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Integration of the methanol power propulsion and energy systems' temporal uncertainties in a Markov decision process framework

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ABSTRACT

The ongoing technological development of methanol energy converters (EC) towards decarbonization means that their dimensions and performance characteristics will be continually updated during the lifecycle of vessels currently designed. These advancements influence the ease of EC integration within the general arrangement of the vessel. The decision to switch from an internal combustion engine to a fuel cell or a hybrid configuration depends both (1) the technology adoption costs (i.e. CAPEX, OPEX) of the EC and (2) on the effect of EC on the actual engine room layout. The state-of-the-art literature has typically addressed these two challenges separately. This study proposes a design method to bridge these two fields by combining the use of (1) Markov decision processes to assess uncertain future methanol EC developments during the vessel lifecycle and (2) a generative probabilistic layout algorithm to quantify the risks associated with the EC systems layout integration. The case study identifies the drivers behind the EC technology choice during the lifecycle of a notional yacht vessel.

KEY WORDS

Ship Design; Methanol; Uncertainty propagation; Markov Decision Process; Maritime energy transition; Layout integration

INTRODUCTION

Background

Greenhouse gas (GHG) emissions produced from the maritime industry have increased by 9,6 % between 2012 and 2018, in spite of operational measures regarding the speed of the vessel being imposed (IMO, 2021). Forecasting studies have shown that emissions may increase between 90 % to 130 % compared to 2008 levels (IMO, 2021). Chen et al. (2019) demonstrated that the targets of International Maritime Organisation (IMO) cannot be met with the current measures in place. In 2023, IMO (2023) introduced the revised target of net zero GHG emissions in 2050 matching the goals of European Commission policy (EU, 2023), which are more strict in comparison to the standards in the study of Chen et al. (2019). Aakko-Saksa et al. (2023) and Lindstad et al. (2021) found that adoption of carbon neutral fuels is key towards reaching the ambitious and challenging emissions mitigation targets. Several energy converter (EC) technologies are available to facilitate the transition towards carbon neutrality. A large proportion of existing fleet are using diesel internal combustion engines (ICE) (2-stroke or 4 -stroke) that when using conventional diesel contribute to emissions generation (Gray et al., 2021).

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Retrofitting of these vessels is a necessary measure towards decarbonization (Gray et al., 2021) and the dual fuel engines have proven popular option (Tadros et al., 2023). Methanol has emerged as one of the prime candidates, being the 4th most widespread fuel (IMO, 2021), because it is in a liquid state and has properties resembling more closely to diesel in comparison to other alternative fuels (Zincir and Deniz, 2021; Harmsen, 2021). Methanol is thought to require minor modifications to be integrated within a vessel (Korberg et al., 2021; Zincir and Deniz, 2021). However, when considering the technologies available to be integrated within the power, propulsion and energy systems (PPE) (i.e. fuel cells (FC), batteries) as well as safety requirements for the fuel Zincir et al. (2023) and redundancy for vessel operation, the modifications will likely prove to be more than minor and thus more investigation is necessary. Souflis Rigas et al. (2023) showed that a large estimation discrepancy exists when attempting to compute the effect on the overall size of the vessel, pointing out the need for further research.

This study aims to compare different methanol energy converters on a lifecycle scope, while factoring in the challenge of layout modifications required for methanol EC technology adoption. A common trend in recent studies so far is to compare the alternative technologies and fuels based on financial and emission objectives (Zwaginga and Pruyn, 2022; Lindstad et al., 2022; Lagemann et al., 2022, 2023). However, these evaluation approaches have traditionally overlooked the challenges of the energy converters integration. Korberg et al. (2021) studied the feasibility of alternative fuels and propulsion configuration based on the total cost of ownership (TCO) and found methanol an advantageous choice, pointing out that FCs would need efficiency enhancement and capital cost reduction to become competitive. Similarly Lagemann et al. (2023) considered the most appropriate propulsion configurations based on uncertain emission regulations and pricing of fuel and carbon emissions and found methanol and LNG as strong candidates, but did not have a clear conclusion on which energy converter (FC or ICE) to use. Assessing the ease of implementing the proposed configuration is crucial before reaching a conclusion about the optimal choice. Lagemann et al. (2022) pointed out that technical and safety challenges may influence the solution outcome. This study aims to consider at a conceptual level the factors affecting the integration of the systems by integrating a probabilistic layout generation tool developed by Souflis Rigas et al. (2023) and Poullis (2022) to compute the probability of shifting to another energy converter during the lifecycle of a vessel, within a Markov decision process (MDP) employed for lifecycle modelling.

Energy converter uncertainties

ICEs, FCs, or a hybrid configuration can be selected for the methanol adoption. FCs are still under development, meaning their specific power density (volumetric and gravimetric) and efficiency rate remain uncertain van Biert et al. (2016); Van Veldhuizen et al. (2023). Elkafas et al. (2022); van Biert et al. (2016); Van Veldhuizen et al. (2023) highlighted that the efficiency rates and the power densities (volumetric and gravimetric) remain highly uncertain, as shown in Table 1. FCs are still a technology under development (EMSA and DNV, 2021), and it is fair to assume that their volumetric power density is far from becoming a deterministic value. Even, methanol internal combustion engines are still under development with their volumetric power density and efficiency rate improvements being part of ongoing research (Juho Repo et al., 2023). Additionally, Table 1 presents the uncertainty in estimating the cost of acquiring the main energy converter. This study focuses on interpreting the uncertainty in volumetric power density via Equation 1 (Torabi and Ahmadi (2020)) into physical dimensions uncertainty that is an input parameter for the probabilistic layout tool.

