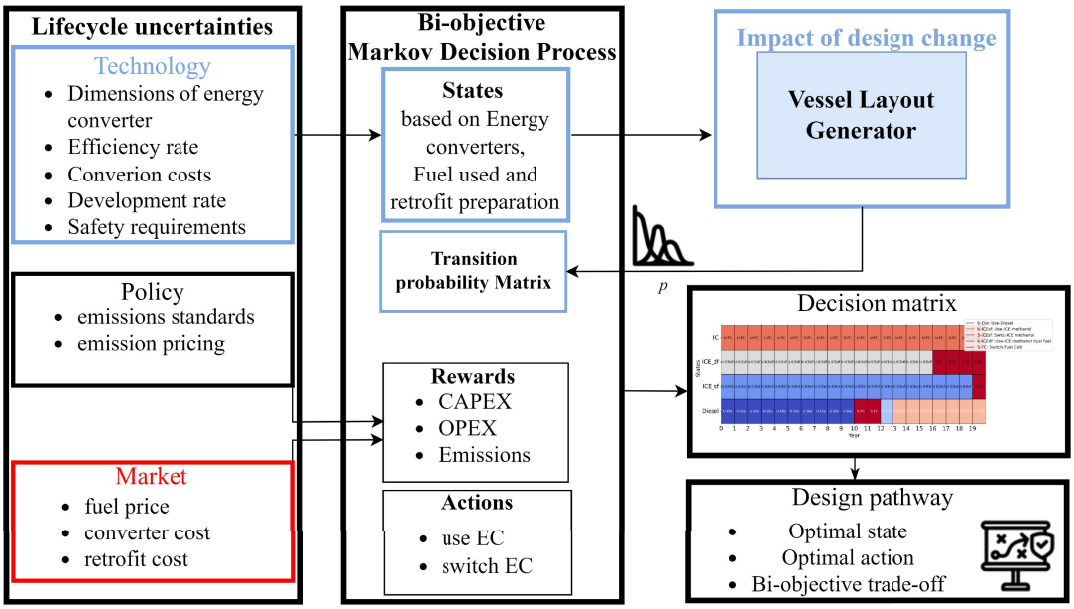

Figure 1.: Design framework, highlighting the key components of the method and the link to the identified lifecycle uncertainties.

- Rewards also include the emissions objectives.
- Retrofit preparation state: aims to quantify the impact of preparation to design pathways.
- States for both fuels and ECs: the state space includes both diesel and methanol ECs to account for more realistic retrofit options.

- **Impact of design change**: The impact of each state configuration on the design change (i.e., change in the layout of the vessel) is computed using the layout tool developed in Souflis-Rigas et al.,[38] to rate the design impact. This layout tool receives as inputs probability distributions of power and energy systems dimensions. It generates layouts by solving the facility layout problem (FLP) using a mixed integer linear programming formulation (MILP). Using Monte Carlo (MC) simulations, it produces output distributions for the length and connection costs of an engine room. It assigns probabilities for the transition probability matrix per action, based on the output probabilities. The transition probabilities reflect the likelihood of transitioning from one EC state to another.

- **Decision Matrix**: provides the optimal action for each state and at each time step [33, 35], when solving the MDP. For this problem formulation, the actions correspond to the decision of whether to continue using the current EC or switch to another.

- **Design pathway**: includes metrics to identify possible design pathways under changing requirements. The decision matrix serves as input to determine the probabilities of alternative retrofit design pathways, as well as potential trade-offs using the metrics explained in Section 2.4..

2.1. Background on Bi-objective MDPs

To the knowledge of the authors, it is the first time a bi-objective MDP has been applied in the field of ship design and more specifically in the context of decision-making for lifecycle EC system selection. Zwaginga et al., Lagemann et al.,[13, 19] evaluated alternative fuels using a bi-objective formulation for dual stage stochastic optimization, but did not use a MDP mathematical formulation. The MDP produces the action-state space for every time step of the process, providing insight into all the possible conversions that

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may take place throughout the lifecycle of the vessel [33]. This way, they provide information regarding the optimal state and action at each time step and the potential transitions occurring between states and actions, in comparison to a stochastic optimization approach that provides info only for the defined stages of the model [39]. MDPs hold the memoryless property, which means that the action selected for a state (s) at time step (t) is independent of the way the decision agent reached that point and depends only on the current state and future rewards [40]. Thus, MDP can generate more valuable insights as it provides sequential decision outcomes at each time step of the defined lifecycle, in comparison to stochastic optimization, which offers insights only for the predefined stages.

2.2. Mathematical formulation of the bi-objective MDP

The tuple that defines an MDP is:

- S — Set of states, indexed by s
- A — Set of actions, indexed by a
- T — Set of transition probabilities from one state (s) to another state (s') depending on the action (a).
- R — Set of rewards to transition to a state(s') depending on the action (a).

Chatterjee et al., Delgrange et al.,[41, 42] presented the mathematical formulation to generate a pareto front for a multi-objective MDP as an adaptation of the value iteration algorithm. The present paper adapts this formulation to solve a bi-objective MDP with finite horizon. The value iteration algorithm is based on solving the Bellman equation (see Equation 1) iteratively [43]. The bi-objective MDP is implemented via a mixed integer programming (MIP) formulation that solves the value iteration algorithm for each time step and applies the ϵ constraint to model the second objective [41, 42].

$$U(s) = R(s,a) + \gamma \max_{a} \sum_{s'} T(s,a,s')U(s') \tag{1}$$

The decision variable specifies the action to be selected for each state at every time step throughout the model's time horizon (see Equation 2). The decision variable is modelled as a binary variable according to Delgrange et al.,[42]. Equation 3 implements a constraint so that only one action is selected for each state. When solving the bi-objective MDP, the decision matrix could be stochastic (meaning solution yields probabilities for each action being selected) or deterministic, meaning one action is selected [42]. For this case, the policy is selected to be deterministic, meaning that for each state, only one action can be selected. This choice is made to gain a better understanding of the produced solution space and make its outcomes directly comparable to the single objective MDP solution that also generates a deterministic decision matrix.

$$y_{s,a} \in \{0,1\} \quad \text{for all } s \in S, a \in A \tag{2}$$

$$\sum_{a \in A} y_{s,a} = 1 \quad \forall s \in S \tag{3}$$

The proposed bi-objective MDP is an adaptation of the finite horizon MDP, and therefore, the MIP formulation is solved iteratively for the time horizon. The financial costs are modelled as the objective of the problem (Equation 4) and the emissions objective as the constraint of the MIP (Equation 5). Both equations 4, 5 are adaptations of the Bellman equation 1. To calculate the objective function (Equation 4) and the constraint function (see Equation 5) for the MIP formulation, the following parameters are defined:

