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DOI
10.1016/j.oceaneng.2016.11.042

Publication date
2017

Document Version
Accepted author manuscript

Published in
Ocean Engineering

Citation (APA)
Kana, A. A., & Harrison, B. M. (2017). A Monte Carlo approach to the ship-centric Markov decision process for analyzing decisions over converting a containership to LNG power. *Ocean Engineering*, *130*, 40-48. https://doi.org/10.1016/j.oceaneng.2016.11.042

A Monte Carlo approach to the ship-centric Markov decision process for analyzing decisions over converting a containership to LNG power

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Abstract

A Monte Carlo approach to the ship-centric Markov decision process (SC-MDP) is presented for analyzing whether a container ship should convert to LNG power in the face of evolving Emission Control Area regulations. The SC-MDP model was originally developed as a means to analyze uncertain, sequential decision making problems. However, the original model is limited in its handling of uncertainty by only using discrete probabilistic values to account for the uncertainty. This paper extends the model to include Monte Carlo simulations to gain a deeper understanding of how uncertainty affects decision making behavior. A case study is presented involving the impact of evolving Emission Control Areas on the design and operation of a notional 13,000 TEU container ship. The decision of whether to invest in a dual fuel LNG engine is analyzed given uncertainties in economic parameters, regulatory scenarios, and supply chain risks. The case study is used to show how variations in uncertain parameters can have a drastic effect on optimal decision strategies.

Keywords: Decision making, Emission Control Area, Markov decision process, Monte Carlo simulation, uncertainty analysis, LNG

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1. Introduction

Understanding the importance of decision making has been recognized as one of the fundamental constructs in engineering design for decades (Kana et al., 2016b; Le Masson et al., 2013). However, understanding the impacts of design decisions for engineering projects that involve physically large and sometimes complex structures is difficult due factors that vary with time, can be fragmented, and are inherently uncertain (Fet et al., 2013; Hastings & McManus, 2004; Kana et al., 2016b; ONR, 2011; Seram, 2013). In regard to marine design specifically, uncertainty arises in decision making from not only endogenous factors, such as technological or engineering uncertainty, but also from exogenous factors, such as regulatory, economic (Niese & Singer, 2013), or weather and climate uncertainty (Vanem, 2015). Due to the complex and sometimes intractable nature of large scale strategic planning and decision making problems, practitioners typically omit the uncertain or stochastic elements when modeling the problem (Fagerholt et al., 2010).

However, Zayed et al. (2002) showed that differing and sometimes conflicting results may arise when comparing deterministic and stochastic methods for the same problem. Zayed et al. (2002) studied the economics of maintenance and scheduling of bridge painting by comparing a deterministic economic analysis using net present value to a stochastic model using a Markov decision process (MDP). They concluded that while the deterministic method may show more promising results at times, its advantages are, "offset by the MDP's ability to incorporate the inherent stochastic nature of the phenomenon being modeled" (Zayed et al., 2002). Thus, properly accounting for the uncertainty is necessary in any decision aiding model.

Accounting for uncertainty is especially true in situations involving uncertain environmental regulations. This paper discusses one specific instance; that is whether a container ship should convert to LNG power in the face of evolving Emission Control Area (ECA) regulations. Studying the impact of ECA and developing models to help ship owners and operators plan for these regulations has been studied since ECA was first introduced (Lin & Lin, 2006). Nielsen & Schack (2012) examined compliance strategies for vessels facing ECA regulations. Their work included a deterministic economic analysis with sensitivity studies. Balland et al. (2013) looked into the effects of uncertainty over the actual emission reductions of certain emission abatement technologies. They employ a two stage optimization technique to address the uncertainty in the decision making. (Rehn et al., 2016) used a systems engineering approach that employed both Monte Carlo simulations and a real options type approach to incorporate flexibility. Kana et al. (2015) employed the ship-centric Markov decision process (SC-MDP) to study temporal effects of regulatory and economic uncertainty on life cycle planning.

This paper extends the work of Kana et al. (2015) and introduces original content by applying Monte Carlo simulations to the SC-MDP model. This is done to gain a deeper understanding of the effects of uncertainty and how they may change optimal decision making behavior. The SC-MDP model is defined as applying Markov decision processes to ship design and decision making. The SC-MDP model has been beneficial in analyzing decision making in the maritime domain due to its ability to handle time-varying uncertainty in both the endogenous and exogenous factors. The model has previously been used to examine decision making scenarios in the maritime domain involving ballast water treatment methods (Kana et al., 2016a; Niese & Singer, 2013), various design options to meet the Energy Efficiency Design Index (Niese et al., 2015), and studying personnel movement during emergency situations on board the vessel (Kana & Singer, 2016).

These previous SC-MDP studies, however, have assumed discrete probabilistic values for the uncertainty in the model. These assumptions can be limiting when applied to conversion issues in the face of evolving environmental regulations because of the difficulty in precisely defining the specific stochastic values. For example, what is the exact probability that a vessel is able to obtain LNG as a bunker fuel at a given port during early stages of infrastructure development? Monte Carlo simulations are used in this paper as a means to properly handle this type of stochastic uncertainty. These Monte Carlo simulations run through a range of uncertainties and input parameters to determine their respective effect on the overall solution. Monte Carlo simulations have been used by others studying the impact of environmental regulations on ships, including Coraddu et al. (2014) who used this technique to examine ship energy efficiency measures to meet both the Energy Efficiency Design Index (EEDI) and the Energy Efficiency Operational Indicator (EEOI). Their technique differs from this work as this research uses the SC-MDP model as the underlying model with which we run the Monte Carlo simulations.