Table 1: Energy converters uncertainties considered (data derived from Elkafas et al. (2022); Zwaginga and Pruyn (2022); MARIN (2024); Wartsila (2024); MAN (2024))

Energy Converter	Volumetric Power Density (kW/m³)	Capex (€/kW)	Efficiency Rate
PEM - Fuel Cell (PEM-FC)	45-500	500-1680	47%-65%
ICE 4-Stroke	120-290	451-677	30% - 45%

$$P_{volumetric} = \frac{Power_{installed}}{L \cdot B \cdot H} \tag{1}$$

in which:

- $Power_{installed}$: installed power of the component
- L: length of the component
- B: width of the component
- H: height of the component

Review of studies on alternative fuels adoption -shaping of the research gap

Besides the studies focused on EC technology development, there are comparative studies for alternative fuels that consider the challenge of adopting alternative fuels in the form of additional space, volume, or weight objectives within an optimization framework. Ritari et al. (2023) investigated several ways to configure the PPE systems within the lifecycle period of a vessel using a total cost of ownership (TCO) minimization framework, but did not consider uncertainties in the dimensions or the performance of the components described. The properties of the potential PPE components were deterministic. Similarly, Zhang et al. (2023) evaluated different PPE configurations for a cruise vessel based on emissions and costs. Zhang et al. (2023) estimated the additional space demand in proportion to the size of the prime energy converters (EC): meaning that the engine room is assumed 5 times larger than the size of an internal combustion engine (ICE) and fuel cells are set to 2.5 times bigger than the fuel cell (FC) volume. Additionally, the conclusions of this study, through time, proved highly sensitive to the carbon pricing variation. Rivarolo et al. (2021) implemented a tool that evaluated various energy converters for a cruise ship based on volume, weight, costs and emissions and calculated volume and weight based on empirical equations derived from market data. The computed volume remains mostly focused on the additional fuel storage, disregarding possible alterations because of the PPEs uncertainties. These studies highlight that the space requirement is a decision influencing factor when comparing alternative fuels and energy converters. Additionally, the development of the EC technologies and their related sizing uncertainties have been totally overlooked. Higher fidelity in the layout modelling can generate more insightful information regarding the actual integratability of the EC within the engine room space.

Table 2 presents the elements that constitute relevant studies on lifecycle analysis and evaluation of suitable main EC (energy converter) technologies. Two elements are not sufficiently adressed:

- Space requirement for alternatively fuelled components integration: has been calculated based on volume requirement for additional fuel storage based on empirical equations or data trendlines and overlooks PPE configuration complexity Rivarolo et al. (2021); Lagemann et al. (2023); Ritari et al. (2023)
- The performance of the components under development (FCs, batteries, ICEs) and their *uncertainty* in terms of *volumetric, gravimetric power density and efficiency rates* as presented on Table 1

Table 2: Overview of objectives of studies focused on alternative fuels

Financial uncertainties	Emission uncertainties	Components performance uncertainties	Space requirements	Determinstic values	Reference
✓	✓	✗	✓/✗	✗	Lagemann et al. (2023)
✓	✓	✗	✓/ ✗	✗	Zwaginga and Pruyn (2022)
✗	✗	✗	✓	✓	Rivarolo et al. (2021)
✓	✓	✗	✓	✓	Zhang et al. (2023)
✓	✗	✗	✓	✓	Ritari et al. (2023)
✗	✗	✗	✗	✓	Korberg et al. (2021)
✓	✓	✗	✗	✗	Kana et al. (2015)
✗	✗	✓	✓	✗	Souflis Rigas et al. (2023)

Table 2 in combination with the overlooked discrepancy estimations in the size effect of the alternative fuelled PPE components integration Souflis Rigas et al. (2023) and the uncertainties in the performance evolution of energy converters - see Table 1, shapes the need to integrate the 4 objectives considered within Table 2. This paper developed a method that combines elements of the studies of Kana et al. (2015) and Souflis Rigas et al. (2023) to take a step further in the accuracy of the lifecycle evaluation and integrate the uncertainty aspects described.

State of the Art of Markov decision process in ship design

Markov decision process has been selected to quantifiably propagate the technical uncertainties of the ECs through time. Kana et al. (2015) highlighted that MDPs are beneficial because they integrate quantified uncertainties related to policy application, reflect the net present value per epoch via the rewards and provide the optimal decision per epoch (*epoch: refers to the executed time steps*). Kana and Harrison (2017) pointed out that MDPs generate an understanding of the decisions made within a time dynamic framework rather than provide one optimized solution on a specific time static case.

Kana et al. (2015); Kana and Harrison (2017) demonstrated through a case study regarding the conversion of a containership vessel to LNG fuel, that the emission regulation advancement uncertainties and supply chain risk uncertainties can be captured within an MDP to generate insight on the conversion choices through time. Niese (2012) developed an MDP framework that accounts for policy to generate a strategic maintenance plan for a ballast water treatment system and showcased the effect of uncertain regulation requirements on the maintenance decisions of deteriorating components. Niese et al. (2015) applied ship centric Markov decision process (SC - MDP) to evaluate the effect of alternative technologies, alternative fuels and operational measures adoption (e.g. engine derating) to the design choices (e.g. principal ship dimensions) being made as well as the rewards generated throughout lifecycle. The design space of the alternative vessels' was produced via low-fidelity modeling. However, this study outlined the potential of MDPs to compare and evaluate the influence of various technologies on the design and the economic viability of a vessel. Overall MDP, provide a reliable method to capture stochastic temporal uncertainties caused by regulation, policy, costs, and technology alterations.

Research contribution

As shown in Table 1 and using equation 1, the uncertainty of volumetric power density can be matched to the uncertainty of the physical dimensions of the component. The focus remains on propagating the uncertainty of the physical systems dimensions throughout the vessel's lifecycle and thus accounting for uncertainties overlooked by previous research. The main goal of this work is to compare the potential ECs through the vessel lifecycle while using the probabilistic layout tool output to define the transition probabilities and see which are the influential factors to the outcome.

METHOD

MDPs are designed to capture and solve a sequential decision-making problem that deals with time dynamic uncertainties in the state space (Kana et al., 2015; Russell et al., 2010).

The key components to define an MDP are:

- states (s): representing a set of states that the agent may be in through time
- actions (a): a finite set of actions that can be selected
- Transition Probabilities (T($s'|s, a$)): expresses the probability upon choosing action a, the agent in state s will move to state s' in the upcoming epoch.