- $P(s' \mid s,a)$ — Transition probability from state s to s' under action a
- $r_1(s,a)$ — Reward for financial objective
- $r_2(s,a)$ — Reward for emissions objective

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- γ — Discount factor
- ϵ — Constraint threshold for V_2 through each time step.
- $V_1(s)$ - expected Value for the financial objective.
- $V_2(s)$ - expected Value for the emissions objective.
- $V_1^{\text{init}}(s)$, $V_2^{\text{init}}(s)$ — Initial values for the expected value of each objective at each time step
- T — Duration of finite horizon, indexed by t. This marks the periods that the bi-objective MDP will be iteratively solved.

$$\min \sum_{a \in A} y_{s,a} \cdot \left(r_1(s,a) + \gamma \sum_{s' \in S} P(s' \mid s,a) \cdot V_1^{\text{init}}(s') \right) \quad \text{for all } s, s' \in S, a \in A \tag{4}$$

$$\sum_{a \in A} y_{s,a} \cdot \left(r_2(s,a) + \gamma \sum_{s' \in S} P(s' \mid s,a) \cdot V_2^{\text{init}}(s') \right) \leq \epsilon \tag{5}$$

A multi-objective optimization problem can be solved either by assigning weights to the objectives or by using the ϵ constraint method [41]. The ϵ constraint method turns one of the objectives into a constraint (see Equation 5) [22, 41, 42]. Chatterjee et al., Delgrange et al.,[41, 42] adapted the value iteration algorithm to generate pareto fronts for multi-objective MDPs using the ϵ constraint method. However, they did not deal with the time horizon of the MDP. The original formulation of the EC selection decision-making problem has been formulated as a finite-horizon nonstationary MDP in [28]. To maintain this formulation, emissions are turned into a constraint (see Equation 5), which is assumed to gradually reduce across the finite horizon to reflect the need for lower emissions to comply with the evolving environmental targets throughout the lifecycle of the vessel.

A profile of values $\epsilon_{(I)}$, $I = 1, \cdots, t$ is created that follows Equation 5 for each time step of the finite horizon. Each epsilon set corresponds to one scenario in the case study. The MIP formulation of the MDP is solved for each time step of the finite horizon. This process is repeated for various epsilon sets to generate the pareto front and quantify the trade-off between emissions and costs for the various states representing the power and energy systems configurations.

The set up described in Equations (2)–(5) applies for each time step of the MDP time horizon. This means that for each scenario of the ϵ constraint, there needs to be a vector of ϵ to apply the constraint for each step of the MDP. The set of ϵ vectors has been derived through trial and error to be able to explore effectively the design space and reflect the uncertainty that emissions regulations bring.

2.3. MDP formulation for retrofit modelling

Considering a diesel vessel as the baseline, preparation for a retrofit to methanol can differentiate the impact of conversions both on the layout and the required conversion costs. The proof of concept in this paper needs to define a set of EC states representing both the level of preparation for retrofit and alternative fuels. The proposed decision-making framework accounts for the identified uncertainties associated with retrofitting to methanol energy converters and provides insights into alternative design pathways. The MDP tuple in this case is an adaptation from [28] and is defined as follows:

2.3.1. State space

Five EC configurations represent the state space of this paper and are categorized based on two fuels:

- Diesel: there are two states depending on whether a vessel operating initially on diesel is prepared for a retrofit (Diesel_p) or not (Diesel). It is assumed that the prepared vessel will have 50 % lower conversion costs (see Figure 10.c) when shifting to a Methanol EC.

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- Methanol: there are three states for methanol that are categorized based on alternative EC configurations that may be selected and correspond to alternative financial rewards. Namely:
  - Configuration using dual fuel ICE with methanol and diesel (ICE_df).
  - Configuration using ICE only with methanol (ICE_sf).
  - Configuration using a FC.

2.3.2. Action space

The action space includes the following types of actions:

- Use fuel and EC: this means that the vessel continues operating with its existing EC configuration.
- Switch to another EC: This action indicates the transition to another EC. There is no switch action to transition to Diesel configurations, as this method attempts to identify decarbonizing pathways.

2.3.3. Transition probability definition based on EC design impact

The transition probabilities are defined by quantifying the impact of the design change to the layout with $Length_{engine\ \ room}$ metric. An uncertainty margin of 20 % has been applied to the dimensions of the components to account for uncertainties relevant to technological development [18]. The transition probability matrices have been adapted from Souflis-Rigas et al.,[28] to include the transition probabilities for both diesel and methanol. These matrices are computed according to Equation 6 and have the same formulation for both the "Switch" and the "Use" actions. Specifically the matrix in Equation 6 presents the action "Use/Switch ICE_df" and assumes for every state that the transition probability to ICE_df is dependent on the layout defined probability. The ICE_df state is defined as an absorbing state with probability 1 when wanting to switch to this technology, because this state represents the EC configuration that the action selects to use or switch to.

$$\mathbf{T} = \begin{array}{r|ccccc} & \text{Diesel'} & \text{Diesel_p'} & \text{ICE_df'} & \text{ICE_sf'} & \text{FC'} \\ \hline \text{Diesel} & p_{\text{Diesel}} & 0 & 1-p_{\text{Diesel}} & 0 & 0 \\ \text{Diesel_p} & 0 & p_{\text{Diesel_p}} & 1-p_{\text{Diesel_p}} & 0 & 0 \\ \text{ICE_df} & 0 & 0 & 1 & 0 & 0 \\ \text{ICE_sf} & 0 & 0 & 1-p_{\text{ICEsf}} & p_{\text{ICE_sf}} & 0 \\ \text{FC} & 0 & 0 & 1-p_{\text{FC}} & 0 & p_{\text{FC}} \end{array} \tag{6}$$

2.3.4. Reward calculation

The rewards for the transition from state EC to state EC' are calculated depending on the defined actions. The cost rewards are computed based on capital expenditure (CAPEX), operational expenditure (OPEX) and Emissions. The functions are defined in Table 4.. The Rewards for each action have been computed based on Table 5.. In all cases, the rewards when switching to another EC account for CAPEX and OPEX. A distinction has been made when switching from a diesel EC to a methanol EC to account for the conversion costs necessary to modify the vessel for methanol integration. When a vessel continues using the same EC, only OPEX is applied. Emission rewards have been computed based on either the EC that the vessel continues using or the EC' that the vessel may switch to.

Table 4.: Parameters of each computed cost.