While design methods exist that provide a methodical process for ship design decision making, such as set based design or epoch era analysis (Rader et al., 2010; Singer et al., 2009), the SC-MDP model can be one tool (out of possibly many) that can be used to these support processes. The SC-MDP model provides a perspective on the sets of decisions that enable the decision maker to determine the percentage of time it is best to convert engines, given a large suite of economic, technological, and regulatory scenarios, as opposed to finding the best option for one static scenario. This helps decision makers understand if and when it is most likely to convert engines, even in the face of large uncertainty. Understanding the effect of uncertainty on the life cycle costs is also very important. Monte Carlo methods enable the decision maker to calculate the range of expected costs both through time and through various system scenarios. Understanding the probability that a given cost expectation will be met through time is possible. Traditional sensitivity analyses are also possible using this model to discern influences of specific aspects of the model.

The goal of this research is to understand how uncertainty affects the decision to convert a container ship to LNG power, as opposed to identifying what the specific uncertainty level is for specific aspects of the problem. The objective of the overall method is to draw from the strengths of MDPs in handling uncertain temporal decision making, and the strengths of Monte Carlo simulations in enabling true stochastic analysis.

2. Methods

A brief discussion of the methods is presented here, while the specifics of how it was applied to this specific case study is given to detail in the following section. The underlying mathematical model behind the SC-MDP model is the Markov decision process (MDP). An MDP is a state-based, stochastic decision making model that consists of four parts: (1) a set of states, S, of the environment, (2) a set of actions, A, that the agent can take, (3) a set of probabilities, T, of transitioning from one state to another, and (4) a set of rewards, R, that are received from landing in a given state after taking a given action. The objective of an MDP is to identify the sequence of actions that maximizes the cumulative, long term expected utility of the decision process. This sequence of actions, π, can be obtained via Equation 1, while the expected utility, U, is found by solving Equation 2, known as the Bellman equation (Puterman, 2005). Here, a is a given action, s is the current state, s' is the state of the following time step, and γ is the discount factor.

$$\pi(s) = \arg\max_a \sum_{s'} T(s, a, s')U(s') \tag{1}$$

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

MDPs are commonly solved via backward induction (i.e. dynamic programming) to evaluate the expected utilities. That is, the model is solved backward in time, by starting at the desired end state, and then moving backwards to find the optimal route and expected value. This method is used to ensure that the sequence of decisions prescribed is optimal (Puterman, 2005; Sheskin, 2011).

Monte Carlo simulations are used to handle the uncertainty associated with defining the rewards and transition probabilities. Value ranges are determined for each parameter and the simulations iteratively selects values at random from each input variable distribution. Thousands of simulations may be run to ensure convergence to a stable distribution. The maximum incremental change is used to show that the system has stabilized and that additional simulations do not affect the solution in any significant manner. This convergence is defined as the cumulative incremental change, $\Delta(i)$, in both the states and actions after each run. Physically, this means that the probability of being located in any given state or taking any given action varies by less than $\Delta(i)$ for each additional simulation run. The convergence metric is defined in Equation 3 where i is the indexed simulation run.

$$\Delta(i) = |\frac{1}{n}\sum_{i=2}^{n} x_i - \frac{1}{n-1}\sum_{i=2}^{n} x_{i-1}| \tag{3}$$

Here x_i is the maximum probability of being in a given state or taking a specific action at a given time (Equation 4).

$$x_i = \arg\max_{a,s}[P(s), P(a)] \tag{4}$$

Sensitivities on specific variables may then be performed to determine which system parameters may be driving its behavior. The sensitivity analysis used in this paper involves setting all the Monte Carlo variables to their mean value, except for the variable of interest, which is allowed to vary through its original range. A detailed case study of this method is presented in the following sections.

3. Case Study: Design for Evolving Emission Control Area Regulations

This case study is designed to show the utility of the Monte-Carlo approach to the SC-MDP model in a maritime example that involves design and operating considerations in the face of uncertain evolving Emission Control Area (ECA) regulations.

3.1. Fixed model parameters

A notional 13,000 TEU containership routed between Rotterdam and China is examined. The route covers 22,000 nm, of which 1100 nm is a designated ECA zone (IMO, 2008). This ECA coverage increases to 6800 nm of the total route in a single year. The specifics behind when exactly the regulation changes is

Table 1: The vessel principal characteristics for the notional 13,000 TEU containership

Length	Greater than 300 m
Beam	Less than 45 m
Draft - full load	13.0 m
Draft - partial load	11.5 m
Block coefficient	0.61
Displacement - full load	112,000 MT
Displacement - partial load	99,000 MT
Ship brake power	Greater than 67,000 kW

described in Section 3.3. Two drafts are studied to simulate a full load traveling to Rotterdam, and a partial load (or back-hauling) back to China (Table 1). The vessel is at sea for a total of 290 days per year, to account for lost time in port and dry-docking.

The Holtrop & Mennen (1982) method was used to estimate the required brake power for speeds between 12 and 24 knots, while estimates from MAN B&W and Wartsila were used to estimate base specific consumption (MAN B&W, 2012; Wartsila, 2014). Combining both the fuel consumption was calculated for all three fuels and for both drafts (Figure 1). When operating in dual fuel mode, the engine burns 95% LNG and 5% HFO as a pilot fuel, which is in line with estimates made by both MAN B&W and Wartsila (MAN B&W, 2012; Wartsila, 2014).

3.2. The Markov decision process

The details of how the individual states, s, actions, a, transition probabilities, T, and rewards, R, are defined is presented in the following section. These variables are used in Equations 1 and 2 to determine the best decisions and the associated expected costs.