- Rewards (R): is the reward given after moving to a new state s' by selecting action a

Note: agent represents the entity that selects the action to be implemented based on the solution followed for the MDP.

Solving MDPs produces a sequence of states through time that are selected based on the optimal value per epoch. The algorithm selected to solve the MDP is the value iteration algorithm using the Bellman equation (see Equation 2), which is typical for solving a stochastic dynamic programming problem Bethke and How (2009). Equation 2 is used to compute the utility for each state per epoch. The sequence of actions selected using Equation 3 compiles the policy of actions to be made per state throughout the defined time horizon. The optimal policy in this case is considered the one that yields the highest expected value.

$$U(s) = R(s,a) + \gamma \max_a \sum_{s'} T(s,a,s')U(s') \tag{2}$$

$$\pi(s) = \arg\max_a \sum_{s'} T(s,a,s')U(s') \tag{3}$$

Russell et al. (2010) described the value iteration algorithm as: *a way to propagate the information through the state space by means of local updates, which provides a way for uncertainty percolation through time*. The selected MDP has a finite time horizon and features non-stationary dynamics, where both the probability and reward vectors evolve over time. Kana et al. (2015) pointed out that the changes in the probability and reward vectors can be caused by degradation, regulatory shifts and logistics risks. In this case study the non- stationary property is derived from the changeable performance properties and technology acquisition/ adoption costs of the ECs.

Novel Transition probabilities definition

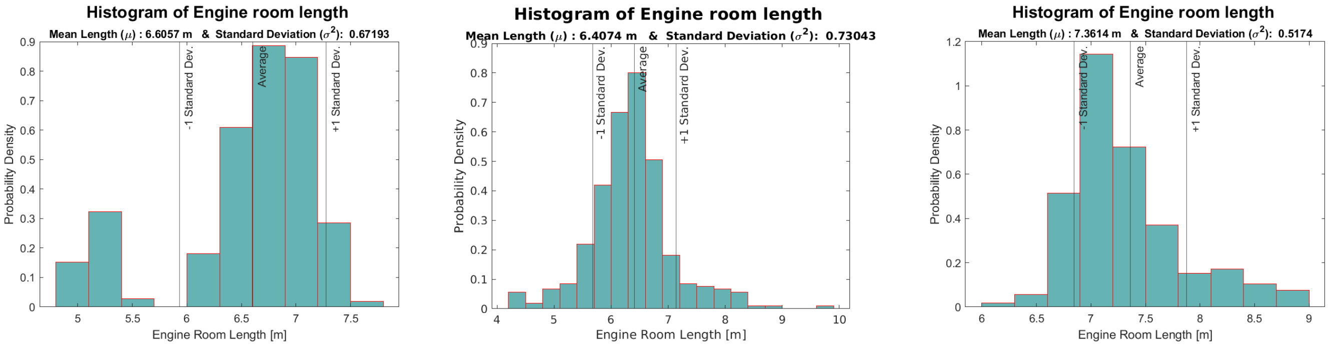
The transition probability in a MDP represents the probability of moving from state B at epoch n (B_n) to state A at epoch n+1 (A_{n+1}) (see Equation 4), depending on the decision-action that is selected per time step Sheskin (2010). However, if the states are considered independent, the probability is equal to the probability of event A, according to Equation 4. For this study, the states are considered independent and probabilities are defined applying Equation 5.

$$P(A_{n+1}|B_n) = \frac{P(A_{n+1} \cap B_n)}{P(B_n)} = \frac{P(A_{n+1}) \cdot P(B_n)}{P(B_n)} = P(A_{n+1}) \tag{4}$$

Probability can be defined by using the relative frequency approach Gebali (2015), as shown in Equation 5. This means that an experiment is conducted N times and based on the N_a times that the selected outcome occurs, a probability is defined.

$$P(A) = \lim_{N \to \infty} \frac{N_a}{N} \tag{5}$$

Connecting this approach to the framing of this study's problem, the probabilistic layout tool by Souflis Rigas et al. (2023) conducts a Monte Carlo simulation (MCS) on the dimensions of components to be fitted in a simplified engine room layout based on various system architectures and generates distributions of engine room length (see Fig. 1). Souflis Rigas et al. (2023) showed there is inconsistency between the input dimensions and the output of the overall engine room size, which is the foundation for using a layout modeling tool to incorporate the dimension uncertainties rather than empirical trendlines. Using the distribution of the engine room length against a specified requirement for the length, Equation 5 can provide the probability of a PPE configuration with uncertain dimensions to fit within the required length. The uncertain dimensions can be derived from the volumetric power density uncertainty underlined in Table 1. Souflis Rigas et al. (2023) therefore highlighted that there is a struggle with available space when existing vessels convert to methanol. A threshold of a required length reflects the requirement of fitting the equipment for the retrofit of an existing vessel from ICEs to using FCs as prime energy converter. The requirement and testing of specific $Length_{\text{engine room}}$ reflects on a potential length threshold that leads to moving a bulkhead and triggering extra conversion costs.



(a) ICE case **(b) FC case** **(c) Hybrid case**

Figure 1: Representatinve engine room length distribution per epoch per energy converter

Framework for Energy Converters case study

The current model framework is based off of a modified ship centric markov decision process (SC - MDP). Figure 2 shows that the model starts by generating the necessary inputs for the MDP - transition probabilities and rewards matrices. Firstly, it uses the uncertainty analysis in the physical space of an engine room that is conducted with the probabilistic layout tool Souflis Rigas et al. (2023) for transition probabilities definition. By computing the fuel consumption for every EC on a yearly basis, the OPEX is calculated. Using the CAPEX values on Table 1, CAPEX is calculated, and based on the action, the reward over time is computed. Rewards are considered to be changing every 4 years until the 12th year. In this case study 1 year equals 1 epoch. The MDP in this case study consists of:

- **states:**
  - Energy converters that can be selected during the lifecycle of the vessel: ICE, FC, Hybrid.
  - Substates have been defined to be able to apply extra maintenance costs after 4 years for Hybrid and FC states. Dall'Armi et al. (2022) showed that the performance of PEMFCs deteriorates after 2 years. Additionally, the lifetime of FCs shows a variation between 5000 and 10000 hours Elkafas et al. (2022). Considering the estimation variation, an extra operational is incurred every 4 years. Substates that would lead to extra maintenance were defined for the FC and the hybrid state. When entering the state of a brand new EC, it is considered that the model will transition until the year the extra maintenance cost is applied.
  - Combination of states and substates generates 9 states in total that can be accessed from the agent, 1 for ICE and 4 for FC and hybrid respectively.
- **actions:**
  - Switch Energy Converter: is the action of switching to an energy converter (e.g. ICE).
  - Use Energy Converter: keep using the same energy converter for the next epoch.
  - There are 6 actions in total, 2 for each energy converter.