Quantity for reward calculation	**Function**
$OPEX_{\text{EC}}$ [€]	fuel consumption$_{\text{EC}}$ [tons/year] · fuel cost [€/ton], EC)
$CAPEX_{\text{EC}}$ [€]	$CAPEX_{\text{EC}}$ [€/kW]· $P_{\text{installed}}$[kW]
$CAPEX_{\text{vessel conversion}}$	$CAPEX_{\text{vessel conversion}}$ [€/kW] · $P_{\text{installed}}$[kW]
$fuel\ \ consumption_{EC}$ [t]	specific consumption [t/kWh] · $P_{\text{installed}}$[kW] · $Operating_{hours}$
$Emissions_{\text{EC}}$	$fuel\ \ consumption_{EC}$ [t] · tCO$_2$eq/t fuel

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Table 5.: Reward definition per MDP action.

Transition	Financial Reward	Emissions Reward	Action
$Diesel_{EC} \rightarrow Methanol_{EC'}$	$CAPEX_{EC'} + OPEX_{EC'} + CAPEX_{\text{vessel conversion}}$	$\text{Emissions}_{EC'}$	Switch to another EC'
$Methanol_{EC} \rightarrow Methanol_{EC'}$	$CAPEX_{EC'} + OPEX_{EC'}$	$\text{Emissions}_{EC'}$	Switch to another EC'
$\text{EC} \rightarrow \text{EC}$	$OPEX_{EC}$	Emissions_{EC}	Use the same EC

2.4. Impact evaluation indices

The following metrics have been applied to evaluate the retrofit decisions during the lifecycle.

- **Optimal state**: is computed by solving the Markov chain for the selected optimal actions based on the MDP decision matrix. Consequently, the resulting optimal state is inherently dependent on both the chosen actions specified in the decision matrix and the formulation of the action space. This metric determines the probability of being at each state for each time step of the MDP. It is visualised using a heatmap that includes a colorscale (see Figure 6.a). The blue colour indicates a low probability, while the red colour indicates increased probability.

- **Optimal action**: is computed based on the optimal state through time, and finding the optimal set of actions for each time step. This metric aims to quantify the probability of selecting an action when being in the optimal state. The applied visualisation is the same as for the optimal state.

- **Optimal expected value**: quantifies the cumulative expected value (for costs or emissions) assuming that the optimal decision pathway generated by the MDP is followed.

- **Bi-objective scatter plot**: aims to quantify the trade-off between the costs for technology conversion and the emissions impact. For the analysis of the bi-objective scatter plot, the optimal state and action are computed at the end of the MDP horizon (i.e., the end of the vessel lifecycle). This aims to quantify the probability of the states and the corresponding actions that may be chosen.

3. Case study

This case study serves as a proof of concept to demonstrate the value of the proposed method, and is described in Section 3.1.. Four scenarios have been applied to better understand the trade-off in the policy between expected emissions and technology adoption costs.

1. Solving MDP as single objective with financial rewards. In this case, carbon pricing is tested as a policy activation mechanism driving the retrofit design choice (Section 3.2.).

2. Solving MDP as single objective with emission rewards. This case aims to set a baseline for the optimal pathway towards lower emissions (Section 3.3.).

3. Bi-objective MDP with costs and emissions objectives: Objectives both for costs and emissions have been applied to quantify the trade-off between the two objectives of the MDP across a spectrum scenario and generate understanding behind the trends in the optimal state and action choice (Section 3.4.).

4. Effect of conversion preparation to design pathway: Niese et al.,[35] highlighted the importance of starting state for MDP frameworks, as it reflects the initial design and operating characteristics of a vessel. In this case the starting state is varied to reflect whether a vessel has been prepared for conversion to methanol or not. For these starting states, both the optimal state and action evolution over time as well as the outcome at the end of the MDP time horizon, are compared. The goal is to identify trends in the generated alternative design pathways (Section 3.5.).

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3.1. Case study parameters and considerations

Table 6.: Systems configuration for each state of the MDP.

Diesel	**Diesel prepared (Diesel_p)**	**Methanol ice single fuel (ICE_sf)**	**Methanol ice dual fuel (ICE_df)**	**Methanol Fuel Cell (FC)**
Diesel Fuel Preparation	Diesel Fuel Preparation	Methanol Fuel Preparation	Methanol Fuel Preparation	Methanol Fuel Preparation
Diesel Day Supply	Diesel Day Supply	Methanol Day Supply	Methanol Day Supply	Methanol Day Supply
Generatorset	Generatorset	GeneratorSet	Diesel Preparation	Hydrogen Supply
Electrical switchboard	Electrical switchboard	Electrical switchboard	Diesel Day Supply	Fuel Cell
Central Cooling Water	Central Cooling Water	Nitrogen Tank	GeneratorSet	Electrical switchboard
SCR Aftertreatment	SCR Aftertreatment	Central Cooling Water	Electrical switchboard	Nitrogen Tank
Exhaust Interface	Exhaust Interface PS	Exhaust Interface	Nitrogen Tank	Methanol Reformer
	Reserved space		Central Cooling Water	Central Cooling Water
			Exhaust Interface	Exhaust Interface

Table 6. presents the systems that each EC includes. The dimensions of these systems, as well as indicative layouts, can be found in the Appendix: section 5.. Compared to the initial implementation in Souflis-Rigas et al.,[28], systems have been added to better quantify the impact of conversion to methanol. The systems: “Methanol fuel Preparation“, “Nitrogen Tank“ and “Methanol Reformer“ aim to capture the impact of the methanol additional equipment and safety requirements on engine room design change. Diesel is the baseline EC configuration for a vessel and it is assumed that it includes aftertreatment. The methanol ECs are assumed not to need aftertreatment.

The operating profile for the sizing of the reference systems was derived by Geertsma et al.,[11], which evaluated the impact of alternative fuels on a hydrographic survey vessel. The operational profile presented in Table 7. corresponds to short sea shipping operation, as the energy demand is low. Based on this operational profile, consumptions and emissions were calculated for the alternative states to compute the financial and emissions objective of the problem. The installed power is assumed to be 1200 kW.

Consumptions have been calculated according to the efficiency rates provided for each EC [28]. The fuel conversion factors to calculate the equivalent CO_2 emissions are provided in Table 8.. Table 9. provides on the right column the consumption rate for each EC. Fuel cell is selected to be a PEMFC, which is considered as a reliable FC technology [44] and the reformer efficiency has been accounted for converting methanol to hydrogen [28]. The consumption rates in the right column of Table 9. have been derived by the cited manufacturers. It is assumed that only green methanol is an available fuel choice when switching to methanol ECs. The assumption is made to keep the focus on the underlying decision patterns and the influence of uncertainty on decision-making.

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Table 7.: Operational modes with corresponding power demand, frequency, and yearly energy consumption.

Operating Mode	**Power Demand [kW]**	**Frequency**	**Yearly Energy Demand [kWh]**
Low speed	141	15%	152280
Hydrographic operations	436	40%	1255680
Economic transit	436	15%	470880
High speed transit	880	25%	1584000
Max speed	1150	5%	414000

Table 8.: Conversion factors to calculate equivalent CO_2 emissions.