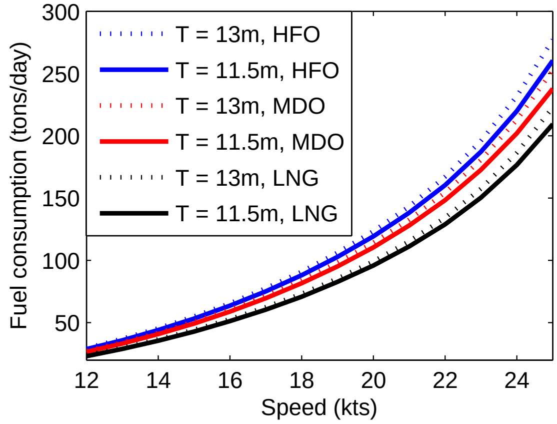

Figure 1: Fuel consumption curves for three different fuels and two drafts. The curves were developed using both the Holtrop and Mennen method as well as estimates from MAN B&W and Wartsila.

3.2.1. States

There are eight possible states, s, split between three state variables. The three state variables are:

1. *The amount of ECA coverage.* The two possibilities for ECA coverage are 1,100 nm and 6,800 nm.
2. *The engine installed.* The two types of possible engines are a single fuel fuel engine that burns either HFO or MDO and a dual fuel engine that burns a combination of LNG and HFO.
3. *The bunker fuel type.* The two fuel options are: 1) a combination of LNG and HFO, and 2) a combination of MDO and HFO. The LNG and HFO option is only valid when the dual fuel engine is installed. When LNG is not available, the dual fuel engine will burn MDO and HFO instead (El-Gohary, 2012). The MDO and HFO option is valid for either engine. When running this fuel combination, the engine alternates between burning MDO in the ECA zones, and HFO elsewhere.

3.2.2. *Starting State*

The simulation begins with an ECA coverage of 1100 nm and a single fuel engine installed that burns MDO and HFO. Selecting the correct starting state is important because the resulting decision paths may be sensitive to these initial conditions (Kana et al., 2016a; Niese et al., 2015). Since this case study examines decisions regarding retrofitting an existing vessel, the starting state is designed to reflect the current design of the vessel as well as current regulatory environment.

3.2.3. *Actions*

Four possible actions, a, are available to the vessel operator when the vessel arrives in port:

1. Do not switch engines, and try to purchase LNG fuel.
2. Do not switch engines, and purchase MDO fuel.
3. Switch to a dual fuel engine, and try to purchase LNG fuel.
4. Switch to a dual fuel engine, and purchase MDO fuel.

The action "Do not switch engines, try to purchase LNG fuel" is only available once a dual fuel engine is installed. The action "Switch to a dual fuel engine, and purchase MDO fuel" is included to account for possible situations where the preferred decision is to retrofit engines immediately in preparation for future lower LNG prices. The preferred decision is the one that minimizes cumulative life-cycle cost.

3.2.4. *Transition Probabilities*

The state transition probabilities, T, are defined as follows:

- The probability of transitioning between an ECA coverage of 1100 nm and an ECA coverage of 6800 nm happens according the inputs selected from the Monte Carlo simulations, as described in Section 3.3.
- The probability of transitioning from the single fuel engine to the dual fuel engine is deterministic based on the preferred action.

Table 2: Summary of the MDP states and their transition probabilities.

State Variable	Initial Value	Potential Future Value	Transition Probability
ECA coverage	1,100 NM	6,800 NM	[0, 1]
Engine	single fuel	dual fuel	1
Fuel (in Rotterdam)	HFO or MDO	LNG and HFO	[0.5, 1]
Fuel (in China)	HFO or MDO	LNG and HFO	[0, 1]

- The preferred fuel type is chosen according to both the preferred decision and the supply chain risk. When the vessel wishes to purchase LNG fuel, but it is unavailable, it will purchase MDO instead.

The relationship between the states and the transition probabilities is summarized in Table 2.

3.2.5. Rewards

The rewards, R, are defined by the cost function given in Equation 5, where f is the fuel costs, o is the opportunity costs, and c is the conversion costs of installing the LNG engine. The costs are calculated after each leg and are accumulated across the life cycle of the vessel.

$$R(s) = min(f + o + c) \tag{5}$$

- f, the *fuel cost*, is calculated via Equation 6. b is the fuel consumption, d is the number of days at sea, e is the fuel price, and p is a given percentage. p accounts for either the size of the ECA coverage or the dual fuel mixture.

$$f = b * d * e * p \tag{6}$$

- o, the *opportunity cost*, accounts for the lost potential revenue from the LNG fuel tanks.

- c, the *conversion cost*, is the cost of converting to a dual fuel LNG engine.

3.3. Monte Carlo parameters

Various economic, regulatory, and supply chain scenarios were modeled as part of the Monte Carlo simulations. The economic parameters that were varied include engine conversion costs, fuel prices, freight rates, and interest rates. The cost of converting to a dual fuel engine was estimated between $220/kW and $340/kW (Banawan et al., 2010). This estimate includes all the auxiliary equipment necessary to fully install and operate on LNG fuel. With an engine power greater than 67,000 kW, total engine retrofit cost was modeled with a uniform distribution between $14 million and $23 million.

The fuel prices for HFO, MDO, and LNG were assigned normal distributions with means of US $650/ton, $950/ton, $500/ton respectively, and standard deviations of US$50/ton. While more advanced fuel projection models exist, for the purposes of this case study, this fuel cost model is sufficient in showing both the utility of Monte Carlo simulations as well as conclusions regarding sensitivity of the fuel prices.

Freight rates were developed from historical data from UNCTAD (2014) shown in Figure 2. Rates from China to Rotterdam were modeled as a normal distribution with a mean of US$1500 and a standard deviation of US$285. Likewise, the rates from Rotterdam to China were also set as a normal distribution, however, with a mean of US$800 and a standard deviation of US$125.