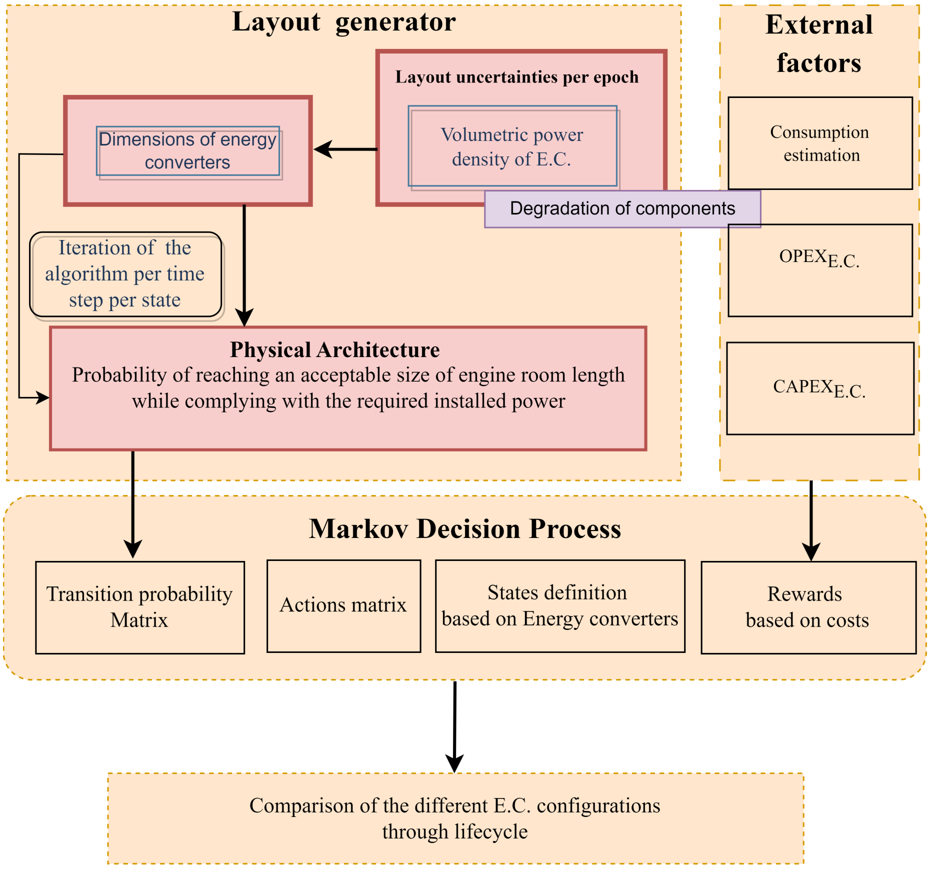


Figure 2: Architecture of modelling framework

- **Transition probabilities**

$$\mathbf{T} = \begin{array}{r} \\ \text{ICE} \\ \text{FC} \\ \text{Hybrid} \end{array} \begin{array}{c} \begin{array}{ccc} \text{ICE'} & \text{FC'} & \text{Hybrid'} \end{array} \\ \left\| \begin{array}{ccc} p_{\text{ICE}} & 1 - p_{\text{ICE}} & 0 \\ 0 & 1 & 0 \\ 0 & 1 - p_{\text{Hyb}} & p_{\text{Hyb}} \end{array} \right\| \end{array} \tag{6}$$

$$p_{ICE} = \frac{\sum_{n=1}^{N_{\text{eff}}} \text{ICE layouts reaching the required length}}{\sum_{n=1}^{N} \text{ICE layouts}} \tag{7}$$

$$p_{Hyb} = \frac{\sum_{n=1}^{N_{\text{eff}}} \text{Hyb layouts reaching the required length}}{\sum_{n=1}^{N} \text{Hyb layouts}} \tag{8}$$

N_{eff}: defines the amount of produced layouts that reach the engine room length requirement.

- Probabilities: are dependent on the action selected. Using Equation 5, the probability of an EC configuration attaining the required $Length_{\text{engine room}}$ is computed. These probabilities change per 4 years (see Figure: 5a), as volumetric power density improvement for each EC is considered (see Figure 4). An example of the transition probabilty matrix definition for the action *Use FC* is given in Equation 6. For the FC state, it is set to stay in the same state and thus a probability value of 1. For ICE, the probability of switching to FC is the remainder of the stochastic row of the p_{ICE}. Similarly, probabilities for the hybrid state are defined. To make the definition of p_{ICE} and p_{Hyb} more elaborate, Equations 7 and 8 are provided respectively. p_{ICE} and p_{Hyb} represent the amount of generated layouts per EC that reached the set Length threshold. The transition probabilities matrices are parametric and dependent on the probability distributions generated by the layout algorithm (see Eq. 4). The transition probability matrices have been kept the same both for the *Use actions* and *Swtich actions* per EC.

  – Probabilities for EC degradation: the probability is assumed 1 that the agent will switch to the degrading sub-states, until the extra maintenance cost (for replacing stacks of the FC) occurs.

- **Rewards:** are dependent on the action selected and the initial state, see Table 3 and the calculation of CAPEX, OPEX is done based on Table 4. For FC and hybrid, an additional maintenance cost was calculated based on CAPEX. This is set 4% of the CAPEX according to Elkafas et al. (2022) and trial and error. The $OPEX_{maintenance}$ is applied only to FC, hybrid states when it is selected to keep using the same EC.