Fuel	**tCO$_2$eq/t fuel**	**Reference**
MDO	3.2	[11, 45]
Green methanol	0.4	[46]

Table 9.: Fuel consumption and corresponding CO_2 emissions for different propulsion systems.

State	**Consumption [t/year]**	**Emissions [tCO$_2$/year]**	**Specific consumption[t/kWh]**
Diesel	795	2543	205 $\cdot 10^{-6}$ [47]
ICE Methanol	1705	682	440 $\cdot 10^{-6}$[47]
ICE dual fuel (Methanol+pilot fuel)	1450 + 119	961	440 + 205 $\cdot 10^{-6}$[47]
Fuel Cell	1645	658	424 $\cdot 10^{-6}$ [48]

3.1.1. Considerations to perceive methanol layout impact

The impact of technology uncertainty on the conversion is calculated with Monte Carlo simulations (see [18]). The reference size for the diesel is $L_{engine\ room}$ = 6.5 m. This metric is calculated via the layout tool presented in Souflis-Rigas et al.,[38]. Diesel is the reference case and therefore it has been assigned an equal probability of 0.5 for transitioning between states, as there is no justified incentive for layout to trigger the transitions for diesel. The probabilities of the remaining states are defined by comparing their effects on the engine room layout (i.e., length). Using the mean value and standard deviation of change in engine room length compared to the reference diesel configuration (see columns $\delta Length$ [m] in Table 10.), the impact of uncertainty is quantified. The states are then ranked with 1 indicating the highest impact, and 4 the lowest. According to this ranking, the probability values have been assigned.

Table 10.: Relative change of overall length and connection lengths.

State	δ **Length [m]**	**Ranking of relative impact**	**Probability value**
Diesel prepared	1.52 ± 1.57	1	0.2
ICE Methanol	0.29 ± 0.34	3	0.4
ICE dual fuel	-0.07 ± 0.28	4	0.6
Fuel Cell	0.83 ± 0.59	2	0.3

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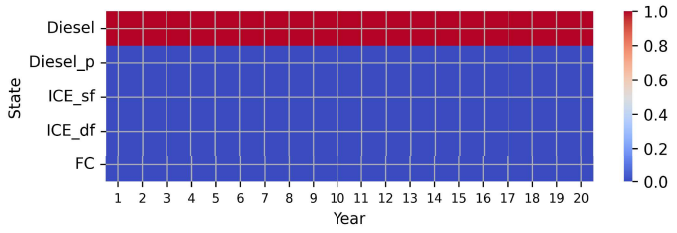
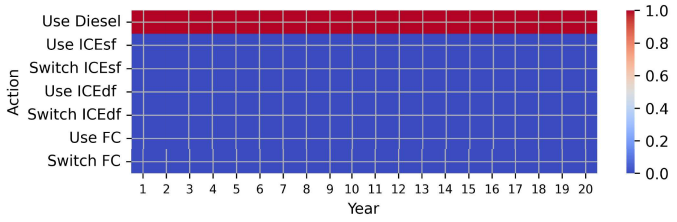
3.2. Solving MDP as single objective using the Costs objective

In this case, financial rewards have been applied to the MDP. To solve the MDP as single objective, the method applied in Souflis-Rigas et al., Kana et al.,[28, 33] has been used. When solving this case for different starting states, it is found that the optimal state and action are dependent on the starting state. This means that the optimal action would be to continue using the EC configuration of the initial state for the complete lifecycle of the vessel.



(a) Optimal state when solving MDP based on costs objective.



(b) Optimal action when solving MDP based on costs objective.

Figure 2.: Optimal state, action based on the policy dictated by MDP solved for costs.

3.2.1. Carbon pricing

Carbon pricing was used to evaluate whether the additional policy costs could trigger a decision to switch to another state. OPEX when applying carbon pricing is shown in Figure 10.b. The optimal state and optimal action when applying carbon pricing remain the same as in Figure 2.. However, when comparing the optimal expected value with and without carbon pricing, a considerable additional cost occurs. Figure 3. shows that the carbon pricing as a policy measure did not prove adequate to trigger actions for switching to another EC. The comparatively low power demand of the case study operating profile does not justify the switching actions to another EC. This means that alternative policy measures are necessary for vessels operating in short shipping. This conclusion is in line with the findings of Minderhoud,[20], who performed a similar case study.

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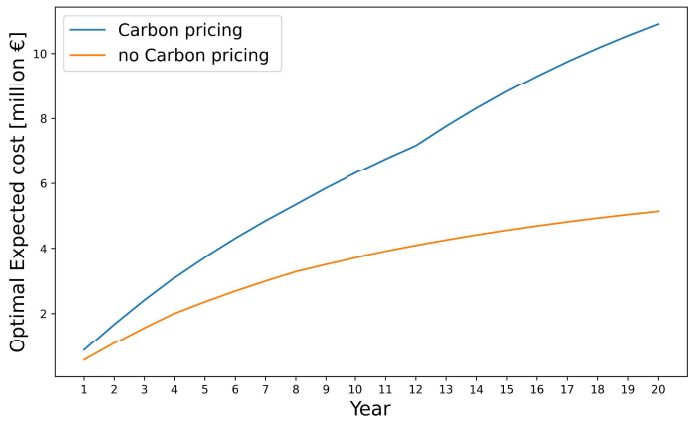
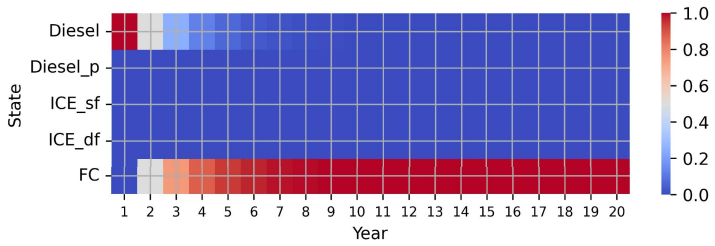


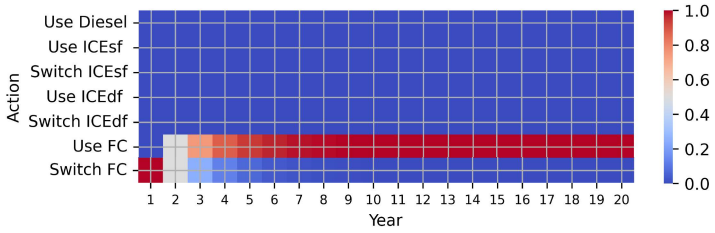
Figure 3.: Optimal expected value with and without carbon pricing.