In addition to the freight rate uncertainty, there is also uncertainty associated with the lost revenue stemming from installation of the LNG fuel tanks that reduce cargo capacity. To model this, the capacity for 244 TEUs is assumed to be lost to accommodate the required LNG fuel tanks and equipment. This lost capacity, however, may not necessarily lead to lost revenue potential. Ships are rarely fully laden due to market conditions or port draft restrictions (Almeida, 2014; Schuler, 2014). For this case, 244 TEUs represent less than 2% of total TEU capacity. According to Alphaliner (2015), the average vessel capacity for traveling from China to Northern Europe is 88% with a standard deviation of 7.5% (Figure 3). Back haul load capacities are typically much less in the range of 50-70% (Søndergaard et al., 2012). Thus, lost revenue only comes into play

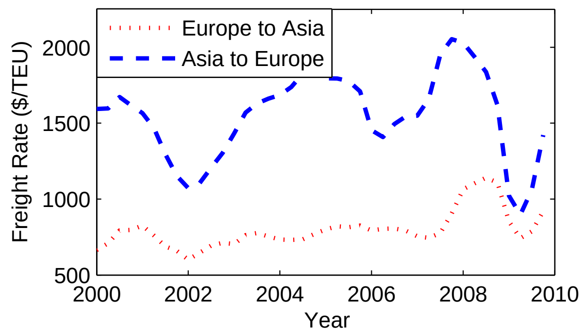

Figure 2: Historical average of freight rates (UNCTAD, 2014). The Monte Carlo simulations assumed a normal distribution of freight rates from Asia to Europe with a mean of US$1500 and standard deviation of US$285. From Europe to Asia the mean was set to US$800 with a standard deviation of US$125.

when market conditions dictate that vessel load conditions are above 98%. The Monte Carlo simulations were structured to match this.

Interest rates were modeled as a normal distribution with a mean of 7% and a standard deviation of 1%. The discount factor used in the MDP is related to the interest rate by Equation 7 (Puterman, 2005) where i is the interest rate and γ is the discount factor.

$$i = (i/\gamma) - 1 \tag{7}$$

Modeling the regulatory uncertainty was more difficult due to the challenge in quantifying the probability of when the ECA regulation will actually change. The attempt at quantifying this uncertainty stems from the desire to examine its sensitivity on the recommended decisions, as opposed to claiming that this particular uncertainty model is actually how the regulations will behave. At the start of the simulation, ECA covers 1100 nm of the total route. The specific year in which the ECA coverage increases from 1100 nm to 6800 nm varies depending on the simulation run. The range is uniformly distributed between 3 years and 10 years. There is also uncertainty associated with whether the regulation actually changes at that given year. This uncertainty is uniformly

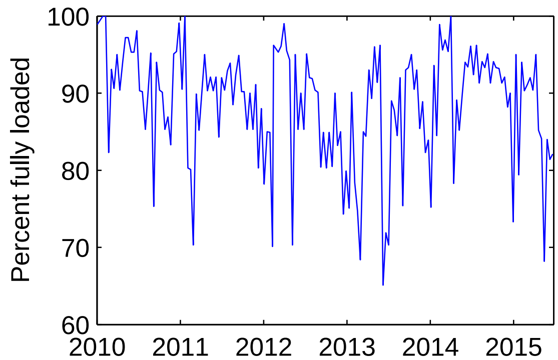

Figure 3: Average vessel load factors from 2010 to 2015 (adapted from Alphaliner (2015). Vessel load factors have averaged 88% with a standard deviation of 7.5%.

distributed between 0% and 100%. For example, one scenario may be that there is a 75% probability that the ECA regulation will increase 5 years from now.

While infrastructure and regulations are being developed for LNG bunkering facilities, there is great uncertainty whether the fuel will be available should a ship go into port and want to purchase LNG. While other literature aims to quantify this development (Danish Maritime Authority, 2012; Lee, 2014), this research is instead focused on the implications of supply chain risk on the decisions. To simulate supply chain risk associated with uncertainty of LNG availability, the probability of obtaining LNG in Rotterdam is modeled uniformly between 50% and 100%, while the probability of obtaining LNG in China is uniformly distributed between 0% and 100%.

4. Results

Three sets of results were explored, covering an examination of the decisions, the economic costs, and the specific design drivers leading to both the decisions and economic costs. Before examining the results, the system was tested for convergence using Equations 3 and 4. For each simulation run, there is some uncertainty that at any given time the system may be in a given state or that a given action may be selected. This uncertainty is in the set [0, 1], and a

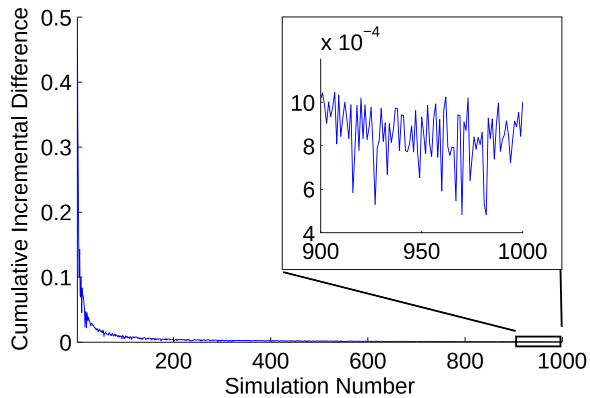

Figure 4: Convergence of the Monte Carlo simulations. The close up shows that after 1000 simulations, the model has consistently converged to a value less than $10 * 10^{-4}$, which is deemed an acceptable range.

running average of this uncertainty is calculated for each successive simulation run. The cumulative incremental difference between the i^{th} simulation run and the $i^{th} - 1$ run is then calculated. For Figure 4, the maximum cumulative difference between all actions, all states, and all speeds is plotted. As is shown, 1000 simulations were run to ensure confidence of convergence. The inset of the figure shows that after 1000 simulations the model has consistently converged to a value less than $10 * 10^{-4}$, meaning that the probability of being located in any given state or taking any given action varies by less than $10 * 10^{-4}$ for each additional simulation run. Since the uncertainty variables in this model have only been estimated to a value of $10 * 10^{-3}$, the authors have deemed this acceptable convergence.