Table 3: Reward definition per action

Use Energy Converter	Switch to Energy Converter
$OPEX_{EC}$	$CAPEX_{EC} + OPEX_{EC}$

- **discount factor(γ)**: is calculated with Equation 9 (Sheskin, 2010), and in this case study interest rate is assumed: i = 7%

$$\gamma = \frac{1}{1+i} \tag{9}$$

Table 4: Parameters of each computed cost

$OPEX_{\text{EC}}$	f(fuel consumption$_{\text{EC}}$ [tons/year], fuel cost [€/ton], EC)
$OPEX_{\text{maintenance FC}}$	4% $CAPEX_{\text{FC}}$
$CAPEX_{\text{EC}}$	f($CAPEX_{\text{EC}}$ [€/kW], $P_{\text{installed}}$[kW], EC)

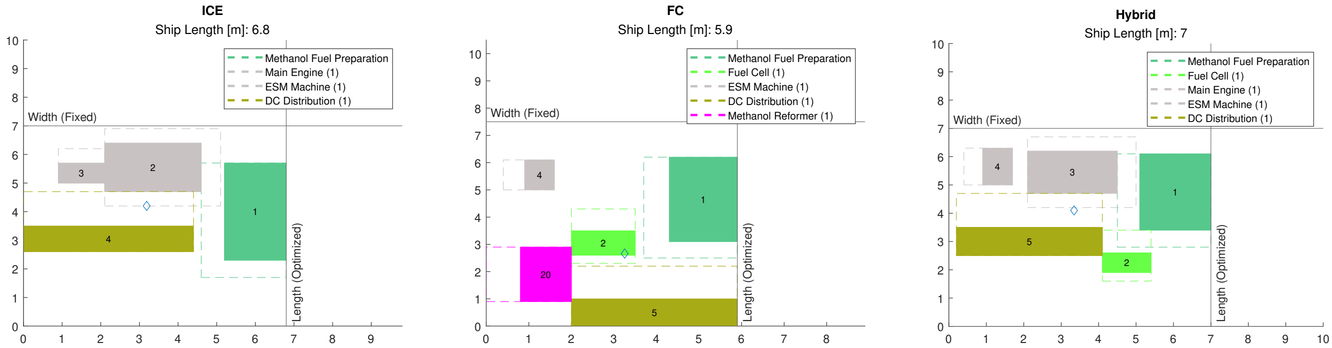
It is worth noting that MDP is memoryless, meaning that the optimal action per time step is selected regardless of the path that the agent followed to reach that state. Based on the solution of the EC decision-making problem, an analysis is conducted of the financial risks of each main Energy converter configuration choice to determine methodological insights and influential parameters to the solution trends.

CASE STUDY

A simplified yacht engine room was selected based on the studies of Poullis (2022), and Souflis Rigas et al. (2023). Table 5 presents the components configurations that were selected to be tested per case and Figure 3 presents indicative layouts for each state, that are generated per scenario in the layout simulation. The operational profile of the vessel was set up based on a master thesis studying a yacht similar to our conceptual vessel (L. Menano de Figueiredo, 2018).

Table 5: Engine room configurations represented per state

ICE	FC	Hybrid(ICE + FC)
Methanol supply	Methanol supply	Methanol supply
ICE	Generator	ICE
Generator	Swtichboard	Generator
Swtichboard	FCs	Swtichboard
	Reformer	FCs



(a) ICE layout **(b)** FC layout **(c)** Hybrid Layout

Figure 3: Indicative layouts per Energy converter

Operational Profile and EC sizing

Based on the maximum required power found in Table 6 the installed power of the ECs was determined. Table 7 presents the installed power selected for each EC state. In hybrid state, FC was sized to be able to meet the power demand during maneuvering and anchor loads (see Table 6).

The consumption was calculated using Equation 10 and the values referred in Table 8. In the hybrid state, the loads below 250 kW are assumed to be satisfied by the FC and the loads above 250 kW by the ICE.

$$\text{fuel consumption} = \begin{cases} \eta_{\text{FC}} \cdot \eta_{Reformer} \cdot Energy_{demand} & ,FC \\ SFC \cdot Energy_{demand} \cdot \frac{LHV_{diesel}}{LHV_{methanol}} & ,ICE \end{cases} \tag{10}$$

where:

- SFC [g/kWh]: specific fuel consumption
- LHV [MJ/Kg]: Lower heating value
- $Energy_{demand}$ [kWh]
- η: efficiency rate of a component

Table 6: Operational profile and yearly consumption per configuration

Load State	Power demand	Frequency	Yearly Energy Demand [kWh]	Methanol ICE Consumption [tons]	PEMFC Consumption [tons]	Hybrid [tons]
Cruising	473	13.8%	1,248,720	549.3	475	549.3
Max Speed	800	7.1%	2,112,000	929	803.3	929
Crossing	562	13.2%	1,483,680	652.6	564.4	652.6
Anchor	155	63.9%	409,200	180	155.7	155.7
Maneuvering	238	2.13%	628,320	276.4	239	239

Table 7: Installed Power per state

Energy converter	$P_{installed}$ [kW]
ICE	840
FC	840
Hybrid	600 (ICE) + 250 (FC)

Table 8: Values assumed for consumption caclculation

Unit	Value]	Reference
sfc [g/kWh]	205	(Warsila, 2024)
η_{FC}	0.58	(Elkafas et al., 2022)
$\eta_{Reformer}$	0.82	(RIX, 2024)
$LHV_{methanol}$ [MJ/kg]	19.9	(Harmsen, 2021)
LHV_{diesel} [MJ/kg]	42.7	(Trancossi, 2015)
$sailing_{time,year}$ [h]	2600	(L. Menano de Figueiredo, 2018)

Considering the uncertainties in volumetric power density of the main ECs (see Table 1), the length and width of the ECs were sampled in the probabilistic layout tool with steadily reducing uncertainty margins changing every 4 years as shown in Table 9. The uncertainty margin is reduced to account for the potential technology development during the lifecycle of the vessel. Figure 4 illustrates the actual distribution of volumetric power densities ranging from 5% to 40% depending on the epoch and the technology. 40 % FC means that there was a 40 % uncertainty range for the width and length of the FC system.