3.3. Solving MDP as single objective using emissions objective

In this scenario, the MDP was solved by applying emissions reward based on Table 5.. The FC configuration rapidly emerges as the optimal state, with the corresponding optimal actions indicating the switch to FCs in year 2 and the use of FCs in year 4 with a probability higher than 0.8. (Figure 4.). By year 3, it has a probability of 0.8 of being the optimal state, and by year 6, it converges.



(a) Optimal state when solving the bi-objective MDP and implementing stricter ϵ constraint.



(b) Optimal action when accounting only for emissions compliance.

Figure 4.: Optimal state, action based on the policy dictated by emissions rewards.

The results of solving the MDP as single objective for cost rewards and emission rewards generate conflicting optimal states and action pathways. Section 3.2. found that the optimal action is to maintain the starting state (diesel) for the complete lifecycle duration. In contrast, Section 3.3. determined that it is optimal to follow actions to use FC as soon as possible. A competitive vessel retrofit pathway should comply with emission regulations and remain cost competitive. Towards this direction, the proposed framework

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explained in Section 2. is applied to generate understanding on the design choices that can potentially satisfy both of the defined objectives (i.e, costs and emissions).

3.4. Bi-objective MDP and effect of different epsilon values to expected value and retrofit pathways

The bi-objective MDP has been solved for 31 different ϵ sets that represent the variation in the emission limits that has been identified as one of the policy uncertainties within decision-making. The ϵ sets were determined with simulation testing. For each time step of the MDP horizon, ϵ is adjusted according to the emissions of the state with the lowest expected financial value. The constraint applied on the ϵ value represents the demand to reach different reduction levels of CO_2 within the lifecycle duration.

The scatter plot points in Figure 5. quantify the optimal expected value regarding the EC costs and emissions at the end of the vessel's lifecycle when following the decision pathway generated by the bi-objective MDP solution. The colour scale used for the points indicates the scenario corresponding to the ϵ set. There are two clusters of points in this figure: the ones on the top left corner and the other on the bottom right. 31 scenarios of the ϵ value have been applied to trigger the change in the optimal policy and better understand the trade-off between emissions compliance and costs for technology adoption. A color scale has been added to trace the points corresponding to each scenario. The left and right point clusters show considerable deficits in both expected emissions and costs. This is explained by the case study inputs: diesel configurations have lower operational costs but higher emissions, whereas methanol configurations have higher costs but lower emissions (see section 5.)

The use of green methanol in EC leads to an increase in OPEX because of its fuel price and the increased consumption compared to Diesel (see Table 9.), as well as the conversion costs reflected in CAPEX to adopt the new EC. The top left corner represents the points that continue using diesel and corresponds to scenarios with higher ϵ thresholds (i.e., higher emissions values are acceptable). To gain better insight into the potential actions and states that these points underlie, the point for scenario 31 is selected (yellow colour). This point was selected for evaluation, as it belongs to a clustered set of solutions. The optimal state and action for this point is depicted in Figure 6..

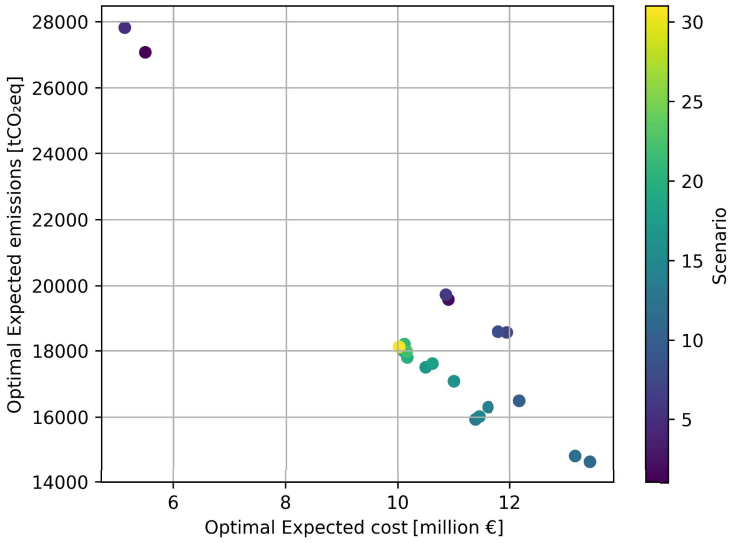

Figure 5.: Scatter plot of the final optimal expected values for the biobjective across 31 scenarios.

Figure 6. provides insight for the optimal state and action for the complete time horizon of the MDP. In this case study, the ϵ held the assumption of constantly decreasing values throughout the horizon of the MDP. It becomes clear that by year 7, there is a trigger point to switch to dual fuel ICE (see Fig 6.b). The likelihood to use dual fuel ICE gradually increases from 0.5 during years 7 to 11 to 0.625 during years 12

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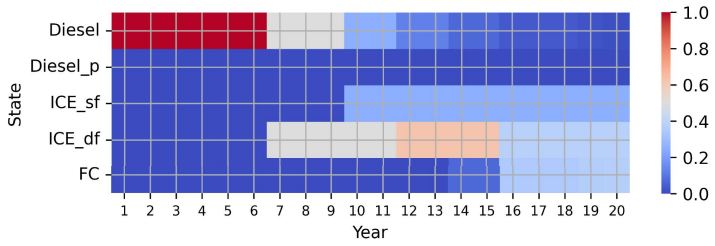
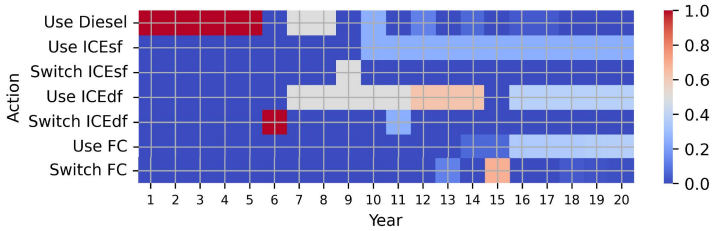
to 14 (see Figures 6.a, 6.b). FC starts becoming a candidate design pathway in year 15 according to the plot 6.b, with probability 0.68 to switch to FC. This is driven by the ϵ emission constraints, which enforce lower emissions as the vessel approaches the end of its lifecycle. However, by the end of the lifecycle in year 20, the optimal state and action are split and uncertain, with dual fuel ICE and FC displaying a probability of 0.37 and methanol ICE 0.25. This can be explained by the rewards set for the bi-objective MDP (i.e., CAPEX, OPEX and Emissions in section 5.), as at the later stages of the lifecycle they are closely matched. Additionally, it is shown that the transition probabilities assigned in Table 10. become less influential when the requirement for a lower emissions objective is enforced.