4.1. Decisions

The key decision defined in this problem is not just whether the ship owner should convert to an LNG engine, but also when it may be best to perform the conversion. The SC-MDP is able to identify when specific actions are preferred throughout the life cycle of the vessel (see Equation 1), while the Monte Carlo simulations provide the likelihood that a given operating environment may be

Table 3: Percent of time a given action is optimal. The "convert engines eventually" action means that it is best to convert to an LNG engine at a time after the first two voyages.

Speed (kts)	Never convert engines	Convert engines as soon as possible	Convert engines eventually
12	67%	33%	0%
14	30%	70%	$< 1\%$
16	8%	92%	$< 1\%$
18	3%	96%	$< 1\%$
20	$< 1\%$	99%	$< 1\%$
22	$< 1\%$	100%	0%
24	0%	100%	0%

in place to yield such actions. Thus, the model presented in this paper enables the ability to identify the percent of time a given action is optimal, and when throughout the life cycle of the vessel it may be optimal. To show this, Table 3 presents the percent of time it is optimal for the vessel to (a) never convert engines, (b) convert engines as soon as possible, and (c) convert engines eventually. "Convert engines as soon as possible" is defined as converting the engines within the first two voyages, while "convert engines eventually" is defined as converting engines at some point after that. "Convert engines eventually" is included to account for those situations where it may be best to hold off on converting the vessel until the ECA regulation has increased.

As speeds are increased, the probability that it is best to convert engines increases. For 12 knots it is best to keep the single fuel engine for 67% of the simulations, and this percent drops significantly with only a small increase in speed. For 16 knots and faster the percent of time it is best to keep the single fuel engine is less than 8%, and at the highest speed of 24 knots, it is never optimal to keep the single fuel engine. The probability that it is best to convert to a dual fuel LNG engine as soon as possible follows nearly the exact opposite trend, with the probability increasing with increasing speed. Rarely is it preferable to delay converting the engines. Kana et al. (2015) discussed in detail the situations where it is preferred to convert engines later in the life cycle, such as when the regulation changes. This analysis, however, shows that those situations are rare, occurring less than 1% of the time in only four of the speeds tested. No matter the speed, there is always a possibility that converting to an LNG engine is preferred; however, as the speed increases eventually there is a point where it is never preferred to keep the single fuel engine.

4.2. Economic Costs

Understanding what decisions will likely be made is only part of the problem; the decision maker must also understand the range of costs that are likely to occur given each decision scenario. The expected net present life cycle costs are given in Figure 5, as calculated by Equation 2. Figure 5a shows the results for a speed of 12 knots, where it is clear there is a large spread of potential costs, given differing starting scenarios. The large beige region signifies the extreme limits, displaying the maximum and minimum, while the blue region shows one standard deviation above and below the mean. The high costs at year zero come from the conversion costs during those situations when it is best to convert to an LNG engine as soon as possible. The solid black line is the mean cost, while the dashed red line is the median cost of all simulations.

Figure 5b shows the costs for a speed of 22 knots. Even at the higher speeds, there is still a possibility that it is best to keep the single fuel engine installed. This is shown by the small beige area around US$0 during the first year. This is also shown in Table 3, where it is apparent that this situation occurs $< 1\%$ of the simulations. The costs for speeds of 14, 16, 18, and 20 knots follow a similar trend as that of 22 knots, however, their specific values vary with the speed. Figure 5c shows the costs for 24 knots, where it is apparent that it is never beneficial to keep the single fuel engine installed.

The final accumulated life cycle costs after 20 years for all speeds is given in Figure 6. The edges of the box represent the 25th and 75th percentile respec-