Table 9: Dimension uncertainty margins per epoch per EC

Year	ICE [%]	FC [%]
0	30	40
4	20	30
8	10	20
12	5	10

To derive the dimensions of the ECs, a PEMFC model of Ballard (2024) was selected as a reference case, and a 4 stroke high-speed engine by Warsila (2024) for the ICE. Their dimensions are shown in Table 10. ICE is assumed to be a methanol-only ICE, and the FC a PEMFC. Dimensions for the additional layout components are shown in Table 11. By fixing the EC height and installed power, the volumetric power density uncertainty is matched to uncertainty margins in the EC's width and length. Using the probabilistic layout tool developed to better understand its effect on the overall size of a simplified engine room, this uncertainty can be integrated within the MDP as a factor reflecting on technical uncertainty and systems integration challenges.

Table 10: Reference dimensions for energy converters

Energy Converter	L [m]	W [m]	H [m]	Power [kW]	Power Density [$\mathrm{W\,m^{-3}}$]	Reference
FC	1.20	0.87	0.51	100	189.52	Ballard (2024)
ICE	2.3	1.4	1.8	865	149.24	Warsila (2024)

Table 11: Auxiliary systems dimensions ranges

Building Block	Length [m]	Width [m]
Methanol Fuel Preparation	2.6 - 3.5	1.6 - 2.1
ESM Machine	1.1 - 1.4	0.6 - 0.9
DC Distribution	3.8 - 5.1	0.8 - 1.1
Reformer	2-2.4	1-1.2

MDP implementation

The MDP time horizon is set to 20 years to observe how the actions are converging. From year 0 until year 12, there is an update of the probabilities per state, the CAPEX and the OPEX, as shown in Figure 5. The inputs are kept constant to evaluate the convergence of the MDP solution.

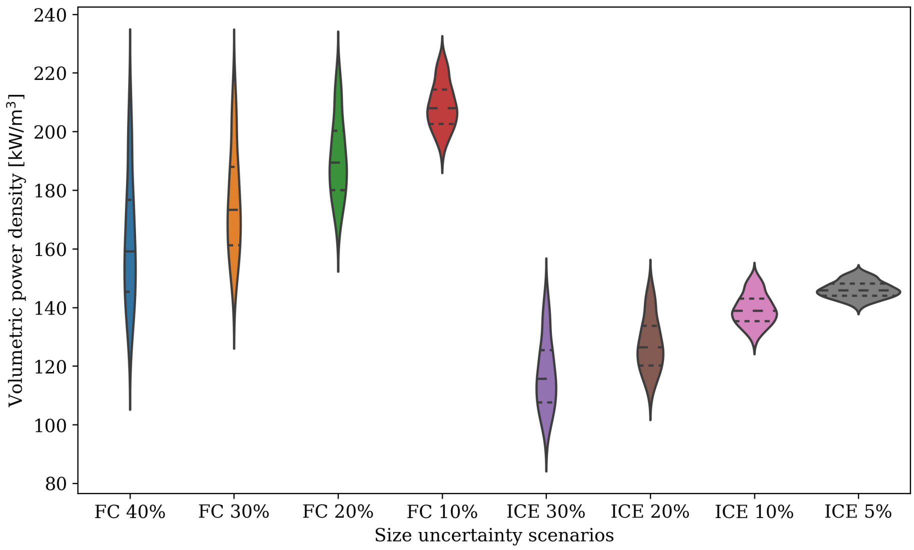
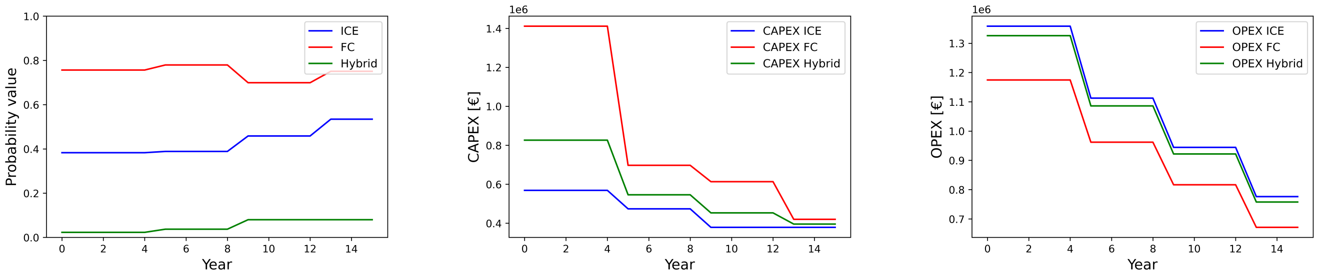


Figure 4: Comparative plot of EC volumetric power densities distribution per epoch

Figure 4 illustrates that ICE has a smaller power density variation than the FCs, which is in accordance with the uncertainty margins found on Table1. The required engine room length is set to 6.52 m based on the mean engine room length of the 30 % ICE case. The computed probabilities for each EC are shown in Table 12 and Figure 5a. Similar volumetric power densities were used for the Hybrid state calculations. It is clear that the FC state displays the highest probabilities and these probabilities depict a similar trend to the trends of volumetric power densities in Figure 4.

Table 12: Probabilities per state per epoch

Energy converter	Yeat 0	Year 4	Year 8	Year 12
ICE	0.382	0.389	0.458	0.534
FC	0.756	0.779	0.699	0.751
Hybrid	0.023	0.037	0.080	0.080



(a) Probabilities per epoch **(b) CAPEX per EC** **(c) OPEX per EC**

Figure 5: Inputs for finite horizon Markov decision process

Figure 4 illustrates the evolution assumed in the volumetric power density of the ECs according to the tightening dimension uncertainty margins selected per time step (Table 9). Volumetric power density is calculated with Equation 1, by fixing the height of the EC and using the installed Power per state (Table 7) and using the variable length and width of the ECs per scenario (see Table 9). To make the layout solution comparable, it was assumed that FCs can be stacked on top of each other, meaning an overall height H = 3 m. Similarly, the reformer in the hybrid configuration is considered packed within the FC unit. ICE height was set to H = 1.8 m according to the reference engine (Table 10).