(a) Optimal state when solving the bi-objective MDP and implementing stricter ϵ constraint.



(b) Optimal action when solving the bi-objective MDP and implementing the stricter ϵ constraint

Figure 6.: Optimal state, action plot for one point of the scatter plot in Figure 5. based on the policy dictated by the bi-objective MDP.

Lastly, the optimal states and actions for the end of the lifecycle are visualised in Figure 7.. It becomes clear that for the majority of the scenarios, there is not a clear decision pathway. The probability of the optimal state is split among the methanol ECs. For the majority of scenarios, FC and ICE dual fuel have increased probabilities that are 0.37 and 0.38, respectively (see Figure 7.a). The methanol ICE (ICE_sf) has a lower probability of 0.25. Actions to use an EC are selected at the end of the lifecycle according to Figure 7.b. This means that in spite of the requirement for a reduced emissions objective, the switch to a methanol EC has been made in a previous time step. The action to "Use FC" is favoured across the scenarios, but marginally compared to the decision to use dual fuel ICE-"Use ICEdf"- (see Figure 7.b). Similarly, the optimal state is split between the dual fuel ICE and the FC. The optimal state is split between diesel and FC in scenarios 1-7. Only in scenarios 9-10, methanol single fuel ICE (ICE_sf) represents a likely candidate with probability 0.8. The analysis of optimal states and actions in Figure 6. reflects scenarios 24 to 31. The inconsistent outcomes for the optimal state and action highlight the need for further investigation regarding the conversion of a conventional diesel vessel.

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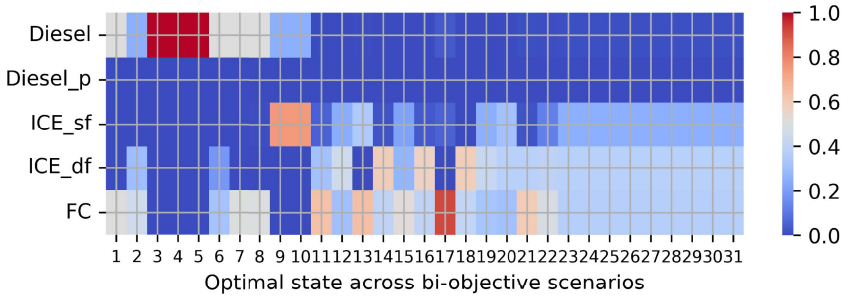
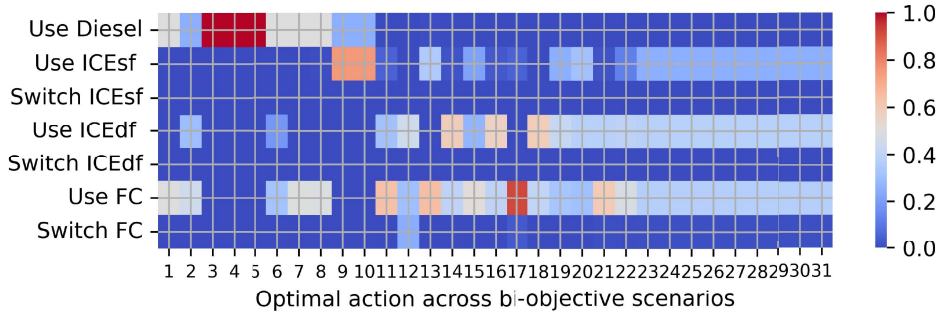


(a) Final optimal state set across the bi-objective scatter plot scenarios.



(b) Final optimal action set across the bi-objective scatter plot scenarios.

Figure 7.: Optimal state and action across all the scenarios of the bi-objective scatter plot scenarios.

3.5. Effect of conversion preparation to design pathways

The goal of this section is to evaluate whether the retrofit decisions may change throughout the lifecycle when the diesel vessel is prepared for conversions. The prepared diesel vessel is therefore the starting state for the optimal state and action computation. The additional costs to prepare for conversion have not been considered. This may provide optimistic rewards for the prepared diesel state, but the investment to acquire the vessel has remained out of scope. To understand the influence of the starting state, this section needs to be read in combination with Figures 6. and 7.. Scenario 31 from the bi-objective MDP plot that was analyzed in Figure 6., was rerun for the different starting state. Figure 8.b shows that already in year 2, the switch to a dual fuel ICE is the optimal action, and up until year 14, the usage of the dual fuel ICE remains the selected choice. Only in year 15, switching to FC is identified as a necessary action, which indicates a stricter emission standard being enforced. But even then, usage of dual fuel ICE retains the highest probability with 0.6 compared to 0.4 for usage of FC. Figure 8.a) confirms that FC and dual fuel ICE (ICE_df) are the optimal states in these time periods, with probabilities 0.4 and 0.6, respectively. The comparison to Figure 6. shows two key findings. Firstly, the prepared vessel switches at least 4 years earlier to the dual fuel EC. Secondly, the decision pathway appears clearer, with only three states being selected.

The pattern remains the same when looking at the optimal states and actions across the points for the end of the lifecycle in Figure 9.. Three actions are more commonly selected across the scenarios. Aside from scenarios 1 to 3 that select to continue using diesel, across scenarios 4 to 31, the usage of dual fuel ICE is more likely with a probability of 0.6. FCs have a probability of 0.4 of being used, and in scenarios 9 and 10, the single fuel methanol ICE may be selected. Therefore, Figure 9. showed that a prepared vessel can lead to a clearer retrofit strategy and demystify decision-making for EC selection towards a retrofit.

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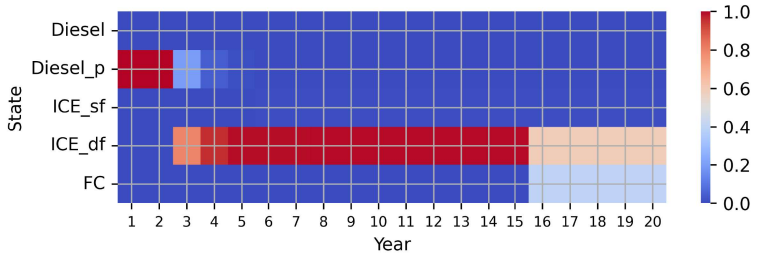
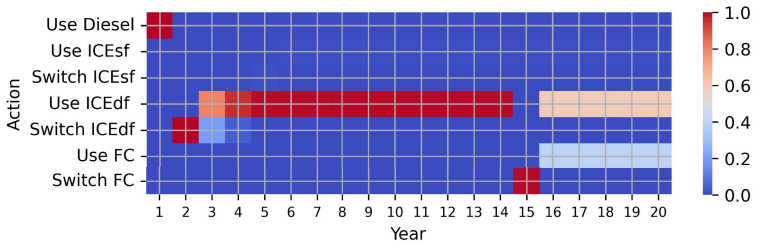
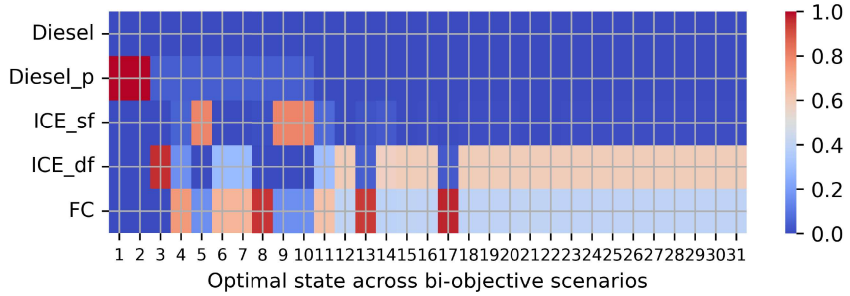