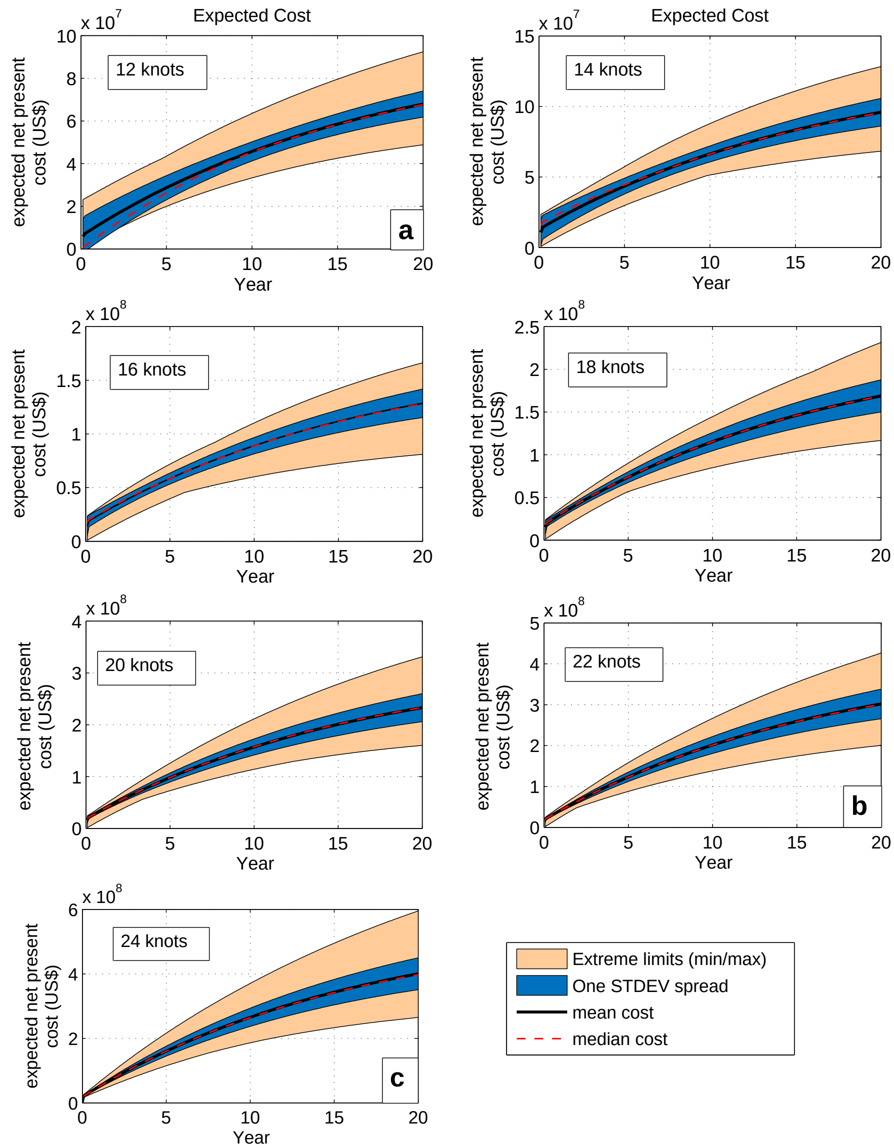

Figure 5: The expected net present cost (US$) for the range of speeds. (a) shows the expected range of costs for the slowest speed tested of 12 knots. (b) shows the range of potential costs for a high speed of 22 knots, where there is a small possibility that is it preferable to keep the single fuel engine. (c) displays the costs for the highest speed of 24 knots where is always preferable to switch to a dual fuel engine as soon as possible. Note the variations in the y-axis between figures to show specifics within each speed.

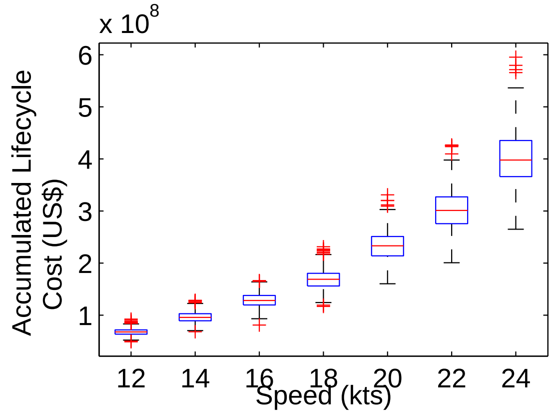

Figure 6: The accumulated life cycle cost varies greatly both between speeds and within individual speeds. The spread of possible costs grows both in magnitude and in percent as speeds increase. Outliers tend to fall on the upper end of costs for the faster speeds.

tively, while the centerline is the median. The red marks that extend beyond the whiskers are labeled as outliers that fall outside 2.7 standard deviations of the data. As seen, the costs do not grow linearly with speed, instead they increase similar to the speed power consumption curves given in Figure 1. The variation of costs within each speed is large, and increases with increasing speed. That is, for a speed of 12 knots, there is just over a 45% variation between the lowest possible cost and the highest cost, while at 24 knots, that variation grows to nearly 68%. Thus, both the percent variation and the gross magnitude of the variation grow with increasing speed. For 12 knots, the variation is between US$52 million for the lowest cost and US$83 million on the high end with a median of US$68 million. For 24 knots, that variation increases to a minimum of US$265 million for the lowest cost and US$536 million for the highest cost with a median of US$400 million. Finally, the outliers for the faster speeds all lay on the high end of the costs. Since these costs were calculated via the MDP model, each result is considered the best scenario given the set of inputs. Thus, should a decision maker not follow the best decision pathway, they can expect their costs to be higher than what is displayed here.

Table 4: Average savings and payback periods for all speeds. Savings are increased and payback periods are reduced as speeds are increased.

Speed (kts)	Average savings (US$MM)	Average payback period (years)
12	2	18.1
14	7	14.4
16	16	10.6
18	29	7.5
20	49	5.1
22	76	3.5
24	108	2.7

For each speed the average savings and time to pay back the engine conversion costs was calculated against a baseline scenario where the vessel continues to operate on a single fuel engine throughout its life cycle and alternates between operating on MDO and HFO fuel. This calculation only accounts for those simulations where it is best to convert to an LNG engine. Thus, for situations where converting engines is only preferable a small portion of the time, the savings only account for those times when it is preferable to convert engines. As shown in Table 4, for speeds less than 16 knots the average savings are less than US$16 million with a payback time of longer than 10 years. For the highest speed of 24 knots, the savings are over US$100 million with a payback of less than 3 years. Due to the large variation in costs, the actual savings and payback period may vary from this average.

4.3. Decision Drivers

Sensitivity studies were performed on the ECA regulation, the supply chain risk, and the fuel prices to determine the drivers behind the decisions. The analyses were performed by holding constant each parameter except the variables of interest. The constant parameters were fixed near their designated mean value, as given in Table 5. 1000 simulations were run for each sensitivity test to remain consistent with the original analysis. Since there is inherently has less total variation in the model for the sensitivity runs, 1000 simulations also provide sufficient convergence.