Table 12 and sub-Figure 5a illustrate that FC has the relatively highest probability of integration in accordance with the higher volumetric power density displayed in Figure 4. From a methodological point of view, the interest lies on observing which kind of actions are selected depending on the newly proposed way of defining the transition probabilities according to Equation 5. The state FC that had more increased power densities presented the highest probabilities of layout integration through time, and the switch to that state was selected on several consecutive steps from the hybrid state, in spite of the extra maintenance cost per 4 years. Additionally, state ICE displays a period of 4 years potentially switching to FC, but selects again *Action:* Use ICE because of the extra maintenance cost.

CAPEX and OPEX for each technology were calculated using Equations 11 and 12. Methanol cost is assumed to be constantly decreasing from 525 [€/ton] in year 0 to 300 [€/ton] by year 12 (MARIN, 2024). The specific CAPEX is set according to the values on Table 1. The trend of the CAPEX and OPEX cost are presented on Figures 5b and 5c.

$$CAPEX_{year,EC} = CAPEX_{EC} \cdot P_{installed} \tag{11}$$

$$OPEX_{year,EC} = fuelconsumption_{year,EC} \cdot fuelcost \tag{12}$$

Figure 6 provides an action pathway for each state of the MDP. In this case, 2 extra states (FC0.25 and hybrid0.25)are plotted to reflect the degradation of *FC and Hybrid states*. In these states, the extra maintenance cost is applied, and because of that, a switch to another EC may occur. Figure 6 shows that the switch to FC is the optimal decision for the *Hybrid state* in several years, which is explained both by the lower OPEX costs that FC offers in comparison to hybrid as well as the much lower probabilities of hybrid layout fitting - see Figure 5. Additionally, the action switch to FC becomes optimal after year 12 for state ICE, which is explained by the convergence of the CAPEX costs for the technology adoption (see Figure 5b). Lastly, a switch action is not selected at all for *FC state*, which is justified by the highest probability of reaching the required engine room length and the relatively low OPEX.

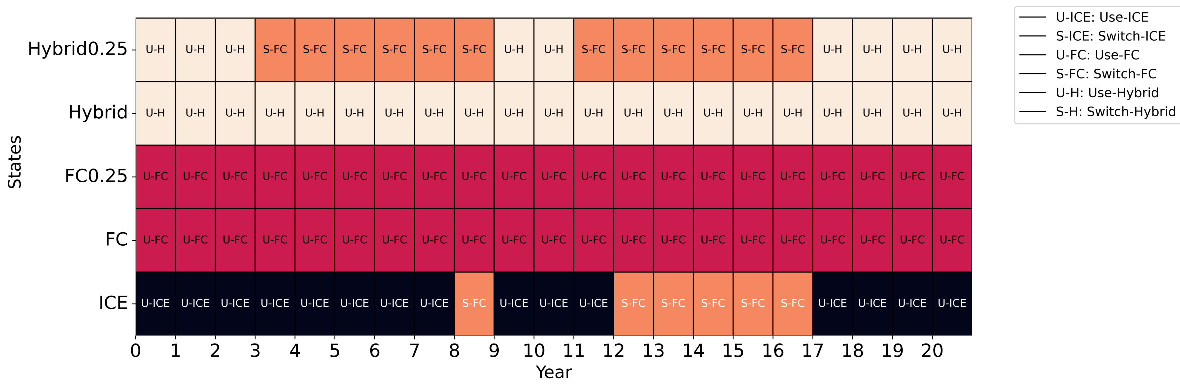


Figure 6: Policy map indicating optimal action per state and per year

Complementary to Figure 6 that prescribes an action path for each state per year, Figures 7, 8, 9 represent the optimal state accessed based on following the actions derived from the MDP policy pathway. This metric was developed based on Kana et al. (2015) and provides the optimal state to select, given a starting state.The colorscale on the side indicates the probability of being in that state,with red meaning 100 % chance and blue meaning 0 % chance. In Figure 7, ICE was selected as the starting state and shows that FC starts being the optimal state after year 12, which is in agreement with the policy of Figure 6. When selecting FC as the initial state, Figure 8 illustrates that FC is the optimal state to be selected. Lastly, Figure 9 demonstrates that for hybrid as the initial state, the switch to FC becomes the optimal after year 4 after completing the degradation phase that is modeled with substates hybrid0.75 to hybrid0.25. This result is in accordance with the policy map produced by the MDP in Figure 6. Figures 6, 7, 8 and 9 prove that both the high layout fitting probabilities, as well as competitive actions rewards, are necessary for a *switch action* to take place. For the ICE initial scenario, the FC state becomes optimal after the interval between the states' CAPEX cost has been zeroed.