(a) Optimal state when solving the bi-objective MDP with the prepared vessel as the starting state.

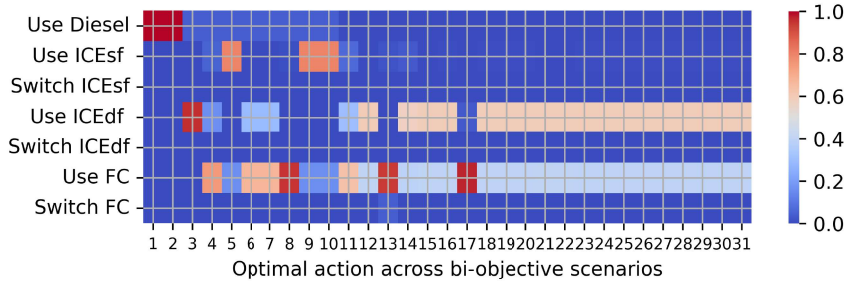


(b) Optimal action when solving the bi-objective MDP with the prepared vessel as the starting state.

Figure 8.: Optimal state, action plot computed for the bi-objective MDP policy for the same ϵ constraint conditions as in Figure 6. and prepared Diesel vessel as initial state.



(a) Final optimal state set across the bi-objective scatter plot scenarios.



(b) Final optimal action set across the bi-objective scatter plot scenarios.

Figure 9.: Optimal state and action across all the bi-objective scatter plot scenarios with a vessel prepared for retrofit as a starting state.

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3.6. Reflection on the evaluated scenario

This section summarizes the results of the different test cases that were evaluated by the model and aims to reflect on why the generated solutions differ in this way. The expected value for costs and emissions in Table 11. is at the end of the vessel's lifecycle and optimal state, and the action indicates the selected design pathway. When comparing the values of the bi-objective set up to the single objective solutions, the bi-objective performs worse in both objectives, even with the carbon pricing applied, and has an unclear design pathway split between dual fuel ICE and FC. However, the single objective solutions are unlikely to conform to the upcoming requirements a vessel faces. It is unlikely that diesel, as the optimal case for costs, will conform with all the evolving emissions regulations in the vessel's lifecycle. On the other hand, FC, which is the optimal state for emissions, can lead to additional unnecessary conversion costs at a time point that the vessel is still compliant and cost competitive using diesel. Therefore, the optimal states produced by bi-objective set up accounting for the trade-off occurring between the conflicting goals provide more feasible solutions under realistic scenarios.

Table 11.: Comparison of scenarios based on expected cost, emissions, optimal state, and action at the end of lifecycle.

Scenario	**Cost [mil €]**	**Emissions (tCO_2eq)**	**Optimal state**	**Optimal action**
Single Objective with financial rewards	5.13	-	DIE	Use Diesel
Single Objective with financial rewards and carbon pricing	10.89	-	DIE	Use Diesel
Single Objective with emissions rewards	-	7197	FC	Use FC
Bi-objective (derived from case in Figure 8.)	13.16	14800	60% use ICE df + 40% use FC	60% use ICE df + 40% use FC

4. Conclusions

This paper introduced a method to better understand alternative retrofit pathways in the context of evolving environmental regulations and emerging PPE technologies. The proposed method is based on a bi-objective MDP to gain a better understanding of realistic design retrofit pathways that are cost-competitive and emissions-compliant. The method was demonstrated by comparing single objective to bi-objective MDP and evaluating its outcomes based on the optimal state and optimal action metrics. Insights are significant both regarding the proposed method and the applied case study.

The method quantifies the trade-off between two conflicting design goals (i.e., reduced conversion costs and emissions). Being able to identify the time points at which a retrofit decision may be an optimal choice is of value to a shipowner and designers. The current case studies did not aim to analyse exhaustively all the potential uncertainties that may occur during decision-making for a retrofit. However, it proved that for short sea shipping, green methanol adoption requires more than instigator measures like carbon pricing, to switch to cleaner energy converters (EC). Although the optimal design pathways may be clear when applying either emissions or financial rewards, the optimal configuration choice is not clear in the bi-objective set up. This happens as the candidate EC states present significant deficits in their CAPEX, OPEX, and emissions (see section 5.) and therefore the underlying decision dynamics call for further investigation.

The application of the optimal action and state metrics to the bi-objective set up generated insight beyond just the evaluation of the domination of the bi-objective scatter plot points. The uncertainty in the design pathway to select when the emission requirements get stricter was quantified. The generated solutions satisfying stricter emissions constraints highlighted the need for a compromise on emissions performance and cost feasibility. However, further development of these metrics for retrofit (design change) decisions is needed to better explain the trade-offs between two or more objectives during the vessel lifecycle.

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When a vessel is unprepared for conversion, the pathway is mainly split between the dual fuel engine (ICE) and the fuel cell (FC). Preparation for conversion generated a clearer design pathway, with dual fuel ICE being the more probable choice at the lifecycle end across the bi-objective scenarios and the duration of the vessel lifecycle. This method quantified the uncertainty of design pathways under conflicting requirements.

For the method advancement, it is valuable to assess both the vessel conversion (i.e., design change) impact as well as the stochastic uncertainty modelling framework. The addition of a third objective for design conversion, representing the consequent costs in more detail, is an interesting direction. The generation of layouts accounting for more systems and their integration requirements, and different levels of retrofit readiness, can help estimate the likelihood of transitioning between technologies. The consumption estimations accounting for the ECs technological development can increase the accuracy of rewards calculation in a bi-objective or multi-objective MDP set-up. A benchmark against stochastic programming formulations can further improve the proposed method and enhance the analysis of uncertainty influence on retrofit design decisions.