4.3.1. ECA Regulation Sensitivity Study

The ECA regulation sensitivity showed clear results. First, there is no variation in the individual speeds in regard to the best decision. A clear bifurcation becomes apparent at 14 knots (Table 6). Below 14 knots it is always best to maintain the single fuel engine, while at and above 14 knots it is always best to convert to a dual fuel LNG engine. There were no instances during this study when it is best to delay converting engines beyond the first two voyages. This study also showed almost no variation in the cost both through the life cycle, and as a cumulative amount (Figure 7). The median cost for each speed remained unchanged in this study. Thus, this study shows that the variation in the results, both in the decisions and the costs, is not due to the uncertainty in the ECA regulation implementation. There were no significant changes in the average savings or payback period as compared to the full analysis. This result that uncertainty regarding the regulation is not a significant driver of the decision to convert to LNG power agrees with the results by Rehn et al. (2016), even though they used a different mathematical model.

4.3.2. LNG Supply Chain Risk Sensitivity Study

The effect of the LNG supply chain risk was tested as to its impact on the results. The decisions are similar to that from the full simulation (Table 7). For the slow speeds of 12, 14, and 16 knots, the probability of it being best to never convert engines is reduced between 3% and 13%, thus increasing the probability it is best to convert engines as soon as possible. For 18 knots and faster, the results were very similar to the original results, varying at most 3% from the original simulation. No instances arose where it is preferable to delay retrofitting the engine until later.

Varying the availability of LNG in port causes a large spread in life cycle

Table 5: Parameters used for the sensitivity studies. The variables for the regulation and LNG supply chain sensitivity were uniformly distributed, while the fuel price sensitivity used a normal distribution.

Parameter	ECA Regulation Sensitivity	LNG Supply Chain Sensitivity	Fuel Price Sensitivity
Engine conversion cost	\$18.8M	\$18.8M	\$18.8M
Interest rate	7%	7%	7%
Lost TEUs to fit LNG equipment (to Rotterdam)	18	18	18
TEU freight rate to Rotterdam	\$1,500	\$1,500	\$1,500
TEU freight rate to China	\$800	\$800	\$800
Probability of obtaining LNG in China	0.5	[0,1]	0.5
Probability of obtaining LNG in Europe	0.75	[0.5,1]	0.75
HFO price	\$650	\$650	$\mu = \$650, \sigma = \$50$
MDO price	\$950	\$950	$\mu = \$950, \sigma = \$50$
LNG price	\$500	\$500	$\mu = \$500, \sigma = \$50$
Year ECA coverage may increase	[3,10]	5	5
Probability that ECA will increase at given year	[0,1]	0.5	0.5

Table 6: Sensitivity due to uncertainty in the ECA regulation implementation. For 12 knots it is always best to keep the original engine, while above 12 knots it is always best to convert to a dual fuel LNG engine as soon as possible.

Speed (kts)	Never convert engines	Convert engines as soon as possible	Convert engines eventually
12	100%	0%	0%
14	0%	100%	0%
16	0%	100%	0%
18	0%	100%	0%
20	0%	100%	0%
22	0%	100%	0%
24	0%	100%	0%

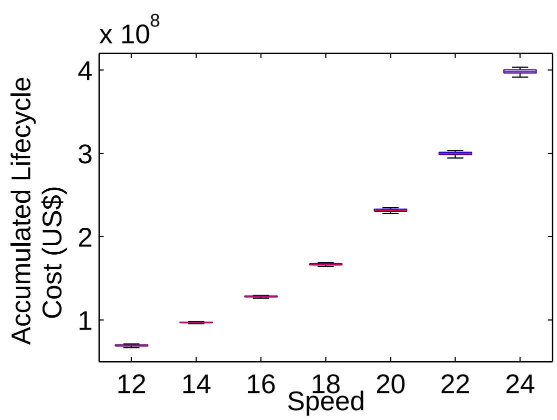

Figure 7: The sensitivity study on the ECA regulation showed almost no variation in the accumulated life cycle costs for individual speeds. The median cost for each speed, however, remained unchanged as compared to the original analysis.

Table 7: Sensitivity due to LNG supply chain risk. The probability of it being best to never convert engines is reduced between 3 and 13%, compared to the original analysis.

Speed (kts)	Never convert engines	Convert engines as soon as possible	Convert engines eventually
12	64%	36%	0%
14	17%	83%	0%
16	2%	98%	0%
18	0%	100%	0%
20	0%	100%	0%
22	0%	100%	0%
24	0%	100%	0%

costs (Figure 8). This variation, however, does not account for the full variation that is present in the original simulation. The percent variation for 12 knots is just over 10%, while for 24 knots the variation is only 36%. Across all speeds, the cost variation only accounts for just over 60% of the total variation shown in the full simulation. There are also very few outliers. Lastly, as with the ECA regulation sensitivity study, there were no significant changes in the average savings or payback period as compared to the full simulation.

4.3.3. Fuel Price Sensitivity Study

The fuel prices were tested as to their effect on both the decisions and the life-cycle costs. This study revealed that fuel price variation is one of the reasons it may be best to delay retrofitting the engine until after the first two voyages (Table 8). Sensitivity studies on the ECA regulation and LNG supply chain did not reveal any instances when it would be best to delay retrofit, while this studied showed the opposite. Variations in the fuel prices displayed a similar trend to that of the original analysis, in that for speeds between 14 knots and 20 knots, there are instances-albeit rare-that delaying the engine retrofit is the best option.