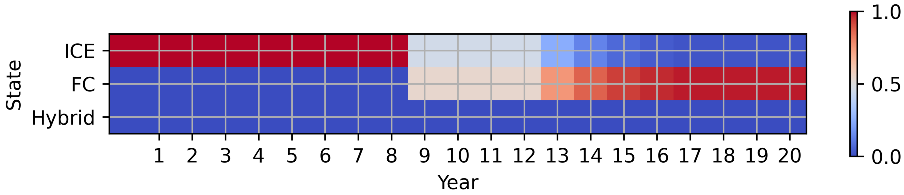


Figure 7: Optimal state accessed per action using ICE as initial state

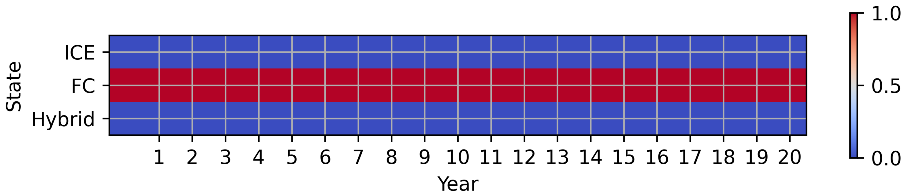


Figure 8: Optimal state accessed per action using FC as initial state

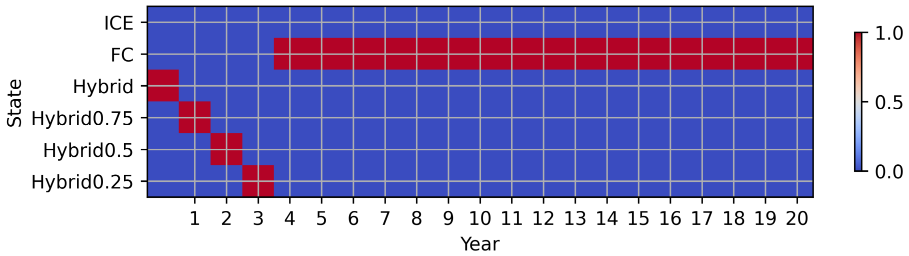


Figure 9: Optimal state accessed per action using hybrid as initial state

Figure 10 is used to plot the cumulative expenses that arise per state if the agent follows the policy proposed per epoch in accordance with Figure 6. To make a reasonable comparison, the most degraded substates of hybrid (Hybrid0.25) and FC (FC0.25) were plotted, in which the $OPEX_{maintenance}$ was applied. Figure 10 shows that FC has the lowest cost, in spite of the extra maintenance cost introduced every 4 years. Also, the cumulative cost deviation between the different states remains around 100.000 €, which is relatively small for a 20-year period. The relative cost convergence can be explained by the selection of *actions: Use EC* and not having to switch to other ECs. To have more robust outputs, the need for more detailed rewards calculation arises.

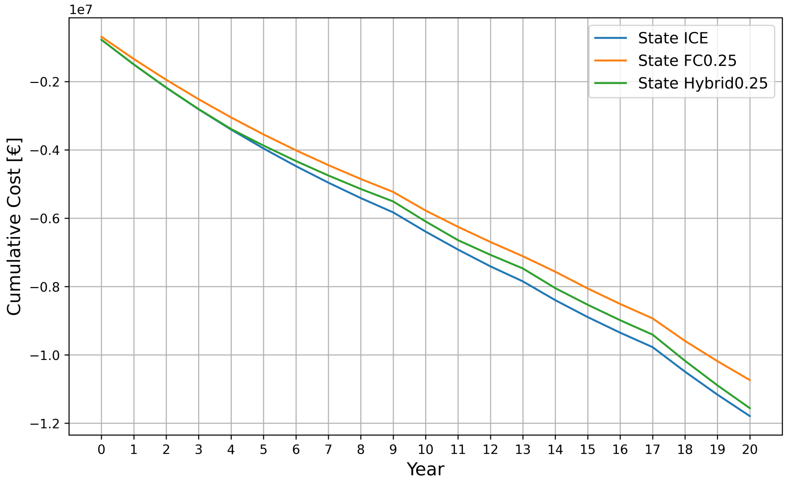


Figure 10: Cumulative cost for each EC option, when adopting the policy of the MDP decision matrix

DISCUSSION

The method presented is an attempt to integrate within a MDP framework, the technical uncertainties that are overlooked in lifecycle studies evaluating alternative configurations for a decarbonized vessel. The probabilities that reflected the integration challenges proved influential as the energy converter (FC) with the highest probability was the only one that the other two states may switch to in the future. Decisions are highly impacted by the reward vectors set for each action, meaning that the bigger differences in Capex costs for technology adoption during the first years of the case study prevented the switch action from being selected for ICE. The extra maintenance cost accounting for FC degradation did not prove triggering enough to cause a switch action and should be modeled in more detail. For more insightful results, a model of higher accuracy for the consumption costs should be applied that can integrate variable EC efficiency rate parameters and compute costs based on produced emissions per EC. Additionally, the selected type of vessels and its power profile influence the OPEX per technology and thus it is valuable to investigate the policy that would come out for alternative operational profiles. Complementary to that, the probabilistic layout tool can be further advanced to handle scenarios with more components and possible system architectures, to increase the reliability of the predicted probabilities. Keeping in mind that this paper focused on applying a novel methodology to combine two normally disassociated tools - a lifecycle model and a probabilistic layout modeling tool, the core idea has proved to function successfully when applied to a proof of concept.

CONCLUSIONS

This paper outlined a way to further advance the lifecycle evaluation of the alternative fuelled PPEs by accounting for ECs' technical uncertainties that have traditionally been disregarded by the state-of-the-art research. The uncertainty quantification of systems layout integration challenges combined with the constant evolution of ECs technologies, led to the proposed method which has advantages worth highlighting. Markov Decision processes offer a very clear structure in which inputs from other models can be integrated and generate insights into decision pathways of PPE configurations towards a decarbonized ship design. The transition probability matrix, relating to selected actions, offers a clear structure to model the stochastic probability of the decision to switch or use a PPE technology based on its fitting to the layout. The reward vector can reflect on costs arising for the adoption of each technology. The MDP produces insight to the evolution of decisions within the lifecycle of the vessel. The coupling of MDPs with the probabilistic layout tool is a method that can account for technical, environmental, and financial uncertainties. The EC case study demonstrated that the probabilities defined for each EC based on their layout, paired with the computed EC costs, strongly influence the optimal decision pathway. The presented method sets the base for further development of both the probabilistic layout tool and the MDP, as well as their coupling, to produce insights for design pathways to be selected towards decarbonization with alternative fuels.

CONTRIBUTION STATEMENT

Apostolos S. Souflis - Rigas: Conceptualization; Methodology; Data Curation; Software; Visualisation; Writing – Original Draft.
Jeroen F.J. Pruyn: Supervision; Writing - Review & Editing
Austin A. Kana: Conceptualization; Software; Supervision; Writing - Review & Editing

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