Acknowledgments

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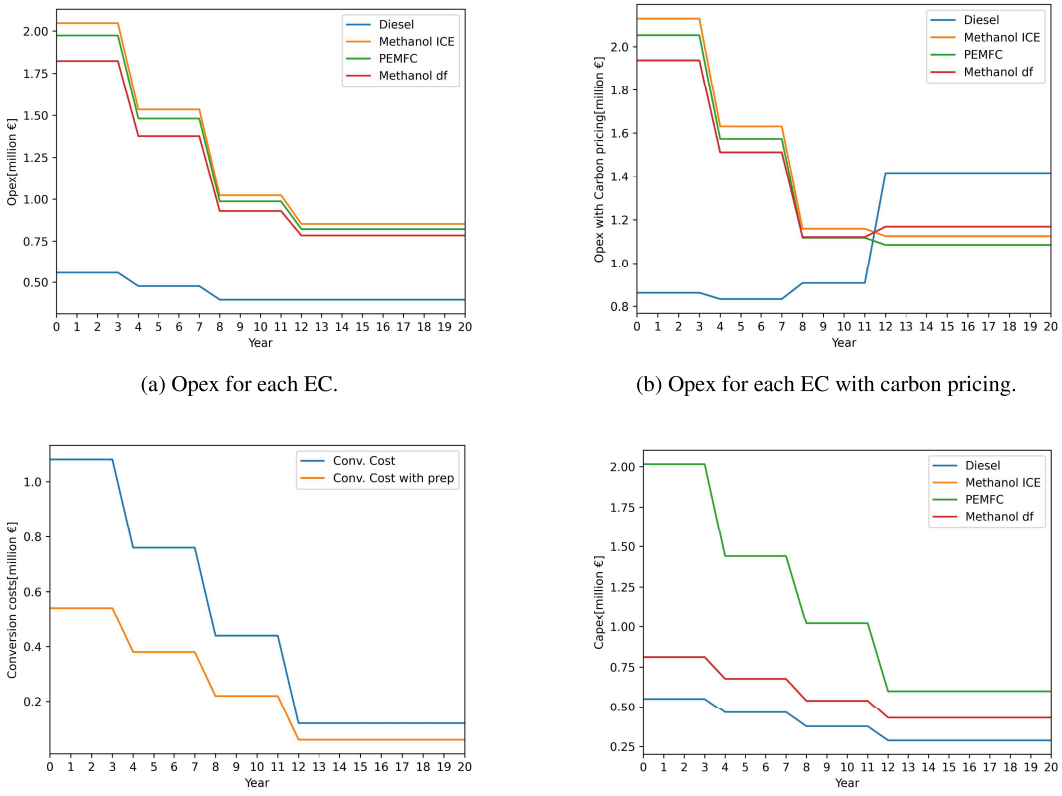
5. Appendix

Inputs for the rewards calculation of the model:



(a) Opex for each EC.

(b) Opex for each EC with carbon pricing.

(c) Conversion costs

(d) Capex costs for EC conversion.

Figure 10.: Inputs for the financial rewards calculation.

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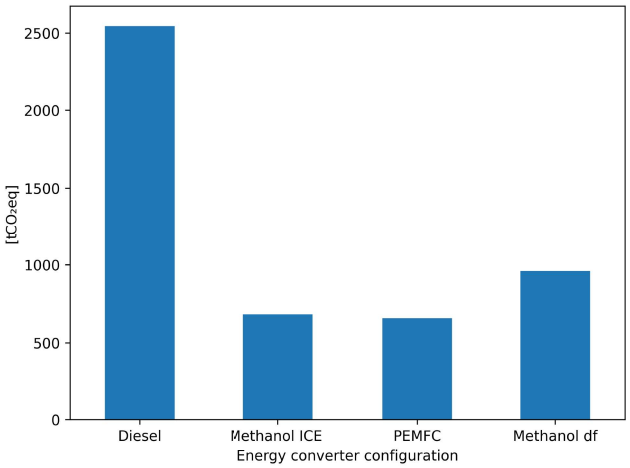

Figure 11.: Emissions per year for the different ECs.

Indicative layout outputs for each EC configuration:

Table 12.: Systems dimensions for energy converters configurations.

Block Name	**Width [m]**	**Length [m]**
Methanol Fuel Preparation	1.8	3
Methanol Day Supply	1	0.8
GeneratorSet	1.3	5.3
Electrical_switchboard	4.4	0.9
Nitrogen Tank	2.5	0.7
Central Cooling Water	0.5	1
Exhaust Interface PS (1)	1	0.1
Diesel Fuel Preparation	0.9	1.5
Diesel Day Supply	0.6	0.8
SCR_DPF	0.9	4
Reserved space	2	3
Fuel Cell	0.8	7

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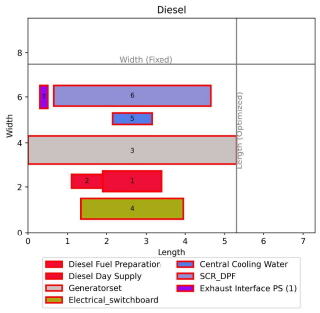
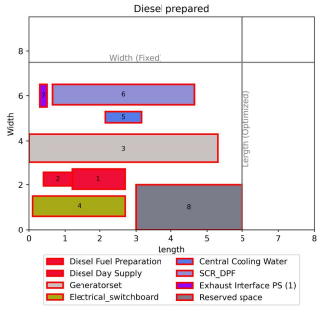
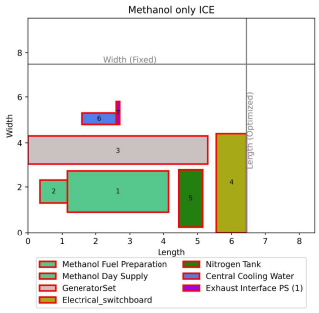


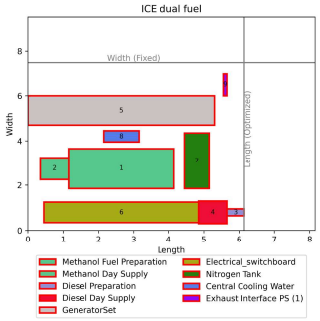
(a) Layout for diesel configuration.



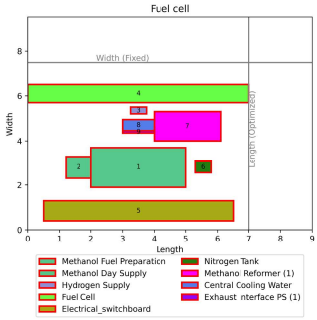
(b) Layout for prepared diesel for conversion.



(c) Layout for methanol only ICE.



(d) Layout for dual fuel methanol ICE.



(e) Layout for Fuel cell.

Figure 12.: Indicative layouts of the states evaluated with Monte Carlo simulations.

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