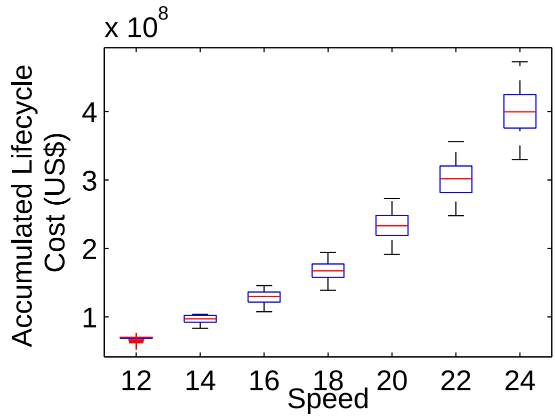

Figure 8: The sensitivity study on the LNG supply chain risk shows a slightly smaller spread than the original analysis. The median cost for each speed also remained unchanged as compared to the original analysis.

Table 8: Fuel Price sensitivity. Fuel price variability may be one of the causes leading to delaying engine retrofits beyond the first two voyages.

Speed (kts)	Never convert engines	Convert engines as soon as possible	Convert engines eventually
12	72%	28%	0%
14	11%	89%	$<1\%$
16	$<1\%$	99%	$<1\%$
18	$<1\%$	99%	$<1\%$
20	$<1\%$	$<100\%$	$<1\%$
22	0%	100%	0%
24	0%	100%	0%

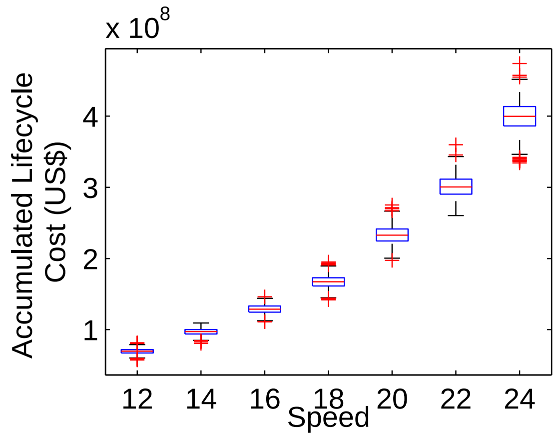

Figure 9: The sensitivity study on the fuel prices shows a slightly smaller spread than the original analysis. The median cost for each speed remained unchanged as compared to the original analysis.

This study also showed large variation in regard to the life cycle costs (Figure 9). Unlike the previous analyses, the variation here was consistent across all speeds, averaging between 25% and 29% between lowest and highest quartile. Combined, this variation accounts for roughly 70% of the total variation in the model. This sensitivity study also had outliers present, meaning that while most of the data is spread through a consistent distribution, variable fuel prices can lead to life cycle costs that are far outside what is expected. The result that uncertainty in fuel prices is a large driver for uncertainty in the decision to convert engines and life cycle costs agrees with the results of Rehn et al. (2016).

5. Discussion

There are several points worthy of discussion following the results of the model:

1. *This model is intended to provide insight into decisions concerning retrofits, not necessarily the decision itself.* It is still up to the individual decision maker to decide whether or not to follow the results of the model. For instance, it is not expected that the decision maker will actually follow

the results in situations where the savings are small and the payback time is long, as is the case for the slower speeds. As the savings increase and payback time decreases with higher speeds, it is at the discretion of the decision maker to decide for themselves whether they wish to convert engines or not.

2. *This model does not cover all uncertainties associated with converting a container ship to LNG power.* Despite giving the best decision pathway for each scenario, this model does not remove all risks that vessel owners face. As with all probabilistic models, there is still a chance that the actual situation may vary from the normal bounds of the results, possibly causing great economic harm.
3. *The model is dynamic.* It can be adapted to include any sub models for this given case study. It would be beneficial to include a more advanced fuel cost and freight rate model, supply chain risk model, and measured vessel fuel consumption curves for commercial use. While these underlying models appear simplistic, the overarching theory and methods still hold.
4. *There is more risk at higher speeds.* The spread of potential costs is much greater at higher speeds, increasing the risk. This is logical because there is greater fuel consumption at higher speeds, causing fuel price to have more effect.
5. *The specific case study provides key insights despite not being fully inclusive.* The case study did not account for the potential profit loss from slow steaming. Also, this paper only discussed decisions related to LNG fuel; however, other ways of meeting upcoming ECA regulations include the use of distillate fuels, or installation of scrubbers. Decisions are also severely impacted by whether the vessel is under charter, and the type of charter. These points do not, however, negate the applicability of the insights gained from the model.

The objective of this model was to provide the quantitative information necessary for helping decision makers plan for uncertain and evolving Emission

Control Area regulations.

6. Conclusion

This paper demonstrated how Monte Carlo simulations applied to the ship-centric Markov decision process can be used to help decision makers decide whether to convert a container ship to LNG power in the face of evolving Emission Control Area regulations. The SC-MDP model was used to identify when the decision to convert engine is preferred throughout the life cycle of the vessel as well as the life cycle costs associated with making those decisions. The study was focused on how to include operation considerations in regard to regulatory and technology uncertainties in the decision making process, as opposed to designing a specific vessel that can be adapted to future requirements in a cost efficient way. Monte Carlo simulations were used to move beyond individual probabilistic values that had limited previous applications of the SC-MDP model in approaching this problem. The Monte Carlo simulations enable a better stochastic analysis than individual probabilistic values. These simulations were also used to develop probabilistic distributions of not only the decisions themselves but also the life cycle costs associated with them.

New insights were gained regarding life cycle decision making for container ships facing upcoming emissions regulations. Uncertainty regarding the regulation showed to have little effect on when certain decisions should be made as well as contributing little to the uncertainty in the life cycle costs. Uncertainty over the availability of LNG as a bunker fuel and fuel prices showed to be more significant drivers causing large variations in the distribution of results.

Acknowledgments

The authors would like to thank Mrs. Kelly Cooper and the U.S. Office of Naval Research for their support of this research.

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